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# **Towards a River Twin: Operationalising Satellite Earth Observation for Large Scale, Rapid Revisit, River Monitoring**

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***“All the larger streams are mysteriously charming and beautiful, whether flowing in the mountains or through the swamps and plains. Their channels are interestingly sculptured, far more so than the greatest architectural works of man.”***

**John Muir**

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# Extended Abstract

Large river systems are a vital resource providing a multitude of ecosystem benefits, yet these rivers are under increasing pressure from anthropogenic activity and global climate change, threatening our use of these resources. There is a substantial disparity between the importance of river systems and our ability to monitor them, to support sustainable management. Many methods of monitoring are point-source based which can be expensive and lack spatial coverage resulting in discontinuity. Satellite Earth Observation has been shown to overcome this spatial limitation to monitoring river processes. However, until recently satellites, with sufficient spatial resolution, have lacked the revisit time to become dynamic monitoring tools for sustainable management. This thesis explores the potential of constellations of multiple satellites to provide high spatio-temporal measurements of these large river systems by focusing on three first order river variables; Surface water extent, hydrology, and river water temperature. From these first order variables, more characteristics of the river system and management scenarios can be derived. This is carried out to provide the foundation for a potential Earth System Digital Twin (ESDT) which is a system for near real-time monitoring of a river system to support management decisions.

Firstly, water surface extent 'masks' were required to measure the distribution of river water which varies dynamically with discharge and channel changes. To do this, the 130+ CubeSat constellation 'PlanetScope' was employed to provide almost daily imagery of the entire globe at 3 m spatial resolution. Traditional classification methods for optical imagery are inhibited by the high radiometric variability of these data, through its combining imagery from different times of day, atmospheric conditions, altitudes, and solar angles. In Chapter 3 artificial intelligence (AI) was used to develop a novel Convolutional Neural Network Supervised Classification which incorporates two different model formats to separate much of the radiometric variability out of the results. This model was tested on 36 rivers in 12 global biomes providing a median F1 accuracy score of 0.93. The difference was more marked in mean F1 score where there were fewer very poorly classified images, resulting in a mean F1 score 0.05 higher than the closest comparative model. This displayed both the generalisability of the model and the types of rivers and landscapes in which it did not perform well. Additional imagery was shown to improve transferability of the model to a new location with just 5 additional site-specific training images significantly improved classification accuracy (F1 increased from 0.81 to 0.90,  $p < 0.01$ ).

Secondly, using the AI-based methodology developed in chapter 3, a novel framework was used to measure the changes in water extent around in-channel river islands as a proxy for stage-discharge, thus providing a hydrological proxy as another first order

riverine variable. The study focused on the Madeira River, Brazil, comparing >2500 PlanetScope images. These results clearly demonstrated the ability of the methodology to monitor the inter-annual dry season as well as the extreme 2023 droughts. This methodology also enabled concurrent identification of the impacts of reduced river stage on shipping channels which significantly narrowed during the dry season by an average of 750 m. Moreover, 65% of AOIs formed isolated pools of river water (which could lead to ecological strandings).

Finally, the third first order component, river water surface temperature, is inherently linked to anthropogenic activity where river water is used for power generation. Two issues currently prevent water surface temperature monitoring by satellites, which has been studied extensively, from being operationalised. Firstly, thermal infrared satellites often lack the temporal resolution to monitor a component as dynamic as water temperature. Therefore, a constellation of constellations approach was undertaken where no single satellite provided more than 45% of the available data, combining imagery from multiple different thermal satellites in a modularised format which enables future satellites to be added to this quasi-constellation. Secondly, the higher spatial resolution PlanetScope imagery was used as an independent water mask to reduce the potential error of mixed land and water thermal pixels from returning erroneous results. This demonstrated the methodologies effectiveness at identifying the downstream thermal pollution effects from nuclear, coal, and hydropower generation with 2°C temperature spikes which persisted variable distances downstream based on individual facets of these river systems.

These chapters are used as the basis to produce the foundation from which an ESDT can be built by providing high spatio-temporal methods for transferable monitoring of large river systems. Rivers are highly variable therefore the methodology for each component cannot be effective in all river systems, but the individual chapters are tested in a variety of locations to assist the user in applying them only when appropriate. In the synthesis, these components were assessed against 5 key tenets to understand how they can be used within an ESDT and what is required to produce an operationalised end product. Despite the improvements made, there are limitations on the minimum width of a river that can be measured, and the improved temporal resolutions may still overlook dynamics within these observed components which cannot be overcome without development of additional satellite systems. Their modular methodology can be continually built upon with additional satellite launches and new artificial intelligence methods. The thesis calls for further application of these methods to complement regular in-situ monitoring to assist sustainable management.

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# List of acronyms in this thesis

|       |                                                           |
|-------|-----------------------------------------------------------|
| ANN   | Artificial Neural Network                                 |
| AMSHG | At Many Stations Hydraulic Geometry                       |
| CNN   | Convolutional Neural Network                              |
| CSC   | Convolutional neural network Supervised<br>Classification |
| DT    | Digital Twin                                              |
| ESA   | European Space Agency                                     |
| ESDT  | Earth Systems Digital Twin                                |
| EU    | European Union                                            |
| FCN   | Fully Connected Network                                   |
| GEE   | Google Earth Engine                                       |
| GSD   | Ground Sampling Distance                                  |
| LEO   | Low Earth Orbit                                           |
| LST   | Land Surface Temperature                                  |
| NASA  | National (USA) Aeronautics and Space<br>Administration    |
| NIR   | Near InfraRed (spectral bands)                            |
| RGB   | Red Green Blue (spectral bands)                           |
| SWIR  | Short Wave InfraRed (spectral bands)                      |
| TES   | Temperature and Emissivity Separation algorithm           |
| TIR   | Thermal InfraRed (spectral bands)                         |
| USGS  | United States Geological Survey                           |
| WST   | Water Surface Temperature                                 |

## **Satellite name acronyms**

|           |                                                                                        |
|-----------|----------------------------------------------------------------------------------------|
| ASTER     | Advanced Spaceborne Thermal Emission and<br>Reflection Radiometer                      |
| CBERS     | China-Brazil Earth Resources Satellite                                                 |
| ECOSTRESS | ECOsysteM Spaceborne Thermal Radiometer<br>Experiment on Space Station                 |
| LSTM      | Land Surface Temperature Monitoring                                                    |
| MODIS     | Moderate Resolution Imaging Spectroradiometer                                          |
| SBG       | Surface Biology and Geology                                                            |
| TRISHNA   | Thermal InfraRed Imaging Satellite for High-<br>resolution Natural Resource Assessment |

# Chapter 1: Introduction

## 1.1 Background and theory

Water is the world's most precious resource (Allan, 2011, Bidlack et al., 2004, Li et al., 2022c). Freshwater, and river water in particular, have long been understood as key resources for socio-economic development and environmental resilience (Hannah et al., 2011, Van Vliet et al., 2023, Anh et al., 2023, Ficklin et al., 2023). Access to freshwater is a basic requirement of life (Chaplin, 2001) and access to fresh and clean water is protected as a human right (UN, 2016). These socio-economic benefits derived from river water are feedbacks from the role of river systems as important ecosystem components - transporting nutrients towards the oceans (Wang et al., 2020a); providing habitat for ecosystems (Dauwalter et al., 2017, Li et al., 2022c); and providing supporting services on floodplains such as soil formation enabling current agricultural practices (Petsch et al., 2023). Direct benefits are also derived from anthropogenic use and management of river systems, including providing drinking water (Weber et al., 2017), power generation (through hydropower and traditional power generation cooling systems; Ahmad and Hossain, 2020, Guénand et al., 2023, Raptis and Pfister, 2016), and as a conduit to transport goods and raw materials (Vinke et al., 2022, Garcia et al., 2021).

Rivers are dynamic systems that are increasingly affected by anthropogenically driven climate change (Cammalleri et al., 2020, Garcia et al., 2021). Natural processes such as flooding and channel migration drive this dynamism, yet these processes are responding to accelerated environmental change, threatening the sustainability of the freshwater resources and ecosystem services provided by river systems (Garcia et al., 2021, Guénand et al., 2023, Johnson et al., 2024, St-Hilaire et al., 2021, Van Vliet et al., 2023, Wasti et al., 2022). Anthropogenic alterations to river channels and their catchments, such as channelisation and land use change, further exacerbate these processes and pressures (Piégay et al., 2020, Goudie and Viles, 2016, Ekka et al., 2020). These combined pressures result in risks to life, property, and these outlined resources (Kam et al., 2021, Elsayed et al., 2024) as humans attempt to co-exist with river systems (García et al., 2021, O'Donnell, 2020). Riverine flooding and channel migration globally cause the costliest natural disasters, inflicting loss of life and damaging property (DeVries et al., 2020, Leenman et al., 2023, Merz et al., 2021, Siddik et al., 2017). When drought events impact river systems they can close shipping channels (Cammalleri et al., 2020, Garcia et al., 2021), reduce power outputs

(Shuai et al., 2024), and combine with warm water to produce algal blooms destroying water supplies (Chapra et al., 2017). Therefore, rivers need to be managed carefully through policy (Nóges et al., 2009), regulation (Farid Ahmed et al., 2023), and industry to minimise risk and manage the competing demands of water resource availability which is vital for managing the competing demands of industry and society (Van Vliet et al., 2013).

In order to manage rivers, it is clear an increased understanding of river dynamics and the ability to monitor these river systems should be at the forefront of research and policy development (Piégay et al., 2020, Torgersen et al., 2022). Monitoring river systems provides the impetus for management to adapt with the dynamism of the river system. For example, altering hydropower releases during dangerously high precipitation events by drawing down reservoirs to provide space for flood pulses, or storing additional water to cope with predicted low flow events (Zeiringer et al., 2018). These hydropower operations can even use the thermal stratification (whereby deeper water is cooler) inherent to deep reservoirs to release cold water during heat waves helping to combat increased river temperatures (Poff, 2018, Pfeifle et al., 2024, Weber et al., 2017). Monitoring can help identify and reduce practices that pollute rivers, risking drinking water potability and ecological degradation (Weber et al., 2017, Van Vliet et al., 2023). However, rivers exhibit high rates of spatial and temporal change and travel through expansive regions making them difficult and expensive to monitor in-situ, especially over an extended period of time. For many locations this has resulted in disparate data or an overreliance on theoretically modelled knowledge (Hannah et al., 2011, Sheffield et al., 2018). Since its inception, remote sensing has been used as a method to combat the difficulties in monitoring the 2 million kilometres (Altenau et al., 2021) of large rivers in the world (Hasan et al., 1956, Hemati et al., 2021). Sensors on board aeroplanes, helicopters, and now uncrewed aerial vehicles (UAVs: commonly known as drones) have progressively reduced the cost and increased the accessibility of collecting monitoring information. While these data capture technologies may provide more options for river managers, they are often still unaffordable and for large river systems, they are limited in their spatio-temporal resolution. All these methods described also only collect a single snapshot in time and therefore, without large resource inputs, struggle to capture the dynamism inherent in river systems.

Here, this thesis follows monitoring trends that look to fill this knowledge gap with Earth Observation (EO) techniques (Piégay et al., 2020, Tomsett and Leyland, 2019), relying on satellite sensor platforms. Methods for monitoring rivers with EO data have existed since the 1970's (Hemati et al., 2021) but they pose their own suite of unresolved issues, some of which this thesis attempts to address. Many riverine components have been measured from space, with a resurgence in research driven by an increase in delocalised computing power and higher spatial and temporal

resolution data capture (Palmer and Ruhi, 2018, Boothroyd et al., 2021b). For the most part these are proof-of-concept, or purely scientific, studies which are lacking research into how to convert the outputs into operational products for users without advanced training in EO (Sudmanns et al., 2020). Many of these studies maximise the effectiveness of EO observations by combining them with in-situ, or aerially captured, datasets (e.g., Freitas et al., 2024) but these are often not available to users, especially in the global south (Sibanda et al., 2021, Crochemore et al., 2020). Whilst these datasets are valuable and provide context and closer observation (Torgersen et al., 2022), the framework for a method of riverine observations should be constructed independently of these sources so it can be used by all parties, with an ability for individual practitioners to include more specific datasets when available.

To operationalise these satellite images for practitioners to gain insights into river systems specialised to their needs, it is proposed that this framework take the form of an Earth Systems Digital Twin (ESDT). ESDTs are a real-time data assimilated vision of a system which could be harnessed to fill this niche in which academic methods are made accessible to end-users (Hoffmann et al., 2023, Wu et al., 2023). One of the key tenets of the current definition of an ESDT is its ability to deal with so called 'big data', such as that produced from EO satellites (Li et al., 2023a). ESDTs can take advantage of progress in deep learning which is now more capable of reaching the high dimensionality, complexity and non-linearity of real life earth systems (Li et al., 2023a). There are many 'geographical processes' ESDTs (e.g., floods, climate change, or weather) under construction including whole earth system twins from NASA (Le Moigne, 2023) and the EU (Hoffmann et al., 2023, Nativi et al., 2021). However, many of these focus on planetary scale processes using 1 km grid cells, whilst other ESDTs are specific to certain areas and again require expensive data sources that others might not have available (Li et al., 2023a, Brocca et al., 2024, Rao et al., 2023) especially in the form of high powered computing that has become a major ESDT factor (Li et al., 2023a). Instead, I propose a framework for building an ESDT which can be copied and adopted into different river basin management plans (Farid Ahmed et al., 2023, Schepel, 2024), that is flexible, and that does not require significant local computing power. The development of such an ESDT is potentially beyond the scope of a PhD thesis, because there are too many variables in a river system to all be included as components in an ESDT and to do so would result in a high degree of redundancy (Olden and Poff, 2003, Cruz and Silva, 2024). However, it is argued that the problem can be narrowed down to the three main river variables, which could be later integrated into an ESDT, so called first order variables that drive a river system (Carbonneau et al., 2012); these are the dynamic extent of the water surface, its hydrology, and its temperature (Carbonneau et al., 2012, Caissie, 2006). Once these three have been included in an ESDT as components, they can be used to describe riverine water quality, quantity, further ecosystem services, and the risk posed by these rivers making

these components the most effective way to operationalize the use of satellite data. These three components can be used to assist the deriving of further 2<sup>nd</sup> and 3<sup>rd</sup> order components, such as resource availability, water quality, or infrastructure risk (Singh, 2022, Ellis et al., 2024, Maniatis et al., 2020). Therefore, by building the EO framework for these processes, an ESDT could be constructed from these for any large river basin with future additional desired components built on the results of those components provided here.

## **1.2 Research aim and objectives**

### **1.2.1: Aim**

This thesis aims to explore how first-order river variables can be measured and monitored from EO, with sufficient spatio-temporal resolution to provide the foundation for the needs of a transferable (between river systems) ESDT. This aim will be achieved via four key thesis objectives:

### **1.2.2: Objectives**

1. Develop an automatable model tailored to PlanetScope imagery to extract river masks of water extent and test this model globally on large river systems in different landscapes to identify its versatility.
2. Analyse spatio-temporal changes in water surface extent using methods developed in (1), taking water surface extent as a proxy for sediment exposure and thus assess the degree to which stage/discharge resulting from low flow extremes influence drought impact.
3. Operationalise a semi-automated satellite-based river water surface temperature monitoring system, using the findings from 1 and 2 to maximise the availability of river temperature data from a pseudo-‘constellation’ of thermal imaging satellite systems and use this system to measure anthropogenic impact on river water surface temperature caused by power plants in three major rivers.
4. Evaluate how objectives 1-3 have furthered the development of a river systems ESDT that can be deployed by river managers and stakeholders and assess what else needs to be done to complete such an ESDT.

### 1.3 Thesis structure and rationale:

The rationale used to select these four research objectives to meet the defined thesis aim is presented here and then expanded upon in Chapter 2, where a full theoretical basis is provided by a literature review chapter. In order to meet these objectives, three research chapters are presented, written and submitted as self-contained academic articles (Chapters 3, 4, and 5), each of meeting one of the first three objectives. Chapter 6 will subsequently present a synthesis of the research carried out to meet the final research objective and present future research directions (Fig. 1.1).

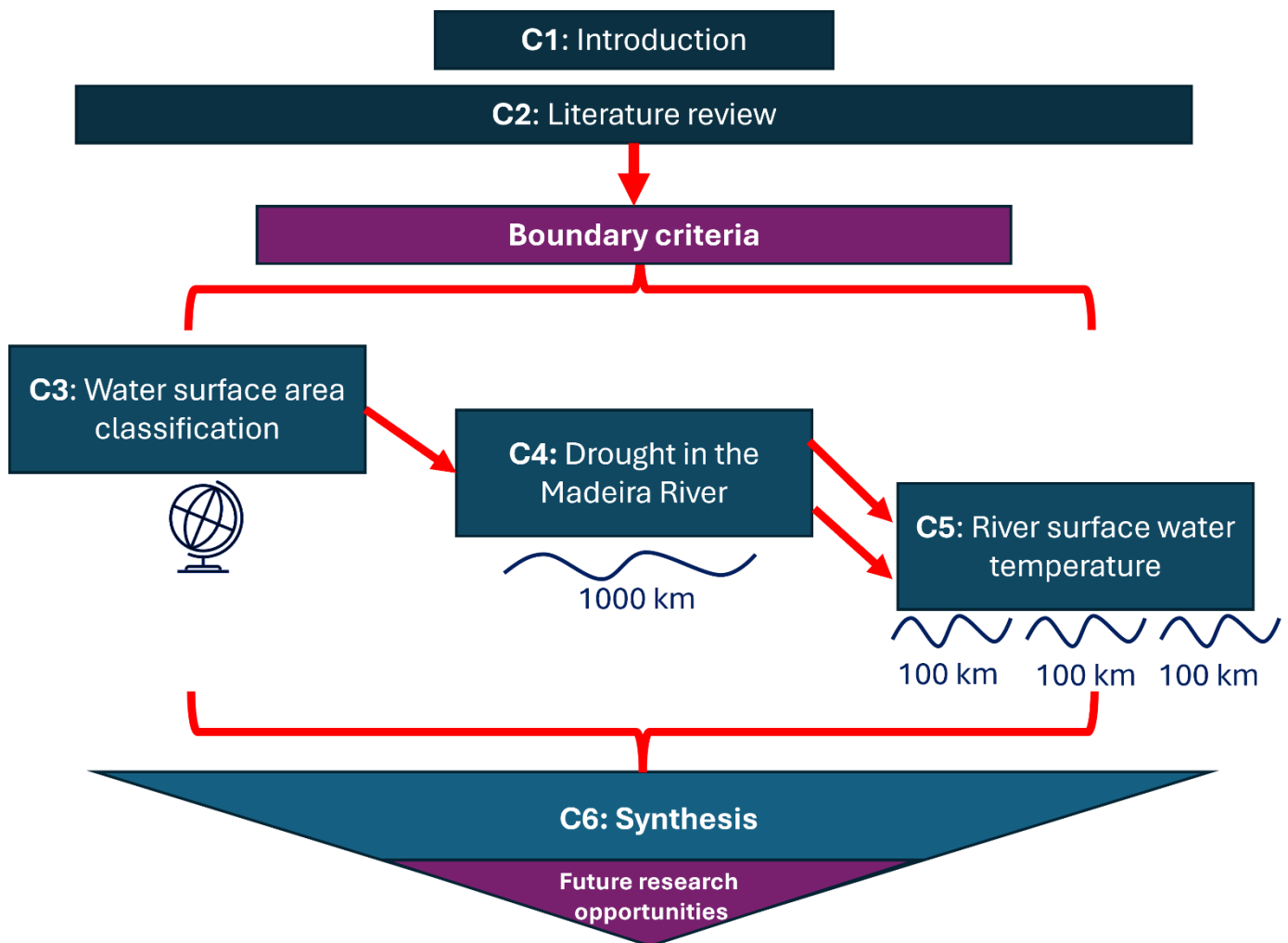


*Figure. 1.1: Graphical representation of this thesis structure. Theoretical basis is provided by the first two chapters producing boundary conditions which define the three analysis chapters. These chapters are modular but build upon one another progressively. The final synthesis chapter evaluates these analyses chapters, and the further research required to produce a river systems ESDT.*

These chapters produce the foundation for an ESDT of river systems and therefore the methodology chosen has some boundary criteria. These criteria are presented here,

but the rationale behind these is established in Chapter 2, section 2.2. First, they should not rely on regional, national, or in-situ datasets. Instead, this thesis focuses on regularly captured EO imagery, that can be applied to almost any region without requiring a data collection framework on the ground. In a similar vein, all the methodology should use open-source software, including Python, QGIS (Baghdadi et al., 2018), and Google Earth Engine (Boothroyd et al., 2021b, Gorelick et al., 2017). This enables future projects to build on the work carried out here and incorporate their own local data in the future. This thesis will focus on rivers with 'wetted' widths over 90 m, which is the standard EO practise (Handcock et al., 2012, Hori, 2021). This minimum river width limits the potential error while encompassing a considerable number of global rivers with vast variability (Frasson et al., 2019). These larger rivers are also disproportionately important for industry and society (Sadoff et al., 2002, Ducruet and Wang, 2018, McDermott and Nilsen, 2014, Raptis and Pfister, 2016) which is why they are focused on.

The first research chapter (Chapter 3) will focus on the development of a robust, repeatable method to map water surface area, to achieve objective 1. There are many existing methods, with a spectrum of different complexities, to extract river surface water "masks" from satellite imagery (Freitas et al., 2024, Xu, 2006, Foody et al., 2005, Hao et al., 2024). However, the majority of the satellites used have temporal resolutions of 5-16 days or spatial resolutions of >100 m for those satellites with higher temporal resolutions (USGS, 2019, USGS, 2021, Mansaray et al., 2021) making it difficult to capture fine-scale spatio-temporal changes, where small variability can have large consequences across a river system. Therefore, Chapter 3 undertakes to develop a water masking technique to use with the PlanetScope CubeSat Constellation, which provides daily imagery of the whole earth at 3 m resolution (Junqueira et al., 2021, Planet, 2018). However, it does this with 130+ satellites in different orbits, over different atmospheric conditions, with 'off the shelf' sensors resulting in images with highly variable radiometric quality (Frazier and Hemingway, 2021). These radiometric challenges inhibit many of the traditional methods of water mask extraction therefore a specific method to manage these problems was built PlanetScope imagery, with findings that can have implications for future CubeSat constellations that are currently proliferating (De et al., 2022). The method uses Artificial Neural Networks in combination with Convolutional Neural Networks (Carbonneau et al., 2020, Marochov et al., 2021) to understand imagery in a global context. The method was tested on 12 biomes around the world to show its applicability to different landscape conditions. Many deep learning researchers are concerned about the need for large amounts of labelled data (Reichstein et al., 2019, Zhou, 2018) and therefore the methodology was designed to require limited label data which can be added to and fine-tuned by non-experts.

The purpose of Chapter 4 was to address objective 2 by using the methodology developed in Chapter 3 and demonstrate its use to quantify space-time dynamics in river water surface extent. The extreme 2023 riverine drought (and its impact on fisheries and shipping) in the Madeira River, Brazil was therefore used as a case study (Garcia et al., 2021, Reuters, 2023). Traditionally, to measure drought river managers rely on fixed gauging locations or modelled discharges based on weather conditions because non-contact remote sensing methods of monitoring river discharge are difficult to develop and implement (Dolcetti et al., 2022). By using the Madeira River as a case study, it was possible develop a method for monitoring low flow events by measuring high temporal variability in exposed in-stream sediment around islands and bars in the river. This enabled measurements of drought impacts throughout the river system rather than at a single gauging point. It produced a proxy for river stage but also a direct method to view the impact of the ongoing drought through the identification of locations of channel constriction and isolation of pools of river water from the main channel. To do so, 2800 PlanetScope images were used to map water surface extent and thus drought impacts on a 1000 km stretch of river, the most of any study of its kind, providing an example of how indicators of drought and stage can be generated via high temporal and spatial resolution satellite images, even in data-sparse regions such as the Madeira River.

The third research chapter (Chapter 5) builds on the findings of the previous chapters to explore Objective 3 by developing a method for improved spatio-temporal monitoring of river temperature from space by using a novel 'constellation of satellites' approach. The PlanetScope methodology from the first and second data chapters is used to map pure water pixels in a collection of rivers where water surface temperature is expected to be influenced by anthropogenic activity. For the first time, this thermal infrared data for river systems is combined from Landsat collections 7, 8, and 9 (Zhu et al., 2019, Ermida et al., 2020), ASTER (Despini and Teggi, 2013, Jiménez-Muñoz and Sobrino, 2009), and the ECOSTRESS mission (Hulley et al., 2017) to provide higher spatio-temporal resolution coverage of water temperature in target rivers than could be achieved via a single satellite system. The modular development of this approach enables future thermal satellite missions to be incorporated into this monitoring tool regardless of their band characteristics, such as government-funded non-open-access satellites (e.g., CBERS; Zhang et al., 2005), proprietary high resolution thermal imaging sensors when they are launched (e.g., HotSat-2; Satellite Vu, 2022, Lalli et al., 2022), as well as further upcoming satellite missions upon launch (e.g., McKinley et al., 2022). This is possible because this novel methodology enables the tasks of segmenting pure-water pixel masks and the extraction of the thermal data (including the atmospheric correction) to be isolated from one another.

Chapter 6 addresses objective 4 of the thesis, by providing a synopsis of the results of the three data chapters and demonstrating how they tie together to provide operational practices for sustainable river management. This evaluated the progress made towards the foundational needed to develop a river systems ESDT and the steps that would need to be undertaken to construct an ESDT dashboard with products for different uses. Chapter 6 discusses how well the research has met these four objectives and in turn the overarching research aim. In doing so, this chapter analysed how the findings from the proceeding chapters have presented limitations that will need to be solved in order to develop a fully operationalised ESDT. Some of the results from the three analysis chapters also present unexpected opportunities to develop additional components from EO data which are outlined as potential avenues for future methodological and research advances in the field.

# Chapter 2: Literature Review

## 2.0 Introduction

This literature review begins by discussing the importance of monitoring rivers, establishing the rationale for the research, and outlining potential beneficiaries (2.1). Next the digital twin paradigm is introduced to develop boundary conditions for the methodology (2.2). These boundary conditions are then reviewed in the context of available satellites and software (2.3). Finally, the river variables that can be monitored by satellite are examined (2.4), with an emphasis on the methodologies previously applied to the three variables selected for this these (2.5).

## 2.1 Importance of monitoring rivers

Monitoring river systems is important to understand how they function and change over time as well as to provide early warning systems (Siddique et al., 2023) and tailored decision support to managers and operators (Brocca et al., 2024). Therefore, the ecological importance, ecosystem services, and socio-cultural-economic benefits, and disaster risk need to be understood to direct this monitoring. These factors are heavily interlinked, with multiple feedback loops, and therefore should be considered holistically whenever possible to provide impetus for river monitoring (Brauns et al., 2022, Johnson et al., 2020, Brierley and Fryirs, 2013). All these components should also be viewed within the lens of the degradation that has occurred to rivers during the thousands of years that human management has altered both river channels themselves and the catchments they sit in (Goudie and Viles, 2016, Brauns et al., 2022), which may have left some river systems more altered than previously thought (Walter and Merritts, 2008, Brown et al., 2017) and biodiversity at a potential crisis point (Albert et al., 2021). Therefore, within a decade of this thesis being published it is likely that many of the ecological properties, ecosystem services, management regimes, and methods of dealing with risk will have changed beyond recognition but it is hoped that these changes will have been monitored and recorded as they occur.

### 2.1.1 River ecology

Rivers are fundamental ecosystems that support vast biodiversity and provide habitat for fish, macroinvertebrates, macrophytes as well as, perhaps surprisingly, supporting terrestrial flora and fauna up to a kilometre from the river channel (Pugh et al., 2022, Hauer et al., 2016, Reid et al., 2019; Fig. 2.1). These rivers act as conduits to water and nutrients supporting life across landmasses (Fassoni-Andrade et al., 2021), all the

way to coastal waters where rivers feed oceanic ecosystems (Milliman and Farnsworth, 2013).

Rivers only encompass about 0.35 % of the Earth's non-glaciated surface (Allen and Pavelsky, 2018) yet along with lakes harbour 12% of the world's animal species (Master et al., 1998). The species that make up riverine ecology do not just inhabit these streams but shape their hydrogeomorphology and therefore the landscape (Johnson et al., 2020). Small invertebrates such as the caddisfly can disproportionately alter the hydrology and sediment dynamics of rivers by tying sediment together (MacDonald et al., 2021). While at the other end of the spectrum, planform can be directly linked to vegetation dynamics (Boothroyd et al., 2021a) and may even be the basis for the types of planforms seen around the world today (Gran and Paola, 2001). Other species are considered keystone species for their environments such as beaver which are ecosystem engineers who build dams and waterways which can control river discharge and provide wetlands for a variety of species (Fairfax et al., 2023). Other Keystone species bring nutrients into otherwise disparate habitats such as Salmon moving upstream from the ocean to the headwaters to breed and then die (Woodward et al., 2021).

Therefore, before considering the ecosystem services and risks these species are under, it is important to understand that the foundation of these environments is the ecology that they support and in turn shapes them.



*Figure. 2.1: Figure adapted from (Hauer et al., 2016) describing the wide-reaching influence of river systems supporting terrestrial and aquatic species to provide a nexus for biodiversity. These are important in their own right but also provide ecosystem services such as fire protection, food, and fuel. Examples of these services provided have also been included.*

### 2.1.2 Rivers at risk

Despite the ecological diversity and importance to ecosystem function of river systems, anthropogenic influence on the function of these systems has caused them to reach crisis point (Albert et al., 2021). These anthropogenic influences are so consequential that the fundamental processes can be argued to now be human-driven, rather than eco-hydrological (Goudie and Viles, 2016). The combination of indirect global and regional anthropogenic climate change being overlaid with direct anthropogenic alterations of river systems results in a multitude of negative impacts (Goudie and Viles, 2016, Van Vliet et al., 2023, Ekka et al., 2020). These include blocking fish passage (Wu et al., 2019), polluting rivers (Xu et al., 2022), increased turbidity (Gardner et al., 2021), altered flow regimes (Arnell and Gosling, 2013, Ekka et al., 2020), increased river temperatures (St-Hilaire et al., 2021), and unsustainably abstracted water (Arthington et al., 2006). These increasing assaults on river systems (Albert et al., 2021; Fig. 2.2) inhibit ecosystem function (Brauns et al., 2022) which has left river systems at even more risk than terrestrial habitats (Albert et al., 2021, Johnson et al., 2024, Almond et al., 2022).

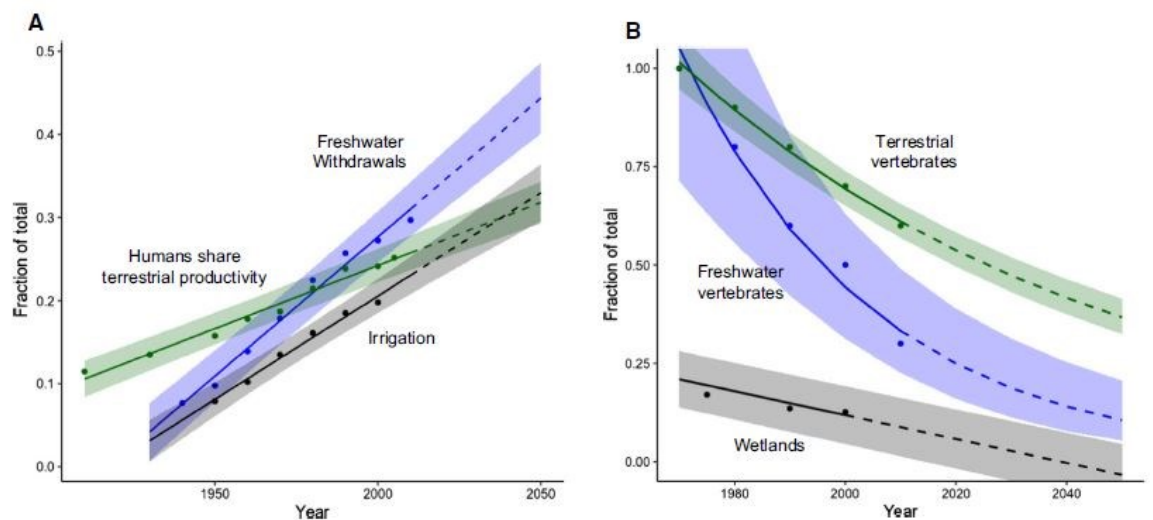


*Figure. 2.2: From (Albert et al., 2021) exhibiting the anthropogenic demands of freshwater resources (a) and the concurrent rapid decline of freshwater systems (b), even in comparison to the well reported decline of terrestrial systems. These factors highlight the increased need for monitoring these river systems.*

Monitoring river systems, their processes, drivers and the state of the ecology they support is clearly of importance to combat these risks (Kuehne et al., 2023). However, monitoring this damage is challenging, as it occurs across multiple spatial and temporal scales with issues as diverse as climatic change to the spread of invasive species (Ahmed et al., 2020, Goudie and Viles, 2016). Part of the challenge in addressing ecological degradation is the uncertainty of what an unharmed ecosystem would have consisted of (Friberg et al., 2016). Therefore, extensive monitoring should

be undertaken to help determine when and where different contentious restoration or management options should be undertaken and backed up with empirical evidence (Brauns et al., 2022). For example, one option is to accept the degree of degradation which has occurred has pushed rivers beyond a threshold, where the most biodiverse and sustainable option is to support new novel ecosystems (Erős et al., 2023, Morse et al., 2014) especially in large river systems that are looked at here which require more pragmatic management (Tockner et al., 2011). While monitoring and supporting improvements in these large rivers is difficult due to the multitude and scale of confounding drivers of river health (Thoms and Sheldon, 2019), large rivers are important and should be monitored extensively as small improvements are magnified along the river course (Buijse et al., 2002).

Finally, there is debate about the application of thresholds upon which anthropogenic activity initiates degradation (Hillebrand et al., 2020), whether these thresholds should be lowered when multiple pollutants occur in unison (Nikolaou et al., 2008), or whether thresholds should be replaced entirely by a conceptual continuum of impacts of the environment (Carbonneau et al., 2012, Fausch et al., 2002). This debate has shown that single studies using point-based in-situ measurements cannot sufficiently describe the interplay between influencing variables (Geissen et al., 2015). Instead it is proposed that more holistic monitoring efforts are required, layering process based information (Piégay et al., 2020) such as the first order physical variables of water surface extent, discharge and temperature (Fruget et al., 2001, Carbonneau et al., 2012) with the chemical and ecological data relevant to the more specific ecological assessment in question.

### **2.1.3 Ecosystem services**

Human civilisation is centred around river systems because these river systems provide ecosystem services integral to development (Wang and He, 2022). Riverine ecosystem services include drinking water, fisheries, agriculture and irrigation, and transporting or cleaning sewage to reduce the spread of disease (Petsch et al., 2023, Wang and He, 2022, Ekka et al., 2020, Rinke et al., 2019). Maintaining water quantity and quality for these purposes is a socio-economic and political issue (Shaw, 2021). By 2050 it is estimated that 1/3<sup>rd</sup> of agricultural land will be irrigated from water resources rather than rain fed (Albert et al., 2021), which will place further stress on over abstracted river systems (Taylor et al., 2024, Khoshnoodmotlagh et al., 2020). This is especially important where rivers cross regional or national borders causing water rights debates (Povilanskas and Razinkovas-Baziukas, 2023). Therefore, monitoring methods need to be applicable over large regions and may require independence from local governance (Mianabadi et al., 2020), to provide objective knowledge (Aamer, 2023). Similar resource pressures exist in subsistence and commercial fisheries, where multiple natural and anthropogenic factors can contribute

to maintaining sustainable fish yields that support populations (Jin et al., 2022, Goulding et al., 2019, Klemas, 2013).

Ecosystem services extend to economic practises such as transporting goods and raw materials (Vinke et al., 2022, Garcia et al., 2021). Power generation is also interlinked with river systems (Petsch et al., 2023), directly through hydropower or indirectly through cooling water to nuclear and traditional coal power plants (Lohrmann et al., 2019, Wang et al., 2021a). However, these benefits result in consequences including thermal pollution (Heggenes et al., 2018), disrupting hydrological regimes, and species migration routes (Bonnema et al., 2020). These activities persist because they are integral to development, although advancements in measuring and monitoring these systems has enabled more sustainable operation of power systems helping to minimise their impact on river systems (Lohrmann et al., 2021, Lohrmann et al., 2019). Higher temporal resolution monitoring may provide the opportunity to maximise energy generation within environmental regulations and resource availability (Rheinheimer et al., 2015, Wang et al., 2021a, ASN, 2023). Another economic ecosystem service provided by rivers is sediment mining, yet it is also a resource that is over abstracted (Santhosh et al., 2021, Diaconu et al., 2023).

Rivers are culturally significant which is hard to quantify yet has led to landmark cases where rivers have been legally recognised to have human rights (O'Donnell, 2020). This cultural importance is often not integrated into river management schemes (Das and Tamminga, 2012). This thesis is heavily focused on the engineering and physical geography surrounding the building of a digital twin to incorporate the monitoring of physical factors. Regardless, I acknowledge that cultural and social values need to be taken into account and there are many community-driven, bottom-up techniques to do so (Fraternali et al., 2012, Beveridge et al., 2020a, Wang et al., 2019b, Lim et al., 2022). Having the foundational understanding of the large trends in river system will only enhance the basis for community driven projects and provide a means for these different forms of data to be built onto.

Rivers have been managed for various purposes over many years (Mossa and Chen, 2022, Downs and Gregory, 2014), therefore monitoring these systems is the key to balancing these purposes (Rinke et al., 2019). However, these economic, social, environmental and cultural values need to be balanced in the management of river systems that have different histories and contexts. Especially as these services do not exist in a vacuum and have downstream impacts on one another. For example, power generation thermal pollution (Raptis et al., 2016), which inhibits sewage treatment works (Hughes et al., 2021), causes algal blooms reducing dissolved oxygen for fisheries and drinking water (Burdick et al., 2020, Weber et al., 2017, Johnson et al., 2024).

#### 2.1.4 Natural disasters

The previous sections have focused on the benefits offered by rivers and the potential degradation of these services under a system that is under increasing stress from climate change and anthropogenic exploitation. However, the concentration of populations around river systems also puts people and property at risk from their associated natural disasters. Floods cause huge amounts of damage and disruption, displacing 68% more people than human conflicts and disproportionately affects those in lower income countries (Kam et al., 2021). The economic cost of flood damage is estimated at €7.6 billion in Europe alone, which could rise to €44 billion by the end of the century (Dottori et al., 2023). The economics vary but the damage from large river floods is universal across the world (Eslamian and Eslamian, 2022, Merz et al., 2021). Hence, flooding was one of the first disasters to be measured by EO and the science for this is still ongoing (Schumann et al., 2023, Tavus et al., 2022, Mateo-Garcia et al., 2021) with it even being the sole focus of some EO powered digital twins (Tarpanelli et al., 2023). Some of these floods can be considered 'flash floods' which are hard to predict or monitor due to their onset speed and as such can cause massive damage on a relatively small scale (Ballesteros-Cánovas et al., 2015). Monitoring the causes and effects of these can help with future prevention and recovery post disaster, which are examples of holistic continuous monitoring systems. There are so many interlinking factors that cause a flood to be damaging that any modelling, whilst important and ever improving, is difficult (Brunner et al., 2021), therefore they require up to date monitoring data for further development.

Pervasive secondary flood impacts include property insurance premiums increasing or become unattainable, making following flood events more damaging to the individual (Cannon et al., 2020). Flood and risk maps provided to insurance companies and public planners are used to assess risks and adequate knowledge of these risks improves the likelihood for insurance agreements to be reached (Lamond et al., 2019). These flood maps are ever changing as flood plains are urbanised, putting more people and properties at risk (Rentschler et al., 2023). While flood protection schemes can somewhat reduce risks, many of the traditional hard engineering structures reduce the ability of rivers to move in their flood plains (Chiu et al., 2021). All over the world rivers are becoming more constrained, creating fewer channels and reducing complexity (Grill et al., 2019) in turn reducing the degrees of freedom with which these channels can move to incorporate flood flows (Hey, 1978). This is often done to prevent floods in one area, but it creates a negative feedback loop, pushing flooding to communities downstream (Chiu et al., 2021). There are claims that 'slowing the flow' with natural process-based solutions (Skidmore and Wheaton, 2022, Dadson et al., 2017) may be a partial solution, which also increases the need to monitor these rivers to prevent synchronising flood peaks which could cause worse floods (Dadson et al., 2017).

Moving towards more natural methods of flood and river management may make some environments more resilient to natural disasters. For example, where river restoration has raised the water table and reconnected the flood plain, these ecosystems have been shown to be more resilient to wildfire with increased biodiversity and recolonisation (Pugh et al., 2022). Similarly, river management can have implications on the damage caused by droughts. Hydrological controls such as dams and water abstraction for agriculture can both worsen riverine drought and provide methods to mitigate the impacts of drought on anthropogenic water supplies (Stahl et al., 2020, Zhou et al., 2021, Van Oel et al., 2018, Cui et al., 2022). Drought can damage food supplies (Montanari et al., 2023) and last much longer than most flood events (Zhou et al., 2021). There are difficulties measuring droughts but due to their high residence time and extended spatial extent, they are perfectly placed to be monitored by EO methods (Balti et al., 2020).

Monitoring the changes in risks and resources associated with river systems is vital in the context of increasing anthropogenically driven climate change (Piégay et al., 2020, St-Hilaire et al., 2021), which is resulting in more extreme weather conditions which increase the probability of both floods and droughts in the same basins (Arnell and Gosling, 2016, Tabari et al., 2021). Therefore, to manage river systems, monitoring needs to be able to cope in the context of climate change and anthropogenic influence acting on dynamic river systems. Methods of collecting and collating these monitoring data and converting them to actionable insights need to be able to manage high spatio-temporal rates of change.

## 2.2 The Digital Twin paradigm

There is a clear demand for monitoring of river systems in a manner that can reduce redundant data to provide actionable insights for river managers, industry and other end users. As data availability increases, there are claims that there is a lack of methods for non-expert policy makers and specialists in applied fields to question these data (Huang et al., 2022). It is argued that Earth System Digital Twins (ESDT) are the framework which can store monitoring data and then display them and direct the course of action taken by river stakeholders (Li et al., 2023a). ESDTs streamline the big data received from EO sensors, IoT, and deep learning and reduce these to actionable insights by providing a digital duplicate of “the high dimensionality, complexity, and non-linearity of real-life earth systems” (Li et al., 2023a). This is especially important when accounting for climatic and land use change where models will need to be continuously assimilated with real-time data as thresholds are surpassed and changes in river systems may not match previous expectations (Hoffmann et al., 2023, Rao et al., 2023). ESDTs are still considered ground-breaking (Brocca et al., 2024) and cover an array of considerably different systems (Rao et al., 2023, Hoffmann et al., 2023, Le Moigne, 2023), with hydrology being one of the first use cases (Tarpanelli et al., 2023).

### 2.2.1 Competing definitions of Digital Twins

Digital Twins started chiefly as manufacturing and engineering concepts, which is reflected in the commonly accepted definition of a Digital Twin: “*A virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning and reasoning to help decision-making*” (ARUP, 2019: pp.17, Singh et al., 2021, Jones et al., 2020). Digital Twin concepts have been refined into three requirements (Grieves, 2014):

1. A physical product
2. A virtual representation of this product
3. A bi-directional data connection between them

Now the concept has been expanded beyond a physical product, the definitions presented could be considered too stringent (DeFelipe et al., 2022, Tomczyk and van der Valk, 2022). As scale and complexity of the systems being duplicated changes so too do the requirements for what constitutes a digital twin (Tomczyk and van der Valk, 2022). When it comes to complex real-world earth systems data there is naturally a limit to the ability to monitor the full lifecycle of systems (Jiang et al., 2021), such as rivers’ characteristics before human history for example, which means by necessity ESDTs have to be open to change over time with new science and monitoring systems.

The core of this Digital Twin paradigm still manages real world problems from a solely mechanical or safety perspective, falling short of the physical environment properties that dictate these (Conde López et al., 2021, Yu et al., 2021). For example, physical equations used to dictate dam safety from concrete decay only take average typical seasonal temperature into account (Kang et al., 2019). In comparison, the next generation of Digital Twins, advancing beyond manufacturing, are redefining what can be classified as a Digital Twin (Boschert et al., 2018). Therefore, for the dam safety example, this might include monitoring water temperature and discharge even if it is difficult to feedback to the model on how hydropower operators are interacting with this information. ESDTs model a more holistic system requiring the development of something approaching a traditional assimilation model that is collecting data and being retrained frequently (Jiang et al., 2021). The difference to these traditional models is that an ESDT need not provide the model, only the environment to train an attachment of modular numeric models which can be gained or lost for different users, conceptually like a GIS system except with near-real time updates to the base layers (Jiang et al., 2021).

### **2.2.2 Tiers of ESDT**

Clearly there is a variety of scope for the scale and complexity of an ESDT and this will vastly influence the resultant structure that makes up each ESDT. Even selecting a river ESDT considerably narrows this scope of this (Hoffmann et al., 2023, Barros, 2024). Thereafter, an ESDT is built up of individual components, in this case characteristics of a river system, and the selection of components will fundamentally impact how the ESDT behaves and what uses can be derived from it. Therefore, conceptual frameworks describe the potential spectrum of Digital Twins (Fig. 2.3). The highest level Digital Twins represent consortiums of some of the biggest policy making and scientific institutions in the world such as NASA's Earth Systems Twin (Barros, 2024) and the European Union's Destination Earth ESDT (Hoffmann et al., 2023). These large-scale ESDTs deal with sustainability on a planetary scale and propose interactions between many parts of the global system including weather prediction and disaster management (Li et al., 2023a). Yet they are proposed to work at a resolution of 1 km grid cells, which is too low for many of the policy makers in charge of river systems and river basin management plans to realistically benefit from, where an order of magnitude higher ( $\sim < 100\text{m}$ ) would be more appropriate.

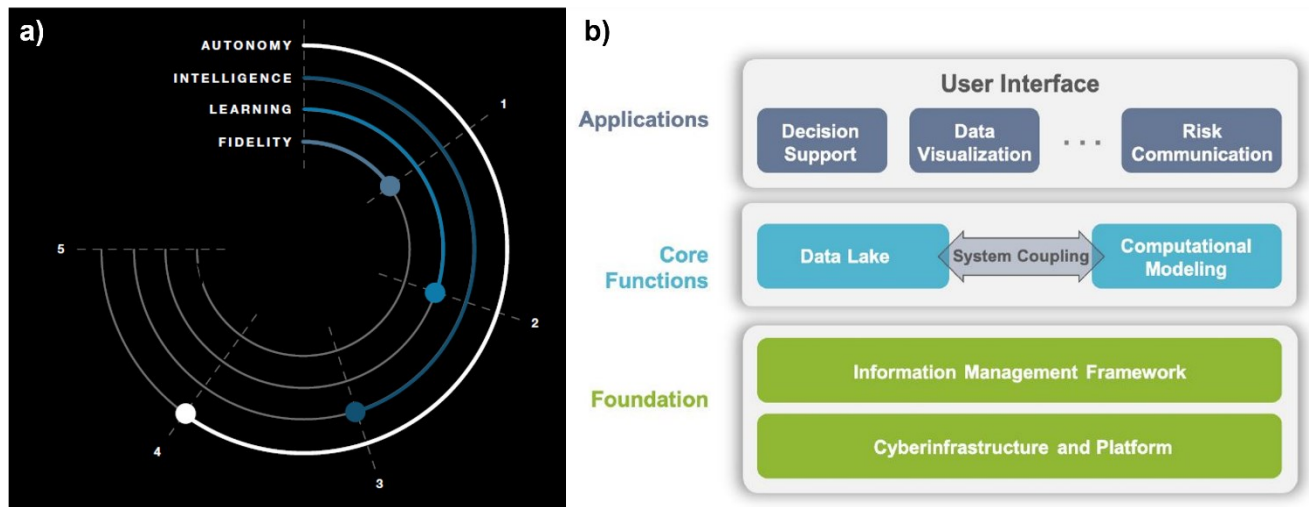


*Figure. 2.3: Conceptual understanding of Digital Twins. A) Assigns a level to the Digital Twin using the minimum highlighted contribution of four properties (ARUP, 2019). B) conceptual requirements of a Digital Twin (Rao et al., 2023).*

These large ESDTs use methodologies requiring the latest advances in high performance computing (Nativi et al., 2021) and cloud infrastructure (Brocca et al., 2024) which is likely to be out of reach for some users. One solution to these problems is integrating higher resolution analysis at a range of scales (Hoffmann et al., 2023) that can be combined together into an ESDT. For example, multiple modularised low level ESDTs are incorporated as interconnecting layers into Destination Earth (Rao et al., 2023) to provide the scales needed for different users.

These localised ESDTs can be too specific, often requiring social and ground data not available everywhere, or being built to rely on models trained in the river of interest (Tarpanelli et al., 2023, Kettig et al., 2021). While this enables commendably higher degrees of accuracy and temporal resolution, it simply is not possible in some river basins or with some data obstructions in place (Hannah et al., 2011). In river systems this has left a research gap, for methodologies that could be used in an ESDT that operationalise regular return period datasets, that are cost effective, and politically insensitive, and returns a product that is adaptable to the needs of individual river managers and users in different scenarios. The development of these methodologies could provide the core functions and foundations (2.3b) for future ESDTs (Rao et al., 2023).

### 2.2.3 Interactive elements of an ESDT

Interactive tools for visualisation and prediction are an integral tenet of an ESDT (Huang et al., 2022, Bauer et al., 2021) therefore consideration should be given for how the results of this thesis could be visualised in an ESDT. Each of the three data chapters

(3,4, and 5) contain many “frozen” case studies of ways to present those data in an ESDT. Much of the work is built using Google Earth Engine (GEE) and the GEEMap package (Wu, 2020, Tamiminia et al., 2020) which are designed for interactive mapping and visualisation. Therefore, the products produced here are readily applicable to direct user visualisation in whichever manner the end user requires.

The components will be presented without future predictions providing the tools for an ESDT environment to be specialised to different use cases, increasing its applicability. Another argument for developing generalisable remote sensing parameters is the spectrum of river types (Brierley and Fryirs, 2013) which requires predictive models to have substantial calibration and input from local experts (Fryirs et al., 2019). Therefore, while an ESDT should incorporate the components developed here with feedback from experienced practitioners to enable bi-directional dataflow and predictive steps, these should not be integral to the components themselves. This bi-directional data flow can be incorporated to assist the development of components which can learn and therefore have wider application if used in an ESDT (Li et al., 2023a). Some components were designed to be easily fine-tuned to different river basins (Chapter 3; Tajbakhsh et al., 2016) and modularised to enable the addition of different techniques as they are formulated (Chapter 5; Huang et al., 2022).

#### **2.2.4 Differences and similarities to the riverscape concept**

It would be remiss not point out the similarities with the riverscape paradigm which has existed for two decades (Fausch et al., 2002, Torgersen et al., 2022) and shares many of the core principles of an ESDT. Riverscapes build on earlier landscape ecology (Torgersen et al., 2022, Cushman et al., 2010) and focus on how ecological conditions are inherently tied to different spatial and temporal scales of analysis in the physical system (Fausch et al., 2002, Macfarlane et al., 2017). This paradigm targets holistic understanding of the river corridor as a whole (Torgersen et al., 2022, Zettler-Mann and Fonstad, 2020) often using remote sensing to tie different scales of analysis together (Glassic et al., 2024). This has led to a number of toolboxes which derive first and second order river metrics from monitoring data, e.g., discharge is a first order metric that drives stream power (Carbonneau et al., 2012, Glassic et al., 2024, Roux et al., 2015). One of the defining characteristics is that it should have a top down, large scale approach that is capable of integrating information from the bottom up (Fausch et al., 2002), which is precisely the same theory behind combining ESDTs at a range of scales (Hoffmann et al., 2023).

Although anthropogenic activities are tied into riverscapes (Dunham et al., 2018) there is not the explicit aim to create products which can feed up to yet higher levels of abstraction. ESDT are built to assist with active management and operation of industries, for example, the operation of power generation in a dynamic riverine environment. Moreover, there has been a recent drive to stress the temporal aspect in

riverscapes (Torgersen et al., 2022) to understand the processes occurring in a river system, whereas an ESDT aims to develop a complete virtual representation of the system that can be incorporated into future projects just as easily as those it was designed for. Finally, it should be made clear that these paradigms are not mutually exclusive; a riverscape project could use an ESDT as a tool to structure data collection and as a virtual environment to test theories in. Therefore, the work carried out here potentially provides the foundation for riverscape-style research to be undertaken using the processing methodologies and environment developed here.

#### **2.2.5 Key tenets of a river-focused ESDT**

Based on the definitions and requirements of Digital Twins and ESDT in particular, a list of key tenets has been developed that should define the components being developed in this thesis to make them more applicable for inclusion in an ESDT.

1. The component must be transferable between different river basins.
2. It should use freely available software and data where possible. If this is not possible data should be accessible for NGOs/Governmental environment groups and academics, and the ways in which this is possible should be highlighted.
3. The components should not require ground/*in-situ* data for the foundational elements to function, thus making it available to more users, especially in developing nations.
4. The components should strive to be automated where possible and require limited specialist knowledge to operate.
5. Finally, it should be operationalized for active use in decision-making to as great a degree as possible.

## 2.3 EO satellites for river management

### 2.3.1 Characteristics of EO Satellites

There is a vast variety of EO satellites currently orbiting the Earth, along with a catalogue of accessible and often useful imagery from decommissioned satellites dating back to the Cold War era (Forti et al., 2022). There are a number of reasons to choose which EO data should be incorporated into this thesis, based on the characteristics of the satellite and the target (in this case river systems) in question (Glassic et al., 2024, Tomsett and Leyland, 2019). Three of these characteristics lead us to the selection of EO as the preferential data source for this study: swath area (also called ground coverage area), spatial resolution (also called ground sampling distance; GSD), and temporal resolution. Remote sensing, as a discipline, encompasses any form of sensor being mounted on a platform provided it is separated from the target to be measured, be that a UAV, aeroplane, helicopter, or satellite (Piégay et al., 2020) and each of these platforms impacts these first three characteristics (Gili et al., 2021; Fig. 2.4). Therefore, a brief understanding of the broader realms of remote sensing is first needed to observe the alternative systems and the data deficiencies that EO satellites are being used to circumvent.

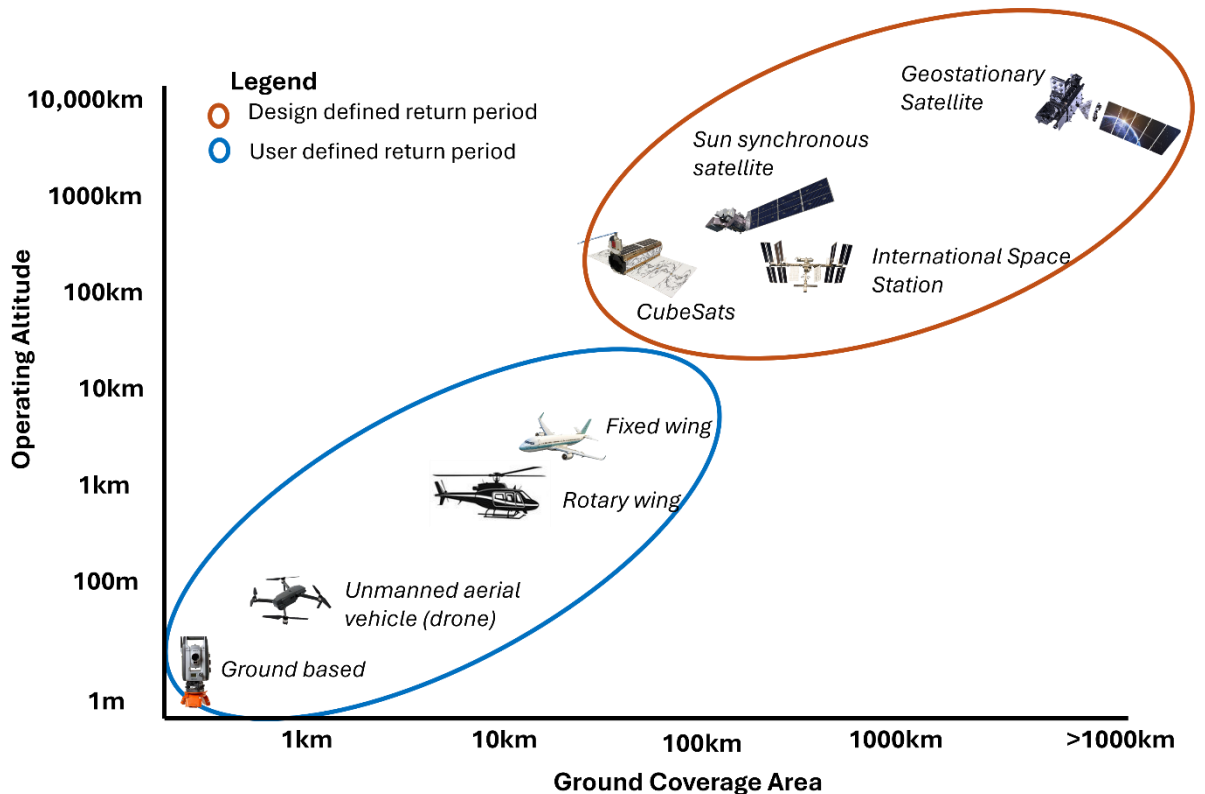


Figure. 2.4: Differences in remote sensing platform altitudes and their respective ground coverage area. A defining feature of why this project relies on Earth Observation satellites is their ability to cover greater areas without requiring users to define when data is collected based on their resources.

Many of the 'closer to earth' platforms, such as UAVs, have a lot of flexibility over their temporal resolution and have high spatial resolution, e.g., many more pixels over a set area thus producing higher fidelity images (Dugdale et al., 2019, Sibanda et al., 2021). However, the drawback of these platforms is that in return for flexible temporal resolution, they require both equipment and operators in the field. The first problem this causes for potential ESDTs is that it reduces the scalability of methods, each river basin in the ESDT would require a UAV or similar platform, a skilled operator, and the finances for them to regularly survey the river (Sibanda et al., 2021). These requirements are difficult anywhere in the world but would especially limit the applications of UAV driven ESDTs in developing countries without the financial power for these regular surveys (Sozzi et al., 2021). The second problem these platforms face is that rivers need to be considered as continuous systems where small interactions cumulate into river-wide changes (Marcus and Fonstad, 2008), the limited swath of these manually operated remote sensing methods would make it impossible to measure all but the smallest whole river basins (Piégay et al., 2020). Finally, as alluded to in section 2.1, there is a disparity between data collected globally and data openly available (Hannah et al., 2011, Crochemore et al., 2020, Yalew et al., 2023). Often with these manually operated datasets there is not just unwillingness to share between different owners but also a lack of infrastructure to support this, which is an issue I do not seek to address here but could be a potential future avenue for adding additional data onto the foundation that this ESDT supplies.

Conversely, Earth Observation satellites have been launched since the 1960's (Sternberg and Schnapf, 1961, Vass and Thomas, 1999) and by dint of their increased altitude overcome many of the drawbacks of airborne platforms. For the most part these satellites regularly capture images every time they orbit over the same point on Earth, trading most of their flexibility for a regular return period of imagery (Roy et al., 2021). Coupled with life spans of 1 to 29 years (Hemati et al., 2021) this provides dependable imagery. These systems are often supported by government with continuity plans (launching satellites with overlapping life spans to prevent interruptions in data capture), and increasingly open-source products which negates much of the cost of using these data (Masek et al., 2020, Wulder et al., 2022). The increased altitude also increases the swath covered in each overpass enabling an ESDT to monitor the largest river systems (Fassoni-Andrade et al., 2021). This increased swath allows for independent imaging of inhospitable areas, assisting international water disputes (Yalew et al., 2023) or helping manage humanitarian issues where natural disasters such as flooding occur in unison with geopolitical instability that prevents traditional remote sensing coverage (Yailymov et al., 2024). While it is clear that EO can provide those data to power an ESDT of river systems, the issues of swath size, return period, cost, and spatial

resolution do vary between satellites therefore the appropriateness of these satellites needs to be considered in the context of the variables they need to measure (see 2.3.2 and 2.3.3 for a comparison between satellites).

Before choosing the data sources based on the differences in EO platforms, it is necessary to understand how their payloads (i.e., the EO sensor itself) differ because this is what actually measures the phenomena on the ground. EO sensors can be divided into active and passive sensors, and then the later can be broken down into the differences in their radiometric and spectral resolutions (Emery and Camps, 2017). Active Synthetic Aperture Radar (SAR) sensors send out signals and measure their return (Sowter et al., 2013). One example is the Surface Water and Ocean Topography mission (Altenau et al., 2021, Pavelsky et al., 2014) which has produced lake and river specific datasets (Frasson et al., 2017, Fu et al., 2024, Riggs et al., 2023). However, there are currently more passive sensors in orbit, i.e., those that measure the emitted radiation from the Earth's surface, including reflected solar energy analogous to a traditional camera (Emery and Camps, 2017). These passive sensors are where the methodology is focused because, despite recent improvements in SAR, passive sensors were found have greater coverage at a higher spatial and temporal resolution (Frazier and Hemingway, 2021, Moortgat et al., 2022, Huang et al., 2025). Satellites are, unsurprisingly, expensive, and despite the breadth of research that can be carried out with many of them (Tamiminia et al., 2020), they are designed with relatively narrow application parameters (ESA, 2024). Therefore, many of these satellites are designed for Earth climate, land use or sea surface monitoring at scales far in excess of those that would be appropriate for use in a river system ESDT. Low resolution imagery is defined as having greater than 100 m pixels, such as MODIS and Sentinel 3 (Tyler et al., 2016, Kittel et al., 2021), and so it is not the focus for this literature review. For the purposes of this study medium resolution is considered to lie between 10 and 100 m pixels, and high resolution is considered to be less than 10 m. Nonetheless, it should be noted, again, that an ESDT should be flexible so as to include other types of sensors in future work.

Optical passive satellites use specific bands of the electromagnetic spectrum to organize the reflected light they receive from Earth into measurable and manageable data formats (Chuvieco, 2016, Emery and Camps, 2017). Spectral resolution refers to the number of distinct bands of light a passive sensor can measure and discriminate between (Chuvieco, 2016). Some 'hyperspectral' satellites can record 100s to 1000s of bands at the same time which enables dynamic indices (Pearlman et al., 2003, Qian, 2021). Hyperspectral satellites currently lack the spatial and temporal resolution desired for this study (Transon et al., 2018, Qian, 2021). The sensors that are focused on in this thesis are considered multi-spectral because they incorporate multiple bands (Fig. 2.5)

usually in the range of 4-16, with the first three often equating to red, green, and blue in the visible spectrum (Chuvieco, 2016). Multispectral sensors sometimes also measure spectra in the longer wavelength thermal infrared spectrum (TIR), between 8-14 $\mu$ m. These bands enable the measurement of land and water surface temperature (WST), i.e., the top 0.1 mm of the water column (Anderson and Wilson, 1984, Torgersen et al., 2001). However, the process of extracting this WST from emitted radiation, based on Wien's and Planck's Laws, has weaker energy measurements at the sensor than optical (e.g., RGB) imagery which produces lower signal to noise ratios (Baldrige et al., 2009, Rogalski and Chrzanowski, 2014). In turn this low signal to noise ratio reduces the spatial resolution that can be captured with TIR sensors (Baldrige et al., 2009).

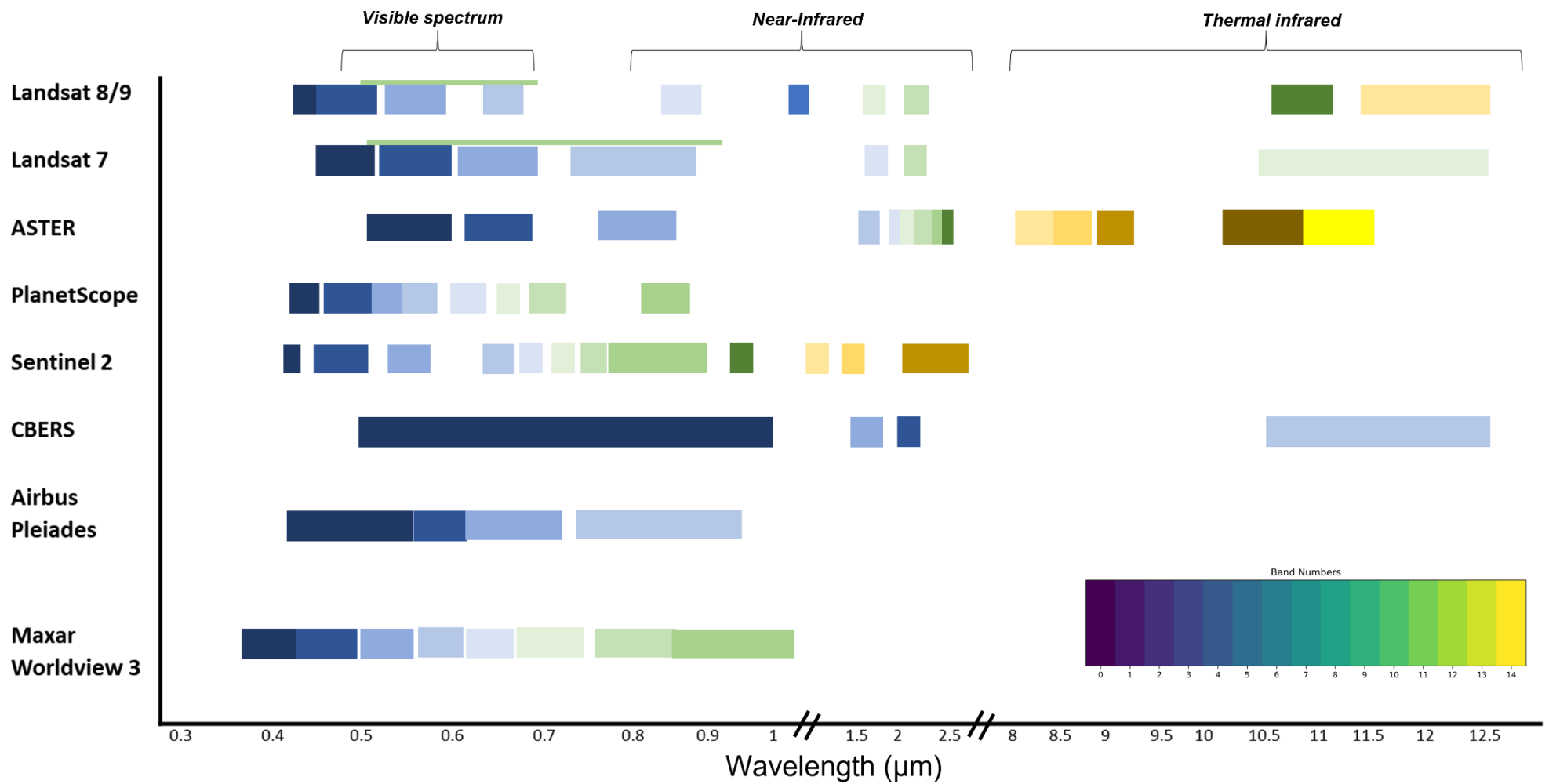


Figure. 2.5: Spectral signatures monitored by the different bands in different satellite missions, only satellites that monitor the visible spectrum are included due to their ability to be used independently.

The final EO characteristics that need to be accounted for are intrinsically linked together, that is the radiometric quality of the imagery, and the pre/post processing carried out. The radiometric quality refers to the sensitivity of the sensor through assessing its accuracy and uncertainty in returning expected values for each of its spectral bands (Wilson et al., 2017). This radiometric quality varies based on the size, construction, orbit, altitude, operating and processing procedures of each satellite (Frazier and Hemingway, 2021). There are levels of processing which need to be carried out in order to take readings on a sensor between 705 and 475 km in space and relate them to changes on the Earth surface. The sensor records a digital number for each pixel (Chuvieco, 2016) which is converted to a 'top of atmosphere radiance' using constants derived during sensor construction. This relates to surface temperature if there were no influence from the atmosphere on recorded radiation (Young et al., 2017). Calculating and removing this atmospheric interference and provides the 'surface reflectance' WST value (Barsi et al., 2003). There is a choice of atmospheric correction method (e.g., Ermida et al., 2020, Meng and Cheng, 2018, Wang and De Liberty, 2005), the majority of which require additional datasets such as atmospheric water vapour, which can be provided by concurrent weather satellite overpasses (Wang et al., 2019a). Increasingly satellite providers are supplying products with these corrections already made (USGS, 2020, Tamiminia et al., 2020, Gorelick et al., 2017). Technological advances are allowing the correction of these values to be calculated on the satellite, before these data are returned to collection centres on Earth (Wijata et al., 2023). In a similar vein, in an effort to improve radiometric quality some satellites are harmonized to bring their results in line with other more consistent satellite sensors (Kington and Collison, 2022). The radiometric quality and the degree to which it can be improved before the images are accessed needs to be considered when choosing which data to use.

### **2.3.2 Government-funded EO satellite systems**

The premium standard for radiometric quality is often taken to be government funded sun-synchronous satellites such as Landsat, Sentinel 2, and ASTER (Table. 2.1) against which other commercial satellites are compared (Wilson et al., 2017, Frazier and Hemingway, 2021). Their sun-synchronous orbit provides near global coverage across all but the highest latitudes and has the same local overpass time throughout its life (Boain, 2004). These factors make these satellites very useful for earth systems monitoring and make it much easier to correct radiometric influences such as the solar angle of measurements which is important as these are billion-pound satellites, which are expected to be in space for multiple years, life spans they often outperform (Wulder

et al., 2022, Twedt et al., 2023). Satellites from this category are funded by National agencies such as ESA, NASA, and USGS because of the huge direct and indirect value to users of this industry, such as the \$25.6 billion estimated economic impact of the Landsat programme in the USA (Loomis and Koontz, 2024). These financial benefits support the construction of EO satellites with this high radiometric accuracy and continuity of sensors. As a result, the Landsat programme (started in 1972) has been running continuously for over 50 years with the most recent Landsat 9 launched in 2021 (Wulder et al., 2022).

*Table. 2.1: Common optical satellite sensors used and their main characteristics of number of bands, spatial and spectral resolution that need to be traded off when choosing which sensor to use. Highlighted satellites are from proprietary sources.*

| Satellite/sensor | Number of Bands     | Spatial Resolution (m)   | Return period |
|------------------|---------------------|--------------------------|---------------|
| Landsat 8/9      | 11 (2 for Thermal)  | 30(90 for Thermal)       | 16 days       |
| Landsat 7        | 8 (1 for Thermal)   | 30(60 for Thermal)       | 16 days       |
| Landsat 5        | 7 (1 for Thermal)   | 30(120 for Thermal)      | 16 days       |
| Sentinel 2       | 13                  | 10-60                    | 5 days        |
| Aster            | 15 (5 for Thermal)  | 15-30 (90 for Thermal)   | 16 days       |
| MODIS            | 36 (16 for Thermal) | 250-1000                 | Daily         |
| CBERS-2B         | 7                   | 2.7-80 (160 for Thermal) | 26 days       |
| Airbus Pléiades  | 4                   | 0.5                      | Daily         |
| PlanetScope      | 4                   | 3.7                      | Daily         |

The size of these satellites allows them to host a large array of spectral sensors, providing a higher spectral resolution than many smaller commercial satellites (Mansaray et al., 2021, Denis et al., 2017). Most of these satellites carry RGB and NIR bands to capture true and false colour images of the Earth, highlighting aspects such as vegetation and water (Chuvieco, 2016, McFeeters, 1996). Although these bands are carried by most EO optical satellites, they do not always capture optical images at the same time as TIR imagery in the case of ASTER (GEE, 2024). Also, other more experimental sensors, such as the ECOSTRESS thermal imaging sensor mounted on the International Space Station (ISS), do not have these bands therefore require additional imagery if true colour images are needed to be used in unison (Fisher et al., 2020). ECOSTRESS was originally only planned to be a 1-year scientific mission but has been extended to 2029 (Hulley et al., 2017, Hook, 2023) exemplifying the need to build ESDTs that can make the most of these experimental missions which can become regular monitoring missions. Landsat's 5, 7, 8 and 9 have all had short wave infrared

bands in the 2 – 2.35  $\mu\text{m}$  range which separates them from many other optical sensors (Hemati et al., 2021). These short wave bands have been shown to be useful for better classification of the differences between urban areas and water leading to the modified normalised difference water temperature index enabling Landsat to produce better classification results using indices than similar satellites without the medium band (Xu, 2006). Finally, many of these satellites carry the long wave TIR bands discussed in section 2.3.1. ECOSTRESS has 5 TIR bands, ASTER carries four of these bands whilst the more recent Landsat 8 and 9 satellites carry two apiece (Abrams et al., 1999, USGS, 2019). Having multiples of these thermal bands enables multi-channel algorithms whereby surface temperature is measured using bands in different wavelengths for a more accurate result.

However, the expense spent and focus on a small number of well-built satellites does not make them completely invulnerable to errors with their sensors. One of the TIR bands in Landsat 8 (band 11), suffered from the now well-known ‘stray light error’ where light from the non-TIR optical system causes unpredictable radiometric errors in the TIR bands (Montanaro et al., 2014, Gerace and Montanaro, 2017). While methods to compensate for this error were proposed (Montanaro et al., 2015), it was recommended to only use the remaining TIR band 10 with single channel algorithms (Barsi et al., 2014, Ermida et al., 2020). This led to similar recommendations for Landsat 9 despite having no stray light issues (Montanaro et al., 2022). Similarly, a strip error problem was found with Landsat 7 whereby images had strips of error or missed imagery in them after 2003 as the scan line corrector failed (Yin et al., 2017). These sorts of errors warn users that somewhere in the operation of EO imagery, regardless of the expected accuracy, measures should be taken to check the quality of the data being inputted to models and ESDT systems in order to prevent errors in results and predictions.

There is a trade-off when choosing between these satellites because the higher their spatial resolution the more likely they are to have a coarser temporal resolution. As stated, medium and high spatial resolution satellites (<100 m pixels) are required to study large river systems (Donchyts et al., 2016), leading to individual satellites, such as Landsat 9, having return periods for the same location of up to 12-16 days (USGS, 2022). This return period is sufficient for some applications (Boothroyd et al., 2021a) but this return period would miss many riverine processes and inhibit management response (Hou et al., 2020, Cooley et al., 2017, Phillips et al., 2022). Flying more than one of these satellites in constellation can increase this resolution, in the case of Sentinel 2a and 2b this is as low as every 5 days, yet this is still likely to miss rapid onset river processes.

The final characteristic that many of these publicly funded satellites share is that they are increasingly available free of charge for science, research, and even commercial use (Zhu et al., 2019, Coetzee et al., 2020, Cornebise et al., 2022). New systems are making them more accessible than ever before, especially with improvements in free cloud computing (Gorelick et al., 2017) and improved API-based download options (Planet, 2024b). This enables global studies and the testing of ideas without the risk of financial costs while also increasing data commons whereby research is available to access for everyone (Harris and Miller, 2011, Tamiminia et al., 2020). This is important for an ESDT that is aiming to operationalize EO based river management monitoring support, where it should be accessible for different communities and river basins.

### **2.3.3 Low Earth Orbit CubeSats**

Commercial satellite data has a direct cost to the user, but these providers are better placed to take advantage of 'disruptive' technologies in ways that traditional government funded organisations such as ESA and NASA cannot (Garzaniti et al., 2021). This means they have the potential to cover gaps in government-funded satellite records to capture aspects such as river dynamics. These commercial companies can make specialised satellites such as the very high spatial resolution Airbus Pleiades mission (Perko et al., 2018), or by relying on investment commercial companies can test the potential of new technology (De et al., 2022, Satellite Vu, 2022). When such products prove to be successful or useful they often gain support from the larger agencies, allowing for data access agreements which enable these data to be included in an ESDT without violating the need for it to be accessible. These data agreements include academic licences (Planet, 2024a), ESAs third party mission scheme (Preston, 2022), and NASAs "Small Sat" programme (Maskey et al., 2021) which supply NGOs and Government organisations with these otherwise proprietary data.

One such disruptive technology is the invention of CubeSat satellites; these are small shoebox sized satellites that are quick and relatively cheap to develop (Davoli et al., 2019). Their small size means that they can be tagged on to other rocket launches or launched in 'flocks' further reducing the cost of development and implementation whilst increasing the temporal resolution by combining the revisit time of every satellite in the constellation (Roy et al., 2021, Davoli et al., 2019). The minimised cost means that new sensors can be built and tested or updated very rapidly with multiple copies or iterations put into space concurrently (Janson, 2023). It is interesting to note that despite the concerns over the increases in space debris, of which the current quantity orbiting around the Earth is unknown (Muntoni et al., 2021), CubeSats do not contribute to this. By regulation, CubeSats are put in decaying low Earth orbits which when coupled with their size enables them to entirely burn up on re-entry, making them exempt from these debris concerns (Ostrom and Opiela, 2021). Moreover, as low air orbit spacecraft (405

km) these satellites often have much higher spatial resolution than sun-synchronous satellites (705 km) through simply being closer to Earth increasing their potential to fill in market gaps for cheap, medium-high resolution imagery.

Planet (formerly Planet Labs) is one company that have capitalised on the potential of these CubeSats to fill one of these gaps in the market which is their mission statement to “image all of Earth’s Landmass every day”. Planet operate a constellation of 130+ 3U (3U denoting that these satellites are built to 10\*10\*30cm dimensions) CubeSats at any point in time (Davoli et al., 2019, Roy et al., 2021) called Doves launched in large ‘flocks’ enabling reported daily return periods (Davoli et al., 2019). The first of these satellites were launched in 2014 (the ‘Dove Classic’ model). Since then, these models have been predominantly superseded by the ‘Dove-R’, and more recently the ‘Super Dove’ model. The early ‘Dove Classic’ satellites had 4 bands: red, green, blue (RGB) and NIR, with the ‘Dove-R’ and ‘Super Dove’ models adding coastal blue, yellow, red edge, and a second green band. As a commercial operator, it should be held in mind that the choice of bands is dictated by customer demand (mostly agriculture; Sharma and Ghosh, 2023), not solely for scientific studies. Each platform in the constellation is in a decaying low Earth orbit, causing imagery from a recently launched satellite to be around 5 m resolution decaying to 3 m by end of life as the satellite moves closer to Earth. All products are provided pre-processed to 3 m resolution. In the context of this study, this high resolution (<10 m) and the proposed daily return period means that one of the market and research gaps that PlanetScope is applicable to is for the study of river systems. These rivers are continuous systems where small processes (only visible by high resolution imagery) at different points on river channel cumulate into river-wide changes, thus research has been called on to focus on applying the highest possible spatial and temporal resolution datasets to avoid discontinuity (Marcus and Fonstad, 2008). Using Earth Observation enables the study of much larger river systems than could be attempted with other remote sensing methods, and at that scale PlanetScope provides the best possible resolution in the bands that it has available.

The large constellation of small cheap satellites does come at the expense of radiometric (and to some extent spectral) resolution (Frazier and Hemingway, 2021). This is fairly intuitive when considered, as data need to be harmonised from 130+ different satellites at different altitudes, with different times of day, with different atmospheric conditions, with different sun angles, different generations of satellite, and off-the-shelf materials (Frazier and Hemingway, 2021). Planet have developed pre-processing techniques to improve their imagery, by harmonising bands to a known accurate satellite - Sentinel 2 and providing surface reflectance products direct to the user.

On top of the radiometric errors that will need to be managed to use these PlanetScope images (addressed in chapter 3 of this thesis), there are cloud cover limitations universal to all optical EO satellites. Optical satellites cannot penetrate heavy cloud cover, and the resultant images are easily identifiable as error, in such a case PlanetScope's high temporal resolution provides the best opportunity to capture gaps in such clouds. However, some amounts of thin cirrus cloud can cause errors in an image and be much more difficult to identify and remove (Cornette and Shanks, 1993, Wang et al., 2021b). In some cases, high levels of processing can limit the impact of these problems by removing the effects of small atmospheric influences on the radiometric quality of results; however, this relies on the radiometric accuracy of the satellite being high to begin with (Jiang et al., 2024). Masking and removing these cloud effects is the most sustainable way of coping with the error that they cause. Most satellite data is provided with a data quality 'band' which can be used to produce simple cloud and error masks, and although PlanetScope has one of these bands, it is not as accurate as larger satellites due to the radiometric limitations discussed above. Artificial intelligence has been shown to be able to produce accurate cloud masks, often using additional data from other satellites, but the amount of data and processing time required for these is correspondingly higher. Therefore, the degree to which these methods are used depends on the users' needs and priorities, but an ESDT should be capable of including different cloud masking modules to suit these user needs and scientific developments. Part of this decision around cloud masking techniques and the combination of satellites used is defined by the degree to which the area of interest is prone to cloud, which is not universal across the world (Melchiorre et al., 2020, Armitage et al., 2013, Collow et al., 2016). In Chapter 4, the degree to which PlanetScope does provide daily data in the context of the reality of cloud cover is tested to provide some quantifiable assessments of this.

#### **2.3.4 Future satellite launches**

There have been record-breaking increases in the number of satellites launched into space per annum (Witze, 2023, Janson, 2023), replete with more advanced and higher resolution sensors (Zhu et al., 2018, Li et al., 2024, de Sousa, 2023). ESDTs should be designed to be flexible or modularised to incorporate planned satellite missions (Brocca et al., 2024) to build up long term monitoring records (Jiao et al., 2021) especially as the current host of satellites have finite lifetimes (Julien and Sobrino, 2021). Test missions should be made compatible with ESDT methodologies as these often use methods incorporated into future satellites or the satellites exceed their planned operating period, making them useful monitoring tools in their own right (Hulley et al., 2017, Lehner et al., 2008, Liddle et al., 2020). There are advances in government-funded optical satellites that should be taken advantage of, such as NASA's Landsat NeXt, which will have 26 distinct spectral bands (NASA, 2024). There are also many

planned launches of satellites with TIR sensors (Table. 2.2). ESA, NASA, and a consortium between France and India are currently aligning their individual TIR missions to provide the daily return periods with 12:30 local time overpasses, when this is not prevented by cloud cover (Hook, 2023). Commercial companies are also planning TIR launches with most focusing on different forms of small or cube sats, in constellations up to 16 satellites (Mo et al., 2018, Hydrosat, 2024) with some launches focusing on 3 m resolution medium wave TIR imagery (UP42, 2024). This shows the breadth of development of the field which should be incorporated into ESDTs when available, and the findings here on how to work with constellations of satellites should be directly applicable when these satellites are available.

*Table. 2.2: TIR satellite missions currently planned or in development, all values for spatial resolution, return period, number in constellation, and first launch are given to the expected accuracy at time of writing. In the case of Satellite Vu, their first launch failed after 6 months therefore the launch date is of their second satellite.*

| Satellite/company        | Spatial resolution | Return period | Number in constellation | Expected launch date               | Reference                                       |
|--------------------------|--------------------|---------------|-------------------------|------------------------------------|-------------------------------------------------|
| LSTM (Sentinel 8)        | 50 m               | 2-day         | 2                       | 2029/2031                          | (Koetz et al., 2022)                            |
| SBG                      | <60 m              | 2-3 days      | 1                       | 2028                               | (Thompson et al., 2020)                         |
| TRISHNA                  | 60 m               | 2-3           | 1                       | 2026                               | (Pinnepalli et al., 2024, Charvet et al., 2023) |
| Landsat NeXt             | 60 m               | 6 days        | 1                       | 2030                               | (NASA, 2024)                                    |
| Constellr                | 30 m               | 1-5 days      | 5                       | 2026                               | (Spengler et al., 2024)                         |
| HydroSat                 | 70 m               | 1 day         | 16                      | 1 <sup>st</sup> Launched July 2024 | (Hydrosat, 2024)                                |
| HotSat (Medium wave TIR) | 3.5 m              | <1 day        | 7                       | 2025                               | (Satellite Vu, 2022)                            |
| AISTech                  | 30-50 m            | N/A           | 20-30                   | N/A                                | (Aistech Space, 2024)                           |
| OroraTech                | 80 m               | <1 day        | 100                     | 2027                               | (Ororatech, 2024)                               |
| Hibiscus                 | 3 m                | N/A           | N/A                     | 2028                               | (SuperSharp, 2024)                              |

As databases of these satellite data have become open source (Zhu et al., 2019), the proliferation of constellation approaches collect more data (Roy et al., 2021, Wu et al., 2021b, Perko et al., 2018), and new satellites are being launched, the quantities of river-relevant data available are ever increasing. This big data is both a blessing, enabling diverse applications globally, but it comes with limitations that need addressing. Traditional methods of analysing and processing these data are not designed for the amount of data now available (McCabe et al., 2017). However, with the advent of cloud computing and cloud storage, petabytes of open-source satellite data can be stored (Gorelick et al., 2017, Gorelick, 2013, Zhu et al., 2019) and only processed on demand. Download of individual scenes is no longer required as whole archives can be

accessed, and analysis can be limited to those pixels of interest (Ermida et al., 2020). To be interoperable with these planned satellite launches methodologies for ESDT components will need to be developed using these cloud computing technologies.

## **2.4 Choice of river variables for ESDT components**

### **2.4.1 Initial review of river variables**

Sections 2.1-2.3 have outlined why it is important to monitor river systems, the framework under which this monitoring should be undertaken, and the satellite systems available to monitor these river systems. However, while there are numerous variables which can be used to characterise river systems, not all of these can be monitored by EO. Furthermore, some variables are particularly important with regards to the sustainable management of river systems. An analysis of the literature was therefore undertaken to assess which river variables would be best suited as components in an ESDT (Table. 2.3). Variables were collated from remote sensing methodological review papers regardless of the platform which had been used to monitor these (e.g., Piégay et al., 2020, Tomsett and Leyland, 2019, Ellis et al., 2024). By including platforms beyond satellite EO, variables and methods which could potentially be adapted to satellite-based approaches in this thesis were included. Thereafter, further components which river managers consider important were also included (Marttunen et al., 2019) especially focusing on components used in river classification systems (Brierley and Fryirs, 2013, Montgomery and Buffington, 1998, Raven et al., 1998).

*Table. 2.3: Aspects of a river system that would be desirable as components in a satellite EO-based digital twin. References direct the reader to evidence of the current best practise in remote sensing these components.*

| Existing methods                                                                                      | Potentially feasible                                                                  | Currently unsupported                                              |
|-------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|--------------------------------------------------------------------|
| Width and channel delineation (Allen and Pavelsky, 2015, Freitas et al., 2024, Moortgat et al., 2022) | Geomorphic Units (Wheaton et al., 2015, Carbonneau et al., 2020)                      | Flow Characteristics (Palmer and Ruhi, 2019, Hackney et al., 2015) |
| Sinuosity (Frasson et al., 2019)                                                                      | In-stream Vegetation (Klemas, 2014)                                                   | Bed Composition (where not exposed) (Marchetti et al., 2021)       |
| Temperature (Martí-Cardona et al., 2019, Al-Murib et al., 2019, Hori, 2021)                           | Water Chemistry (Bistani, 2009, Xu et al., 2019, Qi et al., 2020, Sabia et al., 2015) | In-stream Wood (Abalharth et al., 2015)                            |
| Depth (Fonstad and Marcus, 2005, Geyman and Maloof, 2019)                                             | Floodplain Roughness (Mason et al., 2003, Straatsma and Baptist, 2008)                | In-stream Litter (Biermann et al., 2020)                           |
| Longitudinal Connectivity (Mulligan et al., 2020, Ferreira et al., 2020)                              |                                                                                       | Fish Stocks (Tidd et al., 2016, Klemas, 2014)                      |
| Active Valley Width (Gilbert et al., 2016)                                                            |                                                                                       | Bank Characteristics (McMahon et al., 2017)                        |
| Discharge (Junqueira et al., 2021, Feng et al., 2019, Riggs et al., 2021, Bjerklie et al., 2018)      |                                                                                       |                                                                    |
| Total Suspended Sediment (Beveridge et al., 2020a, Beveridge et al., 2020b, Gardner et al., 2021)     |                                                                                       |                                                                    |
| Elevation changes (Passalacqua et al., 2015, Nevo, 2019)                                              |                                                                                       |                                                                    |
| Flooding (Nevo, 2019, Voigt et al., 2016)                                                             |                                                                                       |                                                                    |

#### 2.4.2 Selection of First Order variables.

As has been explained, the variables chosen to become components that could be used in an ESDT needed to be monitorable by EO, not require in-situ data, be transferable between watersheds, and ideally provide the broadest possible base to make them applicable to as many potential users and future projects as possible. To this end I have chosen to focus on 'first order' variables which control river system function and from which second and third order variables can be derived (Carbonneau et al., 2012) These

primary variables; water extent, hydraulics, and river temperature drive most over environmental variables (Webb, 1996, Fruget et al., 2001), so their inclusion would provide a foundation for users to include other variables of interest to them. Moreover, these first order variables are intrinsically interlinked and therefore monitoring one often depends on results from monitoring another (Caissie, 2006, Carbonneau et al., 2012, Van Vliet et al., 2023).

#### *2.4.2.1 Surface water extent*

Surface water extent is considered the primary component for the foundation of an ESDT as a binary water mask is vital to constrain all other measurements of a river system to ensure that it is the water itself that was being monitored (Pavelsky and Smith, 2008, Yang et al., 2019, Altenau et al., 2021). This geometric variable describes the size and shape of a river system, an area EO has been shown to excel at (Frasson et al., 2019, Mulligan et al., 2020, Boothroyd et al., 2021b, Pekel et al., 2016). Tied into this is the need for accurate width measurements as accuracy in other components is found to be achievable where a river width to pixel size ratio of 3:1 is available (Hori, 2021). Increasingly there has been a reliance on the Global River Width from Landsat dataset (GRWL (Allen and Pavelsky, 2018) and other relatively static water masks (e.g., Pekel et al., 2016, Isikdogan et al., 2020, Altenau et al., 2021). However, these methods suffer from limitations in temporal and spatial scale (Brunner et al., 2021, Brunner et al., 2020), because rivers are highly dynamic systems that do not operate at 'bank full width' that many of these methods measure (Allen and Pavelsky, 2015). In reality, it is most important to monitor these rivers when they are either lower than bankfull or flooded beyond the channel which is the majority of the time (Edwards et al., 2019). Therefore, the development of further components requires a methodology to automate the surface water extent 'water masks' from satellite imagery.

#### *2.4.2.2 River islands as stage/discharge proxies*

Simple geometrical relationships dictate that knowing water extent is one of the integral factors to understanding discharge (Hagemann et al., 2017). Therefore, with water extent monitored, the research can be extended to include hydraulic variables such as discharge which is one of the essential habitat and hydroclimatic variables (Scherer et al., 2024), driving river form and function in rivers (Fruget et al., 2001, Wolman and Miller, 1960). There are multiple aspects of discharge and hydraulics which can be monitored by remote sensing and to a degree they are all desirable for different users (Junqueira et al., 2021, Gleason and Durand, 2020, Smith, 1997, Masafu et al., 2023, Pavelsky et al., 2014). Discharge may be considered the most useful overarching variable in this context; increasingly global discharge data is becoming scarcer as gauging stations are removed and many data are placed behind paywalls. However, despite continued research, the methodology for extracting river discharge from space

has not converged to an accepted method that works across different river basins (Gleason and Durand, 2020). Instead, the decision was made to focus on low flow events which are critical periods for ecosystems, water quality, anthropogenic water use, and other first order variables (Fruget et al., 2001, Poff, 2018). Reductions in channel flow exposes previously inundated sediment and isolates pools of water which can be monitored from space as a proxy for discharge during these low flow events. Monitoring these in-channel changes as a result of discharge changes can provide spatial insight into the direct impacts of droughts when they occur.

#### *2.4.2.3 River temperature*

River temperature is one of the primary first order variables (Carbonneau et al., 2012, Webb, 1996). It has been shown to govern the distribution of ecology within river systems and increases of river temperature can threaten entire river ecosystems (Dugdale et al., 2018, Richter and Kolmes, 2005). Similarly, anthropogenic waste water treatment (EBS, 2024) and power generation (Durmaz and Sogut, 2006, Zheng et al., 2017, Lamaro et al., 2013, Bonansea et al., 2021, Zhao et al., 2023) are reliant on knowledge of river temperature. However, EO-based monitoring of river temperatures requires accurate data on water surface extent and changes in the locations of exposed water surfaces. The need for these precursor variables hinges on the requirement for pure water pixels to monitor river water surface temperature, these pixels cannot be mixed with exposed sediment or bank effects. Moreover, even more so than the previous variables, river temperature is highly temporally dynamic (Tokuda et al., 2019, Dugdale et al., 2013) and as such requires the maximum possible satellite temporal coverage for the use cases highlighted.

#### **2.4.3 Combination of first order variables**

Combining these variables of water extent, discharge, and river temperature explicitly describes the key habitat metrics within rivers, controlling physio-chemical and biological processes (Hannah and Garner, 2015, Dugdale et al., 2017, Rinke et al., 2019) making the combination vital for characterising river systems and ecosystem services. As such, these components provide a larger variety of actional outputs together than they would individually or through any other combinations of variables. This is especially true for future assessments of water quality which is driven through both the quality and quantity of river water (Ellis et al., 2024). The three variables chosen here exhibit the foundation of both the quantity of water through measurements of its hydraulic extent and changes, which along with water surface temperature is integral to monitoring the quality. These are important to understand the river system in context and how it may adapt to future change (Arnez Ferrel et al., 2018, Leopold and Maddock, 1953). They are also requirements in governmental indices (e.g. (Campana et al., 2014) compulsory for assessment of legal water directives (Nöges et al., 2009).

Finally, global climate change is one of the most pervasive factors of our time which will have far reaching impacts across river systems and freshwater resources (Fassoni-Andrade et al., 2021, St-Hilaire et al., 2021, Wasti et al., 2022, Chapra et al., 2017, Arismendi et al., 2014, Arnell and Gosling, 2013, Arnell and Gosling, 2016, Johnson et al., 2024). Therefore, these variables chosen for inclusion as components count among the most impacted by climate change, providing canaries for the state of river health, and observing how these impacts propagate through river systems (Caissie, 2006, Hannah and Garner, 2015, Dugdale et al., 2017, Rinke et al., 2019).

## 2.5 Approaches to monitor first-order variables

### 2.5.1 Water surface extent

A multitude of methods have been developed for classifying water surface within remotely sensed imagery (Li et al., 2022a), the majority of which use basic spectral indices (McFeeters, 1996, Xu, 2006, Hori, 2021, Allen and Pavelsky, 2015). The most common of these is the 'Normalised Difference Water Index' (NDWI; Equation. 2.1; McFeeters, 1996). However, this was found to have high commission error (classifying pixels incorrectly as water when they are not) over urban land areas and other sites of high reflectance (Xu, 2006). When additional spectral bands are available this index can include the short-wave infrared band, designated the 'modified NDWI' (MNDWI; Equation. 2.2) which significantly improves its ability to accurately classify water bodies (Xu, 2006). These indices are simple, fast, and require limited computational power to produce yet despite their simplicity, and with high quality radiometrically accurate satellite data, they are found to be highly accurate (Chen et al., 2024). This accuracy is contingent on the placement of a threshold to develop binary water masks required for the majority of further applications. To speed up this process automated thresholding methods are used such as Otsu thresholding, which works by delineating between peaks in the image's histogram, provided that the distribution is suitably bimodal (Otsu, 1979, Günen and Atasever, 2024). However, for higher resolution imagery it is often found that more intensive thresholding methods, which require considerable user input, are preferable, especially if these data are being used for training further models (Moortgat et al., 2022).

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

*Equation. 2.1: Normalised difference water index (NDWI) for classifying water from optical satellite images using the Green and Near infrared (NIR) bands (McFeeters, 1996).*

$$MNDWI = \frac{Green - SWIR}{Green + SWIR}$$

*Equation. 2.2: Modified normalised difference water index (MNDWI) for improved classification of water from optical satellite images when the short-wave infrared (SWIR) band is available (Xu, 2006).*

These relatively simple indices often form the basis of many global static water masks such as the GRWL (Allen and Pavelsky, 2018). However, rivers are dynamic systems that are changing constantly both in the short and the long term driven by discharge,

channel change, and catchment development. Therefore, regardless of how they are developed, these static water masks have limitations to their use in monitoring large river systems in near-real time (Moortgat et al., 2022). The second problem with both these static water masks and dynamic water masks that use these described indices is that they lack the spatial and temporal scale to monitor many dynamic river properties. Especially around the edges of river banks, the 30 x 30 m pixels used by Landsat are too large to measure accurate changes in water extent (Ling et al., 2019, Li et al., 2023b). Super resolution mapping has shown a lot of promise to combat these spatial limitations but many do not sufficiently improve the resolution of pixels such as MODIS to make them the most effective option (Yin et al., 2021, Lanaras et al., 2018, Foody et al., 2005) whilst other higher spatial resolution methods do not sufficiently improve the temporal resolution to monitor river systems (Cornebise et al., 2022).

Therefore, other satellite systems, often commercial, need to be used to improve the temporal scale of results. PlanetScope is the best potential candidate for this with daily imagery capture (See section 2.3; Roy et al., 2021), putting it at the forefront of river water science (Mansaray et al., 2021, Wirabumi et al., 2021, Junqueira et al., 2021, Niroumand-Jadidi et al., 2020, Freitas et al., 2024). Although PlanetScope lacks the short-wave infrared band needed for MNDVI indices. Therefore, different methods have been developed to automate the extraction of water masks from this imagery, many of which use CNN and ANN artificial intelligence methodologies (Leach et al., 2022). ANNs use weighted paths to predict a labelled version of the training dataset using a process called 'backpropagation', the number of weighted neurons and the layers these are in are defined by the user (Mas and Flores, 2008, Goodfellow et al., 2016, Lee et al., 2019). The degree to which the weights have predicted the correct labels is used to alter the weights for another training iteration (known as an epoch) until the methodology has found the weights which can best produce the correct labels in the training data (Goodfellow et al., 2016). ANNs function as a pixel-based classifier whereby they process each pixel independently of the surrounding pixels. In contrast, a CNN uses a convolutional moving grid that takes account of the context of the surrounding neighbourhood of pixels, thus enabling the texture and patterns of multilayer images to be learnt (Gavrilov et al., 2018). Different architectures combining CNN and ANN layers with different algorithms for defining how neurons interact, have been shown to have better performance in specific tasks. For satellites with good radiometric quality, the state of the art in these methodologies are fully connected neural networks (FCNs) which have been shown to have very high accuracies (Moortgat et al., 2022). However, in the case of satellites such as PlanetScope, which have been reported to have radiometric quality issues (Frazier and Hemingway, 2021), more specific methodologies are required to generate accurate water masks (Freitas et al., 2024). In this thesis, a methodology to do so based on the so-called 'CNN-supervised classification (CSC)' approach, originally designed for airborne imagery, was

developed (Carbonneau et al., 2020, Marochov et al., 2021), based on the hypothesis that the fact this method was designed to extract water masks from a range of disparate aerial imagery sources will enable it to be robust to inter-image differences stemming from radiometric error between individual PlanetScope scenes.

### **2.5.2 Remote sensing of river stage/discharge**

River stage and/or discharge has been measured with the assistance of remote sensing and specifically by satellite EO using a variety of different methodologies and sensors (Pavelsky et al., 2014, Hagemann et al., 2017, Bjerklie et al., 2005, Tarpanelli et al., 2021, Gleason and Smith, 2014, Gleason and Durand, 2020, Kääb et al., 2019, Masafu et al., 2023). The most common methodologies use in-situ or modelled discharge measurements (e.g., Iozzi Sperandelli and Zenker Gireli, 2023, Riggs et al., 2021) with satellite imagery to develop river stage to discharge relationships (Hagemann et al., 2017, Lin et al., 2023). However, these simple correlation models often lack spatio-temporal resolution and have accuracy limitations (Rodrigues do Amaral et al., 2024, Domeneghetti et al., 2024).

Instead, there have been many promising developments using higher return period optical imagery including the use of at-many-stations hydraulic geometry (AMHG) which uses hydraulic geometry relationships between width, depth, velocity, and discharge (Equation. 2.3; Leopold and Maddock, 1953) once converted to a power equation (Equation. 2.4) to find discharge from satellite derived river width along a river reach (Gleason and Wang, 2015, Gleason and Smith, 2014). These often use gauged or reanalysis products to measure discharge to solve these equations and enable future measurements from width alone at these points (Gleason and Durand, 2020). This method has been extended to use PlanetScope for daily measurements (Feng et al., 2021, Feng et al., 2019) although discharge is not well estimated from PlanetScope alone without further data fusion with stream gauges (Feng et al., 2019). Moreover, many of the discharge studies which use PlanetScope are constrained to streams in the relatively simple arctic landscape (Feng et al., 2021) or are location specific methods using indices such as NDVI to monitor river width and fixed radar monitored discharge to build these equations making them difficult to transfer to other basins (Junqueira et al., 2021). There are also some limitations to the AMHG method itself, with many uses requiring hydraulic reanalysis products which have varying accuracies depending on the location and product. Width changes are also assumed to be directly linked to discharge, but differences in channel shape and artificial anthropogenically driven changes in conveyance are difficult to account for, especially where the depth is not known. This depth is difficult to extract from optical imagery and would add more steps and uncertainty to the methodology (Niroumand-Jadidi et al., 2020, Fonstad and Marcus, 2005).

$$(i) \quad w = aQ^b$$

$$(ii) \quad d = cQ^f$$

$$(iii) \quad v = kQ^m$$

*Equation. 2.3: Hydraulic Geometry equations which define the relationship between river channel characteristics for conveying discharge. Where Q is discharge, w is width (i), d is depth (ii), v is velocity (iii) and a,b,c,f,k, and m are constants found when solving these equations (Leopold and Maddock, 1953).*

$$F = a_{x1,x2...xn} E^{bx1,x2...xn}$$

*Equation. 2.4: At-many-stations hydraulic geometry power equation to enable collection of discharge along many river cross sections to approximate discharge. Where x1 to xn are cross section locations, F and E are river specific constants based on hydraulic geometry relationships and F can be approximated from measured river width (Gleason and Smith, 2014).*

The remote sensing of river wetted area can provide a direct proxy for stage/discharge if collected at a high enough temporal resolution to show these changes in wetted area throughout the hydrological cycle. In particular, in channel river islands have been used to focus these wetted area to stage/discharge relationships, because the size of these islands correlate with river depth and the impact of extreme events can be directly observed (Ling et al., 2012). This methodology also enables the measurement of impacts caused by different river stages, such as measuring inundated areas which indicate droughts or floods. This form of direct impact measurement represents an additional benefit of this methodology which would not be possible with discharge information alone. Previous methods have used a limited number of EO images and few islands often over an extended period of time (Sun et al., 2018, Gao et al., 2013, Shi et al., 2017). These studies typically focused on long term sediment dynamics because they lacked the temporal resolution to accurately look at changes in seasonal discharge. To address this gap, a combination of PlanetScope's high-frequency return period and a methodology centred on river islands was explored to approximate changes in discharge. This approach concurrently highlighted key areas affected by shipping constraints, channel change, and fish stock isolation, factors that traditional methods, such as discharge alone, might have overlooked.

### 2.5.3 Monitoring water surface temperature

There have been extensive studies using long-wave thermal infrared (TIR) bands on satellites to assess river WST (Sobrino et al., 2020, Li et al., 2023c, Dugdale, 2016). These studies use long wave TIR in wavelengths between 8 and 12  $\mu\text{m}$  because these wavelengths align with the peak of the emission spectrum curve for a black body (theoretical perfect emitter), at 300 Kelvin, which is similar to the Earth's temperature making it possible to measure deviations from this. Conversion from the photons absorbed by a TIR sensor to a WST measurement requires a stepwise processing framework (Fig. 2.6). Advances in technology have enabled a proliferation of algorithms to carry out this conversion, with relative benefits and limitations stemming from the sensor (e.g., number of TIR bands) and application (e.g., land, urban, water) they were designed for (Meng and Cheng, 2018, Gerace and Montanaro, 2017). This specialisation of algorithms for different applications renders pre-computed or generic land surface temperature datasets, such as the Landsat land surface temperature product (Cook et al., 2014), unsuitable for monitoring river WST accurately.

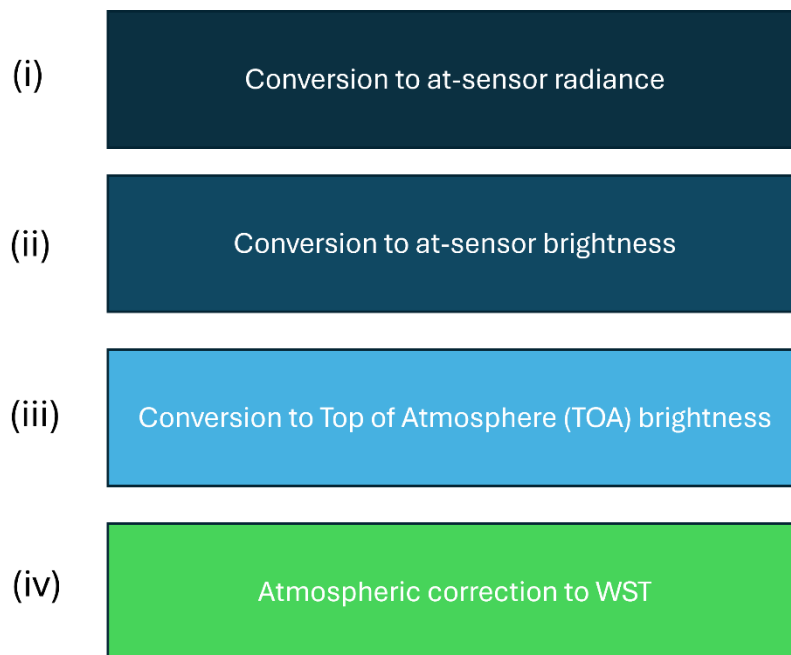


*Figure. 2.6: Traditional processing steps to retrieve WST and LST from TIR satellite imagery. Note that some of the algorithms that carry out atmospheric correction also combine some of the steps ii to iii together into these algorithms.*

To extract WST from TIR requires solving the radiative transfer equation that is constituted of the surface emissivity, Planck function, and radiance from factors other than the target such as the atmosphere. There are a variety of ways of doing so, many of which differ from the traditional single channel algorithm methodology (Fig. 2.6) which will be described first.

The first step in extracting WST from TIR satellite imagery is to convert the signal received by the sensor into a digital number, referred to in this case as at sensor radiance. In almost all cases this is carried out by the satellite data provider because it relies entirely on the calibration and design of the sensor (Kalluri et al., 2018). Thereafter, it is common to convert the radiance to a real temperature value as seen from the satellite, termed at-sensor brightness. This is done through an inversion of Planck's temperature law (Equation. 2.5; Jiménez-Muñoz and Sobrino, 2009).

$$T_{sen} = \frac{K_2}{\ln\left(\frac{K_1}{L_{sen}} + 1\right)}$$

*Equation. 2.5: Inversion of Planck's equation for converting at sensor radiance to at sensor brightness. Where  $K_1$  and  $K_2$  are constants provided by the satellite designers, and  $L_{sen}$  is the at sensor radiance.*

At-sensor brightness does not relate specifically to objects on the Earth's surface because it does not account for their emissivity values. The emissivity value is the ability of an object to emit energy in relation to a perfect black body emitter (Dugdale, 2016). Water is a very good emitter of energy and therefore has an emissivity very close to a black body around 0.991 (Martí-Cardona et al., 2019). There has been some historic debate about factors that can influence water emissivity values (Wen-Yao et al., 1987), especially in the oceans which many large surface forces, however in rivers the consensus of the literature is to use a constant emissivity value (Ling et al., 2017, Torgersen et al., 2001). The considerable differences between both the temperature and emissivity of land and water mean it is vital to understand which substance the satellite pixel corresponds with for accurate measurements. The mixed-pixel problem refers to pixels that contain both water and objects such as banks, islands and vegetation, therefore returning artificially high temperatures for the water. Solving the mixed-pixel problem is one of the main requirements for using TIR satellite data for WST. Therefore, accurate and thorough water masking should be carried out to identify pure pixels before conversion to TOA temperature through the inclusion of emissivity is carried out (Equation. 2.6).

$$WST = \frac{T_{sen}}{1 + \left[\left(\frac{\lambda T_{sen}}{\rho}\right) \ln(\epsilon)\right]}$$

*Equation. 2.6: Conversion of at-sensor brightness temperature ( $T_{sen}$ ) to surface temperature in regard to the emissivity of the target ( $\epsilon$ ). Where  $\lambda$  is the mid-point of the band in questions wavelength  $\rho$  plancks constant (Avdan and Jovanovska, 2016).*

While there are examples of studies using the steps described so far (Avdan and Jovanovska, 2016), these do not account for the effects of the atmosphere such as upwelling radiance, downwelling radiance, and transmissibility of these signals through the atmosphere which can have significant impacts on temperature accuracy (Meng and Cheng, 2018). One methodology used to correct for atmospheric effects using a single TIR band was the statistical mono-window method, a simple linear regression model derived from the radiative transfer equation (Ermida et al., 2020) that takes TOA brightness and converts it to WST by using a look up table of total column water vapor values that has been calibrated against a dataset of known air temperature, water vapor, and ozone profiles (Equation. 2.7). This is made considerably more efficient through GEE cloud computing which allows the total water column vapour to be looked up for time of day and site of the satellite imagery without needed to download all these additional data from the cloud.

$$WST = A_i \frac{T_{sen}}{\varepsilon} + B_i \frac{1}{\varepsilon} + C_i$$

*Equation. 2.7: Statistical mono-window atmospheric correction method for TIR data (Ermida et al., 2020). Where A, B, and C are constants from a look up table, with i indicating the total water column vapour bin used to select values from this look up table.*

Other algorithms exist which use different methods available when more than one band is available (Rozenstein et al., 2014, Rongali et al., 2018) often combining some of the steps used in a single channel algorithm (Fig. 2.1). One example is the temperature and emissivity algorithm (TES) which takes advantage of the five TIR bands on ECOSTRESS and is the planned methodology for the SBG mission (Hook, 2023). TES combines the conversion to brightness temperature step and the atmospheric correction step together by using multiple bands to concurrently extract the emissivity of the target as well as its temperature (Hook, 2023) negating the need to know the emissivity apriori. Regardless, the method developed proposed here is modularised so that alternative TIR algorithms can easily be added and removed as they are developed.

Studies using these methods for WST extraction get absolute accuracies of <2°C for rivers (Despini and Teggi, 2013, Naimaee et al., 2024, Tavares et al., 2020), which is less accurate than the larger less dynamic sea surface temperatures (Jung et al., 2022), but sufficient for monitoring large watersheds. However, these studies often rely on a limited number of images and therefore have a constrained temporal resolution (Martí-Cardona et al., 2019, Baughman and Conaway, 2021, Bonansea et al., 2021, Lamaro et al., 2013). This limited temporal resolution would inhibit the function of an ESDT, where dynamic river WST can inhibit anthropogenic practises or ecological resilience at rates beyond current satellite TIR measurement potential. Therefore, this study

combated this by enabling users to access multiple medium resolution TIR sensors, using recent cloud computing methods, to maximise the available temporal resolution. This new 'constellation' approach enabled the inclusion of other TIR sensors such as ASTER (Despini and Teggi, 2013, Jiménez-Muñoz and Sobrino, 2009) and ECOSTRESS (Hulley et al., 2017, Fisher et al., 2020) which are underutilised in the river surface temperature realm. While the modular construction provided the potential for future planned launches to be incorporated into the same framework to further increase the temporal resolution.

Along with temporal resolution, the ability to define and remove mixed-pixels limits the ability to include TIR WST as a component in an ESDT, due to the potential for error stemming from the differences in temperature and emissivity between land and water. Generic pre-computed temperature datasets are available such as the Landsat land surface temperature product (Cook et al., 2014) as well as LST algorithms that have been developed for GEE (Ermida et al., 2020, Wang et al., 2020b). While these make it much easier for many users to access satellite derived surface temperature, they do not allow the user to access the emissivity defined by these algorithms. Therefore, if the water mask is not accurate enough, temporally or spatially, then they will often incorporate mixed pixels such as exposed sediment bars (such as that highlighted chapter 4) likely introducing error. This is compounded by the onboard resampling of Landsat's TIR bands to 30 m resolution which creates further mixed pixel problems (Martí-Cardona et al., 2019) which some users neglect to mention (Naimaee et al., 2024). Therefore, this project uses the daily PlanetScope archive with my water mask model to remove pixels that are not pure water, due to exposed surfaces or channel change at resolutions that might not be captured by traditional water mask methods. For the first time, it is proposed to combine this higher resolution water mask with the constellation approach defined above to incorporate multiple sensors with high spatial resolution water masks regardless of whether these sensors have their own RGB and NIR bands for the development of water masks. Thus, the framework developed here would enable satellite WST to be included as an ESDT component by combating the mixed pixel problem and increasing the temporal resolution of TIR data availability.

# Chapter 3:

## An AI approach to operationalize global daily PlanetScope satellite imagery for river water masking

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### 3.0 Abstract

Monitoring rivers is vital to manage the invaluable ecosystem services they provide, and also to mitigate the risks they pose to property and life through flooding and drought. Due to the vast extent and dynamic nature of river systems, Earth Observation (EO) is one of the best ways to measure river characteristics. As a first step, EO-based river monitoring often requires extraction of accurate pixel-level water masks, but satellite images traditionally used for this purpose suffer from limited spatial and/or temporal resolution. This problem is addressed by applying a novel Convolutional Neural Network (CNN)-based model to automate water mask extraction. Notably, this approach was shown to overcome radiometric issues that frequently present limitations when working with CubeSat data. The classification model was tested on 36 rivers across 12 global terrestrial biomes (as proxies for the environmental and physical characteristics that lead to the variability in catchments around the globe). This approach produced a median F1 accuracy score of 0.93, suggesting that a compact and efficient CNN-based model can work as well as, if not better than, the conventional very deep neural networks which was most apparent in the mean difference which give greater weight to poorly classified images (F1 0.05 lower for these methods), whilst requiring less training data and computational power (2 hours compared to 40). It is further shown that this model, specialised to the task at hand, performs better than a state-of-the-art Fully Convolutional Neural Network (FCN) that struggles with the highly variable image quality from PlanetScope. Although classifying rivers that were narrower than 60 m, anastomosed or highly urbanised was slightly less successful than the other test images, fine tuning could circumvent these limitations to some degree. Indeed, fine tuning carried out on the Ottawa River, Canada, by including just 5 additional site-

specific training images significantly improved classification accuracy (F1 increased from 0.81 to 0.90,  $p < 0.01$ ). Overall, the results show that CNN-based classification applied to PlanetScope imagery is a viable tool for producing accurate, temporally dynamic river water masks, opening up possibilities for river monitoring investigations where high temporal variability data is essential.

### 3.1 Introduction

Rivers provide a multitude of ecosystem services but also pose risks to property and life through flooding and drought events (Rinke et al., 2019, Arnell and Gosling, 2016). Despite their importance, data about key characteristics of rivers (Hannah et al., 2011, Gardner et al., 2021) at spatial and temporal scales amenable to their management are not readily available. The dominance of field measurements in the river sciences often means cost and time constraints prohibit the kind of extensive records that would be required to understand such large and dynamic systems (Piégay et al., 2020). Consequently, river managers have increasingly turned to Earth Observation (EO) science, using remote sensing (Piégay et al., 2020, Pavelsky and Smith, 2008), to provide the necessary data.

The crucial first step in calculating any river characteristic from EO data is extracting an accurate water mask. This foundational component governs all further analysis by defining which pixels contain exclusively water. Therefore, a typical data pipeline for the extraction of river habitat data from satellite imagery involves taking a satellite image, defining a water mask, and subsequently using the combination of this water mask and the original image to calculate characteristics such as discharge, width, or temperature. (Pavelsky and Smith, 2008). Currently, many studies rely on historical water masks from pre-processed EO datasets (e.g., the Global River Width from Landsat dataset (GRWL; Allen and Pavelsky, 2018) or the Surface Water and Ocean Topography mission River Database (SWORD; Altenau et al., 2021) that are static in time and are assumed to be centred on average bankfull river width (Allen and Pavelsky, 2015). However, in reality, water masks are dynamic, varying as a function of hydromorphic changes that occur in all river systems. Because manual delineation of water masks is laborious and time consuming (Mahoney et al., 2020), this leads to a need for automated procedures for generating water masks.

Traditional methods of water mask creation include use of the Normalised Difference Water Index (NDWI; Sekertekin et al., 2018). Since the NDWI uses the green and near-infrared wavelengths (McFeeters, 1996), it is suitable to use with data from the majority of satellite EO missions. Extracting water masks based on the NDWI involves using histogram thresholding methods that generate very little computational demand; however, this technique relies on the choice of specific threshold values that vary with region (Frazier and Hemingway, 2021). Even when automating the choice of threshold for individual images (Otsu, 1979), segmentation errors persist. This unwanted spectral response occurs most often in heavily vegetated or urbanised regions where shadows, and reflection patterns similar to water, disrupt the expected response (Zheng et al., 2021) which led to the development of the Modified NDWI (Xu, 2006). However, the MNDWI requires a Short-Wave infrared band, precluding its use with higher-resolution

VIS-NIR commercial satellites (Planet, 2018, Gleyzes et al., 2012). Algorithms such as RivWidth (Pavelsky and Smith, 2008) use computer vision-based techniques to smooth the results of these threshold methods (Ziou and Tabbone, 1998, Dougherty, 2020). By combining these methods with cloud infrastructure, the process can be extended globally in the form of RivWidthCloud and operationalised to be reapplied to new imagery (Allen and Pavelsky, 2018, Yang et al., 2019). However, the RivWidth method is still built on the MNDWI water mask foundation (Zou et al., 2018) and thus inherits its limitations. Alternatively, some authors use fractional pixel analysis to help separate some of the complexity in the output from OTSU NDWI thresholding (Cooley et al., 2017) but these do not address the root problems with NDWI.

As an alternative to thresholding methods, a variety of machine learning methods (Abburu and Golla, 2015) such as Support Vector Machines (Foody and Mathur, 2006) or cluster analysis (Genitha and Vani, 2013) have been considered for water mask generation. However, while these approaches generate acceptable results, especially at coarse resolutions, they have not as yet produced masks with the precision required for segmentation of higher resolution imagery. Furthermore, these algorithms are rarely sufficiently generalisable to be extended to 'big data' (Ling et al., 2019) derived from satellite constellations. Yuan et al. (2021) hypothesised that Artificial Neural Networks (ANN) perform better than these other machine learning approaches by being able to "learn" sensor discontinuity. However, on their own, ANNs will suffer from the same issues with generalisability due to their tendency to specialise to their training location (Foody et al., 2003).

While there are some drawbacks associated with these methods, these approaches have also demonstrated the power of remote sensing for water resource science and management. These studies have tended to use open-source data from Sentinel and Landsat sensors, which have provided spatially extensive research avenues for provision of river data. However, these EO data are intrinsically restrained by their coarseness in spatial and temporal resolution (Gleason and Durand, 2020, Junqueira et al., 2021), which consequently limits their usefulness in characterising dynamic freshwater environments that change at very fine timescales. However, the recent development of EO satellite constellations, such as PlanetScope, offer potential for mapping rivers at much higher temporal resolution via daily data collection (Frazier and Hemingway, 2021). This, coupled with the relatively fine spatial resolution of PlanetScope imagery, means that the required characteristics of river systems can potentially be measured and monitored across more river systems globally (Junqueira et al., 2021, Feng et al., 2019). PlanetScope satellites have already been used for tasks such as measuring water quality parameters (Niroumand-Jadidi et al., 2020), such as suspended sediment concentration (Wirabumi et al., 2021), in various waterbodies. In the context of rivers, such studies could be enhanced and extended with dynamic water

masks. Unsurprisingly, the effectiveness of these satellites does not match Landsat or Sentinel in understanding water quality (Mansaray et al., 2021) but by combining these more 'traditional' satellites with high resolution water masks extracted from PlanetScope, the best of both products could potentially be achieved (Gabr et al., 2020).

Working with satellite constellations raises a range of considerations for the creation of accurate water masks. An important one, is that the ability of satellite constellations to observe rivers globally at high spatio-temporal resolution increases the variety of conditions over which a model is required to generalise. This need for generality demands robust water mask extraction methods capable of consistently extracting water masks from across the continuum of rivers that exist globally. Another important consideration is that often, satellite constellations such as PlanetScope constitute smaller, low-cost sensors, whose radiometric quality and lower signal to noise ratio (in comparison to 'conventional' satellites) means that water mask extraction methods must be robust to variance in image quality (Haq, 2022).

Convolutional Neural Networks (CNN) show promise for providing the robust approach required by taking a deep learning, neighbourhood based, approach (Moortgat et al., 2022, Marochov et al., 2021, Carbonneau et al., 2020, Yasir et al., 2022, Qayyum et al., 2020). CNNs tile a fixed number of pixels and then pass a smaller 3D kernel over these tiles; the height and width of the kernel is the number of image rows and columns, as specified by the user, and the depth of the kernel is the number of spectral bands in the image. The neural network uses this kernel to "learn" the space-intensity relationship between pixels within a class. The goal of this operation is to learn the high-level features which dictate which class (i.e., land or water) the tiles belong to. The output of a CNN is a prediction, returned in the same form as the input: a set of tiles which have been given a single class value (Reina et al., 2020). Due to the fixed number of pixels, the real-world spatial extent of this tile is directly related to the ground sampling distance of the pixels in the image. Therefore, unless the CNN is predicting from hyperspatial imagery (<10 cm) the output can appear pixelated. Two predominant methods are often employed to overcome the pixelation issue. Fully Convolutional Neural Networks (FCNs) are often currently considered state of the art (e.g., Tiramisu; Jégou et al., 2017), using traditional CNN architecture to learn 'deep' characteristics but combine this with up-sampling to provide a pixel level result (Long et al., 2015). These have been applied successfully in water classifications (Carbonneau and Bizzi, 2023, Isikdogan et al., 2017) and can be relatively efficient for CNNs (Moortgat et al., 2022). A variety of structures of FCN have been developed for water masking (e.g., Li et al., 2021), however, all these methods still require significant computational resources and deep learning expertise for effective implementation. Moreover, most FCNs also require more detailed training data (e.g., Moortgat et al., 2022); which adds an additional challenge that can create barriers for practitioners aiming to build water masks. Some authors

have overcome this by using Open Street Map annotations to confirm water presence for model training (Mazhar et al., 2022) but along with using water presence maps (Pekel et al., 2016) these methods cannot be used with PlanetScope due to PlanetScope's georeferencing accuracy and edge effect errors caused by scale/resolution mismatches. Another concern stems from the high variability of radiometric quality in PlanetScope data, meaning that an FCN model will encounter challenges in effectively addressing radiometric differences between images without particularly large training sets.

A second strand of research, termed 'CNN supervised classification' (CSC) has been proposed (Carbonneau et al., 2020). This uses a pre-trained CNN to provide localised (within test image) training data for an ANN Multi-Layer Perceptron (MLP) model which in turn provides pixel-level semantic segmentation (Yuan et al., 2021, Carbonneau et al., 2020), thus potentially overcoming significant radiometric differences between images. This method has been highly successful for mapping river habitat types in hyperspatial RGB imagery (Carbonneau et al., 2020), but other applications (including glacier mapping using medium resolution Landsat imagery; Marochov et al., 2021) demonstrate CSCs viability for segmenting satellite data where the target size (be it river or glacier width) is commensurate with these larger resolution satellite inputs. The CSC method only requires relatively imprecise training data, drawing patches over land or water on an image, which can be collected very quickly with limited *a priori* skills, as opposed to multi-step GIS workflows (Moortgat et al., 2022) or working with semi-automatic classifiers. I therefore hypothesise that such an approach is well-suited to producing water masks from PlanetScope imagery and thus test the use of a relatively shallow model architecture (i.e., fewer layers than in other recent publications on FCNs and CSCs), with a view to demonstrating the viability of the proposed methodology for non-specialists.

In this paper, daily PlanetScope individual images are employed and a novel Artificial Intelligence (AI) algorithm is developed capable of generating water masks for these high temporal resolution data at a spatial resolution of 3 meters. This builds on previous CSC applications (Marochov et al., 2021, Carbonneau et al., 2020) but the method has not been previously tested with the large ratio between target size and pixel resolution presented here. Moreover, this study constitutes the first application of this method used for the extraction of daily river water masks, requiring vastly more imagery to be classified by practitioners than would be available with traditional satellites (e.g., Landsat's 16-day return period). In turn this produces an added computational requirement that is hypothesised to be better met by the shallow CSC built here as opposed to more traditional architectures used in earlier CSC applications such as the very deep VGG16 model. This represents yet another reduction in processing requirements when compared to the computationally intensive needs of very deep

FCNs favoured in alternative large water masking studies (Isikdogan et al., 2017, Isikdogan et al., 2020, Carbonneau and Bizzi, 2023). The proposed AI algorithm enables the automation of water mask development, so future EO-based river studies can be attempted without the requirement for manually extracting water masks from each image in a temporal stack. As noted, the fine spatio-temporal resolution of PlanetScope, and difficulties with using CubeSats more generally (e.g., limited spectral resolution, issues calibrating within a constellation (Maskey et al., 2021), requires the model to be able to generalise to a much greater degree than other EO-based water mask algorithms (Feng et al., 2019, Junqueira et al., 2021, Moortgat et al., 2022, Isikdogan et al., 2017). Thus it is also hypothesised that the 'self-contained' nature of the CSC method would cope with these radiometric issues better than a FCN would.

In order to create a model that can generalise globally, I also examine the potential to include a 'human-in-the-AI-loop' in this context. Here, the potential to improve classification performance in a specific use case is tested by fine tuning it with limited additional training data. The overarching aim was therefore to develop and evaluate an AI algorithm that automates the extraction of river water masks from PlanetScope imagery. This aimed to overcome computational limitations associated with previous methods while ensuring practitioners could easily create and enhance training data, by pioneering a robust shallow CSC algorithm. In order to achieve this and satisfy the first research objective of this thesis, the following three sub-objectives were developed which provided not only insights into the feasibility of the proposed method but also highlights its viability as a tool for water mask generation on which to base further EO river research and analysis:

1. Develop a CSC-based classifier, with minimal processing demands, capable of extracting river water masks from PlanetScope imagery and compare its accuracy to 'conventional' image segmentation algorithms and a state-of-the-art Fully Convolutional Neural Network
2. Apply the CSC approach to a range of global rivers to understand when, where and how effective the approach might be across 12 global biomes.
3. Test the extent to which the inclusion of limited additional training data improves classification accuracy at a specific river, shedding light on the viability of a 'human-in-the-AI-loop' classification strategy.

## 3.2 Methodology

### 3.2.1 PlanetScope imagery

Planet PBC operates the PlanetScope constellation of 130+ CubeSat (i.e., small, low-cost) satellites (Planet, 2022), imaging a large proportion of the globe every day (Planet, 2018). There have been 3 generations of these PlanetScope “Dove” satellites, improving the radiometric quality of images as well as adding 4 additional bands in the most recent 2021 “SuperDoves” (coastal blue, green 1, yellow, and red edge; le Roux et al., 2021). Here, the focus is solely on four-band imagery enabling interoperability across the whole 5-year range of historical and current PlanetScope imagery. Given the new SuperDoves do not include a shortwave infrared band (shown to improve water delineation; Xu, 2006) it is not expected that the increased complexity of 8 bands would provide significant classification improvement.

PlanetScope satellites capture imagery at 3 to 5 metre resolution depending on the individual satellite’s altitude (Planet, 2018). This imagery is resampled to 3 m making PlanetScope the highest resolution continuously recording satellite system (Frazier and Hemingway, 2021). Higher resolution imagery is obtainable but hindered by requiring the user to task it to a specific limited location and time at additional cost (Cornebise et al., 2022). EO data captured by these satellites is pre-processed before provision to the end-user. In this pre-processing the imagery is calibrated against ground stations and MODIS data to remove the effects of the atmosphere on reflectance received at the sensor (Planet, 2018). As such, all imagery utilised in this study used the PlanetScope’s pre-processed surface reflectance product. This enables a reduction in the client-side model processing pipeline and also reflects the trend in satellite remote sensing towards the use of analysis-ready products (Gorelick et al., 2017). To help correct for different relative responses from individual satellites in the constellation and other adverse climatic effects, the PlanetScope product can be downloaded normalised against Sentinel 2 (Kington and Collison, 2022). However, interoperability between the constellation is difficult because there is a high turnover of satellites due to their short lifespans. In addition, their limited payload capacity requires smaller technology placed closer together than traditional satellites, which leads to relatively high potential error between PlanetScope sensors (Frazier and Hemingway, 2021, Maskey et al., 2021).

### 3.2.2 Training and testing imagery

To develop a water mask algorithm able to generalise across a diverse range of rivers, training data (Lew and Schumacher Jr, 2020) covers a variety of global rivers. Traditional river classification systems (Kasprak et al., 2016, Rosgen, 1994, Brierley and Fryirs, 2013) could provide the framework for this training set. However, the

algorithm was also required to distinguish rivers that exist in the context of different land uses, meaning that the training selection framework must be globally holistic. Therefore, the World Wildlife Fund (WWF) global biomes were used to dictate globally representative landscapes from which to select test and training data for the algorithm (Olson et al., 2001). Of the 14 WWF biomes, Tropical Coniferous Forest and Mangrove Forest were removed because their relative size and positioning limited the number of rivers that could confidently be placed within their boundaries. The Natural Earth 10 m wide river centre line vector file (Kelso and Patterson, 2010) was used to select rivers in the remaining 12 biomes. This threshold ensured that rivers were resolvable within the 3 m resolution of PlanetScope, allowing for the inclusion of narrower rivers than other coarser datasets (e.g., GRWL) whilst still ensuring the presence of large perennial streams. A range of river types and sizes were included to incorporate the full range of potential study areas (Fig. 3.1). The final selection of rivers comprised water courses between 25 and 7400 m wide, selected to provide global coverage, with 3 rivers from each of the 12 biomes resulting in a total of 36 individual rivers. This selection encompassed as many different forms of river systems and catchment as possible. These included urban single thread rivers including the Thames, multithread braided rivers such as the Ahuriri, NZ, very wide rivers in the Amazon River, Brazil, and Slave River, Canada, the narrowest rivers in the study including the Trent, UK and upper Rio Grande in Argentina, and land use context ranging from rainforests to deserts to the Arctic, such as the Popigay in Russia. Thus, the full extent of transferability in this method was able to be tested.

For each river, a minimum of 3 scenes were delineated and downloaded. These were from different dates and different positions on the river. These dates were distributed throughout different seasons at all sites to maximise potential applications of the water masks generated, with the requirement that the river channel contained water (if an intermittent river) and this water was not entirely frozen. Two scenes were used as training data and the third used as hold-out test images, conferring a nominal test/train split of 66/33 (Yin et al., 2021, Carboneau et al., 2020). This is weighted slightly more towards testing than the 80/20 split used in some studies (Moortgat et al., 2022). However, the aim of CSC is to be able to predict many different scenarios from the training set and therefore there should be a larger weighting for test data (Carboneau et al., 2020). As such, 5 additional hold-out images were added to further test the algorithm. These contained anomalies such as snow, excessive shadow, or cloud cover that had evaded the Planet Explorer cloud mask.

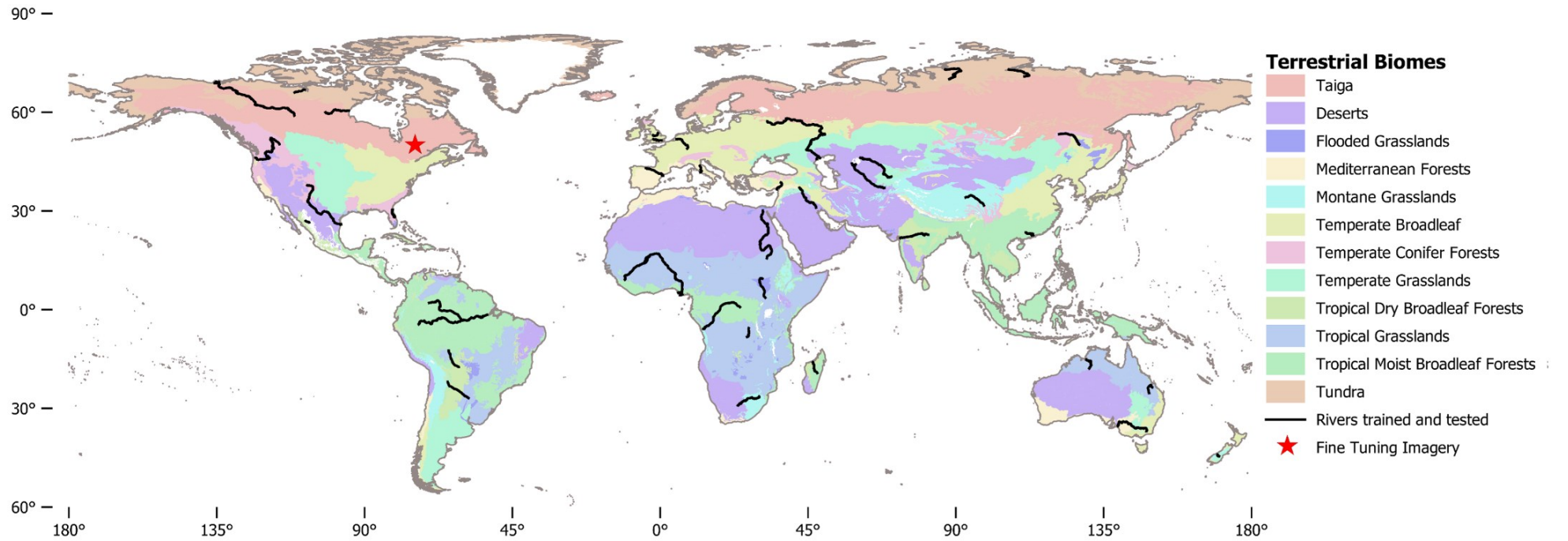


*Figure. 3.1: The Global terrestrial biomes presented by (Olson et al., 2001) overlayed with the rivers used in this study for testing and training. 12 biomes were selected for this study with 3 rivers selected from each biome. Additional sites used for testing the ability of the algorithm to be fine-tuned were in the area here.*

### **3.2.3 Data labelling**

Training data were labelled manually using QGIS 3.16.5 with the GRASS 8.7.5 plug in (Baghdadi et al., 2018). This workflow involved delineating land and water in a shapefile by drawing polygons over the clear land and water sections of an image. There was no precise requirement for the extent of polygons but a reasonable coverage of the unambiguous land classes across the image, taking 3-5 minutes, was expected (see supplementary materials for examples). This was then saved as a raster of the same dimensions as the original image. Labels consisting of large clear polygons were drawn to simulate the requirement for training data to be quick to assemble. Test images were labelled with the “Semi-Automatic classification QGIS plug-in” version 7.10.10 (Congedo, 2021). A minimum of 8 sample polygons were delineated per image to train this semi-automatic classifier, and more were included where necessary when a visual inspection of the accuracy of the result was not considered sufficient. This method was used because every pixel in an image was classified. Alternative attempts at manual delineation often excluded the hardest to classify, channel edge pixels which were most important for understanding model success. The resulting training data consisted of 72 scenes which were then divided into 20 by 20-pixel training tiles starting in the top left corner of each image for CSC model calibration. Of these, only training tiles which were purely water or purely land were included in the training data (Marochov et al., 2021). These were balanced against the smallest class to prevent overfitting (Gavrilov et al., 2018), resulting in 393,000 training tiles. Additional training sets consisting of 10 by 10 and 32 by 32 tiles were also produced to enable comparison between models trained using different tile sizes.

### **3.2.4 CSC model architecture**

Our water mask classification model was run on a PC with a 12-core Intel i7-12700K with 32 Gb RAM and a NVIDIA GeForce RTX 3070 GPU with 8 Gb RAM and 5888 CUDA cores. TensorFlow and Keras (Abadi et al., 2016) were chosen to develop the model. The classification models produced here were based on similar approaches developed and used in a variety of remote sensing fields known as CNN-supervised classification (CSC) models (Carbonneau et al., 2020, Marochov et al., 2021). CSC models require training a fully connected sequential CNN model which predicts a tiled test image, analogous to a rough sketch of the river channel due to these larger CNN tiles. The results from this CNN are thereafter used to train a localised MLP model which enables semantic (i.e., pixel level) segmentation specific to the spectral signatures of the scene in question.

Three relatively simplistic CNN models were developed with tile sizes of 32 x 32, 20 x 20 and 10 x 10 pixels respectively, hereafter referred to as M32, M20, M10. Each of

these three sequential models is made up of 9 fully connected layers including two convolutional layers and two dense layers (Fig. 3.2). All layers used the 'RELU' activation function with the exception of the final 'SoftMax' output layer (Géron, 2022). The convolutional layers and first dense layer have 32 neurons each. The convolutional layers have a kernel size of 3 by 3 which dictates the dimensions of the convolutional window which moves across the tile. The models are compiled with the 'sparse categorical cross entropy' loss function, and an 'Adams' optimiser, both of which are broadly adopted in image classification (Goodfellow et al., 2016). These values were selected based on an assessment of the loss and accuracy outputs during grid based hyperparameter tuning training runs which used the TensorFlow TensorBoard call back to assess which combinations worked best. All models were run for 10 epochs after this was found to be enough to result in convergence (see supplementary material). The output of these CNNs was in the form of the likelihood of each tile being land or water.

Transfer learning is a field of AI that takes advantage of the weights in pre-trained classification models developed from millions of training images (Zhuang et al., 2020). The desire to use 4-band imagery here prevents the use of transfer learning on models trained with 3-band RGB imagery and solutions that are currently available in the literature. Models that enable transfer learning using variable band numbers are not yet commonly accepted (de La Comble and Prepin, 2021). Hence, many methods take the architecture of these very deep CNN models developed in "Kaggle" programming competitions but do not keep the pre-trained weights (Marochov et al., 2021). However, models such as the commonly adapted VGG16 model, were developed with a thousand output classes (Simonyan and Zisserman, 2014). It was hypothesised that a more simplistic model would be more effective when attempting to satisfy the performance requirements desired from a binary output (Nativi et al., 2021). By using a much shallower architecture I believe that the models will converge quicker because they are not using the large processing power of traditional methods to learn intricacies in 'high level' features, such as straight lines (Zoph et al., 2018). These high level features are largely superfluous to this study's requirements because the relatively low resolution of PlanetScope means that these higher features are often not visible in the imagery. For example, learning aspects of spectral combinations in riverbanks would be of use with higher resolution imagery but here the 3 m resolution edge pixels are often mixed, negating these lessons. Therefore, developing shallower models allows for reduced tile size, potentially improving results and reducing processing time. These factors make the CSC models developed here both more effective and applicable to a larger user base who lack high-performance machines (Boothroyd et al., 2021b). Nonetheless, a 'control' CSC model was developed to test this theory, using this VGG16 architecture to generate a very-deep CNN with a 2-neuron 'SoftMax' output layer added to provide the desired output. This used a tile size of 32 by 32 pixels, the minimum size enabled by VGG16. This very deep network was only run for 50 epochs before convergence,

where upon visual inspection the validation loss value ceased to be improved by additional training (see supplementary materials for loss curves).

The subsequent MLP stage was kept simple to account for the very different inputs that might be used to train the model, due to the global diversity of river environments. Therefore, this neural network consisted of 4 dense fully connected layers using the same 'ReLU' and 'SoftMax' activation functions as the CNN phase. The first 3 layers had 64 neurons and the last again had 2, one for each potential output. The same compilers were used in this stage as in the CNN stage. The MLP was only run for a single epoch as it became apparent that with many of the images with smaller rivers more epochs resulted in overfitting. The result from this section also used NumPy's argmax function to convert the softmax results into a binary classification. The final stage of the model includes an additional morphological operator to eliminate speckle from the water masks output by the MLP stage and constrain results to the main channel (Riggs et al., 2021, Pavelsky and Smith, 2008). For this, the OpenCV 'dilate' function was used with a kernel size of 3 (Bradski and Kaehler, 2000). Thus, any pixels not immediately adjacent to 2 or more other pixels were converted to the alternative classification in the same neighbourhood. This procedure removed the majority of speckle without removing smaller watercourses in the images.

To compare the models to a more basic classification algorithms, the Otsu segmentation method was also applied on all test images (Otsu, 1979). This uses histograms to statistically split the imagery into two classes without the need for training data or a *priori* knowledge of the imagery. To compare against state-of-the-art AI models the Tiramisu FCN (Jégou et al., 2017) was trained using the same images as the other models. However, this requires pixel level classification training data that is much more time consuming to develop. To assist with this process, the DoodleVerse package (Buscombe and Goldstein, 2022) for semi-automatic image classification was used. Any training images that were not satisfactorily classified or were too large for DoodleVerse were classified using the same QGIS Semi-automatic classifier previously used for holdout image classification. A tile size of 224\*224 was used due to the greater information requirements of a FCN. Because this model requires considerably more training data than CSC, an augmentation script was applied that added additional altered (e.g., flipped/rotated) tiles containing at least 5% water in the image. To further reduce the impact of the limited water coverage in the training images the focal loss function was used to put greater importance on the weights for water tiles (Lin et al., 2017). The Tiramisu model was run for 20 epochs before convergence.

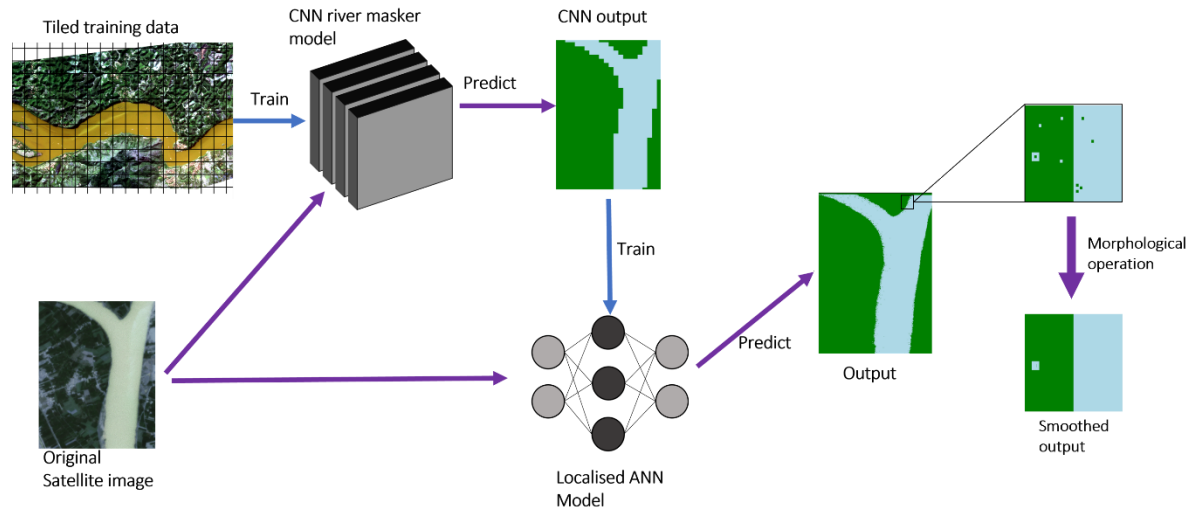


*Figure. 3.2: Conceptual diagram of the CSC structure used in this study. A pre-trained 9-layer CNN which uses its predictions to train a 5-layer MLP. The final results are processed by a morphological operator to remove any remaining speckle. The CNN architecture consisted of a convolutional layer, a batch normalisation layer, a max pool layer, a second convolutional layer, a second max pool layer, a flattening layer, a dense layer, a drop out layer and the final output dense layer. The MLP architecture consisted of a normalisation layer, 3 dense layers and then a final output dense layer.*

### 3.2.5 ‘Human-in-the-loop’ model enhancement

Our CSC approach was expected to be able to use minimal processing power to provide accurate predictions despite the variability of PlanetScope imagery. However, the model is unlikely to be capable of accurately predicting the water mask for every river globally, at all times of year, regardless of the quality of the satellite imagery and any corrections applied. This is because the infinite variability of global river systems (Thoms and Sheldon, 2019, Frazier and Hemingway, 2021) means that it was not feasible to train the model on every eventuality or user requirement. However, the ability to train with minimal processing power enabled us to test an additional ‘human-in-the-loop’ computation stage to understand whether retraining (i.e., fine tuning) the model through the inclusion of a few additional images, quickly labelled using a low effort approach such as the QGIS ‘magic wand’ (Baghdadi et al., 2018), can effectively improve classification results in a specific river system not previously seen by the classifier.

To test the ability of this model to be fine-tuned in this manner, an independent study site in Southern Canada was chosen where imagery was already available for this study which the model had not already seen. 20 images from the Ottawa River were collected. 15 were used as test images and processed the original M20 CSC model developed here. The remaining 5 images were quickly labelled using the QGIS ‘magic wand’ tool, producing additional training data in less than an hour. The original CSC was then retrained with this additional training data included, for a total of 408,000 tiles, effectively

biasing the training data to this new river system (which now has more training data than other rivers) with the same architecture, number of epochs, and learning rate. The 15 test images were predicted again to assess if this ‘human-centric’ CSC was more effective at correctly predicting these images.

### 3.2.6 Statistical analysis

Three validation metrics were employed to different degrees. *Loss* (see section 2.3) and *Accuracy* (eq. 1) were used during training of the CNNs to assess the ability of each model to predict randomly assigned test data (Goodfellow et al., 2016, Yuan et al., 2021). Although this was important for improving CNNs during the building phase, it only showed their ability to predict known tiles as water and land and was not necessarily linked to the final results. The main measure of classification accuracy was therefore the F1 score (Eq. 4), which measured the ability of a full CSC model to predict a holdout image at a pixel scale. This F1 score is sometimes considered the harmonic mean of *Precision* (eq. 2) and *Recall* (eq. 3; Carboneau et al., 2020). It is a well-accepted method of balancing where a model correctly predicts a pixel and where it provides false positives or negatives (James et al., 2021, Goodfellow et al., 2016). Therefore, if a model predicts a single class for a whole image, it will not score highly despite, by process of elimination, having correctly predicted all instances of one of those two classes.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3.1)$$

$$Precision (P) = \frac{TP}{TP + FP} \quad (3.2)$$

$$Recall (R) = \frac{TP}{TP + FN} \quad (3.3)$$

$$F1 = 2 \frac{P \cdot R}{P + R} \quad (3.4)$$

*Accuracy* (Eq. 3.1) considers the True Positives (TP) and True Negatives (TN) which are respectively water and land pixels which have been identified correctly. It then divides these by the total predictions made, including False Positives (FP) and False Negatives (FN) that represent water and land pixels predicted incorrectly, thus giving the ratio of correctly identified pixels. For assessing predictions of holdout images, F1 score (Eq. 3.4) was used because it takes account of potential class imbalances. It does this through combining *Precision* (Eq. 3.2), how many water pixels identified were correct, and *recall* (Eq. 3.3) which is the ratio of correctly predicted water pixels to those that should have been predicted.

Statistical analysis was carried out using the SciPy package (Virtanen et al., 2020), which was also used to compare F1 scores against river characteristics (e.g., river width and planform, anthropogenic influence) and imagery metadata, to understand whether differences between F1 scores for biomes were caused by intrinsic landscape characteristics or were artifacts of the satellite imagery itself. River width was expected to be a limiting factor on predictive ability, due to the requirement of tile-sized sections of water being needed to provide pixels to train the MLP. Width was manually extracted from the widest river reach in the image, provided that the width was maintained in this reach for at least 20 pixels (60 m) downstream to represent the width of a single tile at the CNN stage of classification. Width measurements were log transformed based on the hypothesis that the differences in the narrower widths would have a greater impact than differences between larger width values. The NIR band is integral to NDWI measurements because NIR wavelengths are strongly absorbed by water (McFeeters, 1996), and this was also tested in a similar manner to understand its influence on the results. The 5<sup>th</sup> to 95<sup>th</sup> percentile range of NIR values in an image was used as this represented the difference between land or water excluding the most over- or under-exposed areas of the image. Linear regression was used to test the potential relationship between these environmental characteristics/imagery metadata and classification accuracy (F1). For the ‘human-in-the-AI-loop’ tests, a paired samples t-test was used to differentiate between F1 scores before and after the inclusion of the fine-tuned test data. A Box-Cox transformation was used before testing to achieve a normalised distribution, removing the effects of skew towards the better-predicted imagery.

## 3.3 Results

### 3.3.1 Model selection

The various CSC models took between 36 minutes and 2 hours 11 minutes to train, excluding the time taken to tile imagery and save it as TensorFlow Record file types. In contrast, the Tiramisu FCN model required 40 hours at ~2 hours an epoch. The simpler models (M10, M20 and M32 tiles) all converged within 10 epochs. The very deep layered network based on the VGG16 architecture (also 32 x 32 tiles) converged over 50 epochs, while the comparator Tiramisu model converged after 20 epochs. All models produced some highly accurate water masks but also struggled with some imagery and biomes (Fig. 3.3). Training metrics describe the ability of the CNN stage of the model to predict a random selection of the training tiles providing an indication of the internal ability to learn during training. Here these training metrics corresponded with tile size and depth. The very deep model (VGG16) yielded the highest accuracy (0.94) compared to M32 (0.87), M20 (0.85) and M10 (0.84), and the lowest loss (0.13) compared to 0.31, 0.34 and 0.35 for M32, M20 and M10 respectively. By way of comparison, the Tiramisu FCN achieved a training accuracy of 0.92 and a loss of 0.04.

The final learning curves for each of these models are included in the supplementary material. However, training metrics only measure the ability of the CNN to predict tiles taken from the training set, which could be related to those used to train the model. These training metrics do not provide an assessment of the CNN's ability to predict hold-out image tiles or the full CSC model's ability to predict the whole of a new hold-out image, and surprisingly, these training metrics were found to not correspond to the best final predictions. In predicting hold out images, the M20 model produced the highest median F1 score (0.93), making it the most successful model, while the M10, M32, and very deep CSC models were all similarly effective but slightly lower scoring (0.90, 0.92, 0.92). While the Otsu segmentation approach scored a similar median classification result (0.90), its much lower mean value (Table 1) and longer-tailed error distribution (Figure 3) highlights the considerably poorer performance of this 'conventional' classification approach in comparison to the CSC-based models. Using the comparator Tiramisu FCN, only 4 of 36 images were predicted with sufficient accuracy to justify recording F1 scores ( $F1 = 0.52$  to  $0.87$ ; see supplementary material), highlighting how good training/validation performance does not guarantee accurate predictions of hold-out imagery. The FCN was therefore not included in further model comparisons.

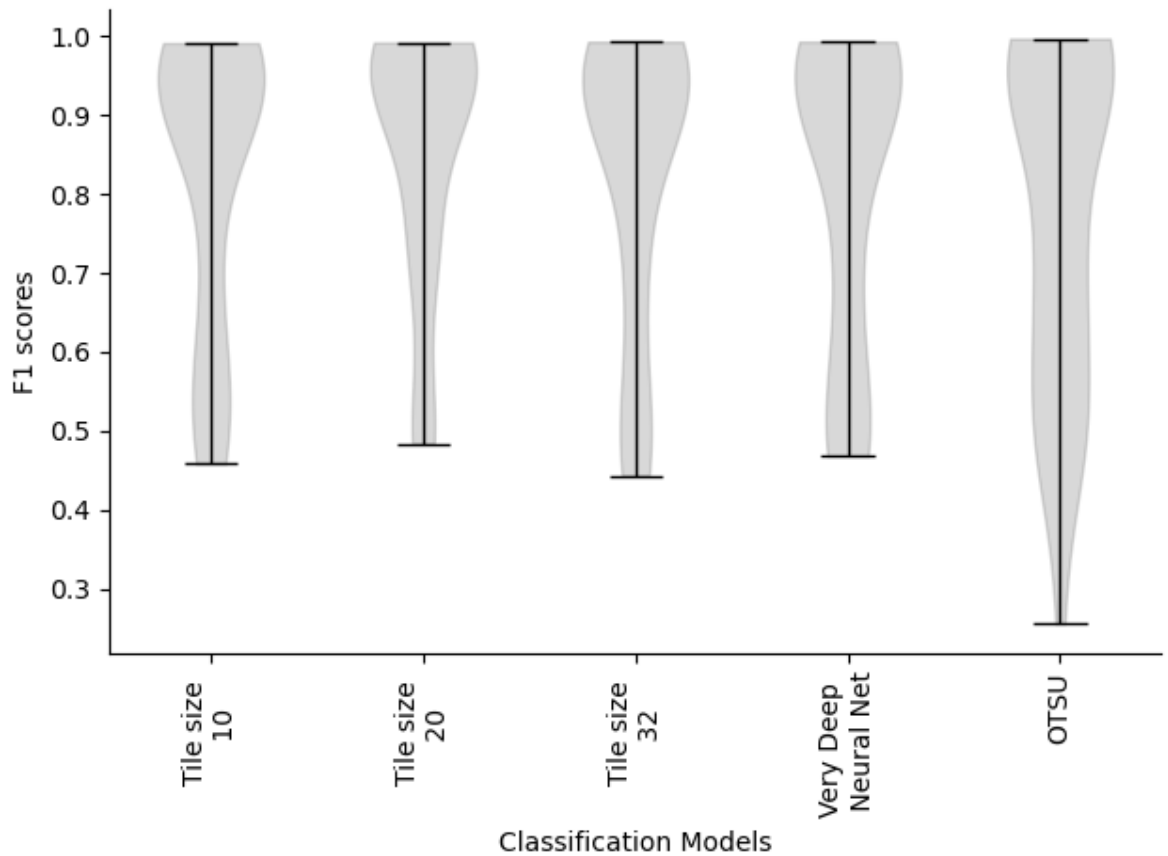


*Figure. 3.3: Comparison of the ability of tested models to predict hold-out images. All models shown here are skewed towards high F1 scores. There are different distributions of the scores for the weakest predictions made by each model. M20 in particular never predicts as poorly as the other models and has a thinner tail suggesting no clustering of poorly predicted images.*

Overall, M20 produced water masks with  $F1 \geq 0.9$  for over 60% of the hold-out images making it the best model in this study (Fig. 3.4). While it produced the best F1 scores in 6 of the 12 biomes (Table. 3.1), other models performed better in some other biomes with varying degrees of departure from M20. In fact, the Otsu thresholding method (the simplest used here, which produced some highly inaccurate results [e.g., average F1 of 0.5 for Mediterranean Forest]), also produced near perfect F1 scores in polar-type biomes such as the Taiga (average F1 of 0.99). The clear histogram response facilitated separation of the water from non-water pixels which also allowed M20 to perform similarly well ( $F1 = 0.98$ ). The Otsu method also exceeded the accuracy of all other methods in the Tropical Dry Broadleaf (0.80 compared to 0.66-0.69) biome despite still producing less than desirable results. Nevertheless, in all other cases it was not better than M20.

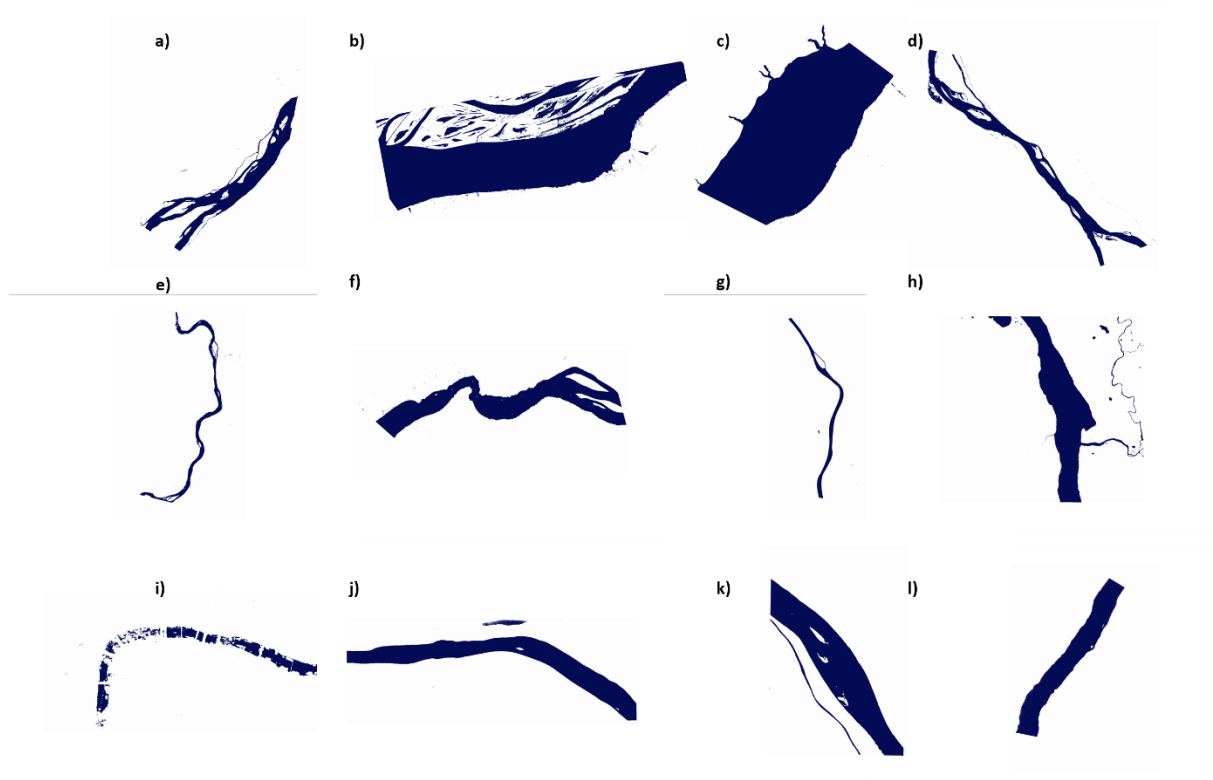


*Figure. 3.4: Selection of water masks produced using M20. The majority of these rivers scored an F1 accuracy >0.97. However, the River Thames, through central London, is also included with a score of 0.85 to display model results in the most complex urban environments with multiple watercraft and bridges in a small spatial area (i). In this case, it has still produced a fairly accurate water mask in demanding circumstances. Rivers shown here a: Niger (Mali), Tropical Grasslands. b: Amazon (Brazil), Tropical Moist Broadleaf. c: Volga (Russia), Temperate Grasslands. d: Nile (Egypt), Flooded Grasslands. e: Betsiboka (Madagascar), Tropical Moist Broadleaf. f: Xi (China), Tropical Moist Broadleaf. g: Victoria (Australia), Tropical Grasslands. h: Pyasina (Russia), Tundra. i: Thames (UK), Temperate Broadleaf, j: Mackenzie (Canada), Taiga. k: Slave (Canada), Taiga. l: Congo (Democratic Republic of the Congo), Tropical Grasslands.*

*Table. 3.1: Comparison of water mask model averages and their performance in different biomes. For each variable, the best performing model has been highlighted. Mean F1 score was used for comparing biomes because each of these had a limited number of images, limiting the usefulness of median F1 score.*

| Biome                                      | (mean<br>average<br>score) | Tile<br>Size<br>10<br>CSC | Tile<br>Size<br>20<br>CSC | Tile Size<br>32 CSC | Very<br>(VGG16) | Deep<br>CSC | Otsu<br>thresholding | NDWI |
|--------------------------------------------|----------------------------|---------------------------|---------------------------|---------------------|-----------------|-------------|----------------------|------|
| <b>Overall Median</b>                      |                            | 0.92                      | 0.93                      | 0.92                | 0.92            |             | 0.90                 |      |
| <b>Overall Mean</b>                        |                            | 0.83                      | 0.86                      | 0.83                | 0.81            |             | 0.78                 |      |
| <b>Overall Range</b>                       |                            | 0.53                      | 0.51                      | 0.55                | 0.52            |             | 0.74                 |      |
| <b>Tundra</b>                              |                            | 0.90                      | 0.89                      | 0.77                | 0.76            |             | 0.82                 |      |
| <b>Taiga</b>                               |                            | 0.98                      | 0.98                      | 0.96                | 0.97            |             | 0.99                 |      |
| <b>Montane<br/>Grassland</b>               |                            | 0.64                      | 0.74                      | 0.75                | 0.64            |             | 0.63                 |      |
| <b>Temperate<br/>Coniferous<br/>Forest</b> |                            | 0.77                      | 0.65                      | 0.81                | 0.65            |             | 0.79                 |      |
| <b>Temperate<br/>Broadleaf<br/>Forest</b>  |                            | 0.68                      | 0.77                      | 0.70                | 0.69            |             | 0.58                 |      |
| <b>Temperate<br/>Grassland</b>             |                            | 0.97                      | 0.97                      | 0.97                | 0.97            |             | 0.97                 |      |
| <b>Tropical Moist<br/>Broadleaf</b>        |                            | 0.96                      | 0.98                      | 0.98                | 0.98            |             | 0.98                 |      |
| <b>Tropical Dry<br/>Broadleaf</b>          |                            | 0.66                      | 0.69                      | 0.67                | 0.64            |             | 0.80                 |      |
| <b>Tropical<br/>Grassland</b>              |                            | 0.87                      | 0.99                      | 0.81                | 0.96            |             | 0.98                 |      |
| <b>Mediterranean<br/>Forest</b>            |                            | 0.82                      | 0.87                      | 0.87                | 0.86            |             | 0.50                 |      |
| <b>Deserts</b>                             |                            | 0.79                      | 0.82                      | 0.77                | 0.78            |             | 0.67                 |      |
| <b>Flooded<br/>Grasslands</b>              |                            | 0.90                      | 0.91                      | 0.92                | 0.84            |             | 0.70                 |      |

### 3.3.2 Variability within biomes

Water mask generation was consistently more accurate for rivers in some biomes (such as Tropical Moist Broadleaf) than others (e.g., Tropical Dry Broadleaf biome; Fig. 3.5, Table 1). Understanding these inconsistencies requires analysis of within-biome causes

of poor model performance. Ecoregions were plotted separately for M20 to reveal those that produced similar results, possibly due to internal factors (Fig. 3.5). The 12 biomes can be visually categorised into 3 groups in terms of their performance: consistently good, varied, and poor (Fig. 3.5). In the 'poor' group Montane Grassland, Temperate Broadleaf and Temperate Coniferous biomes yield some water masks that are highly accurate (Fig. 3.6a), but along with Tropical Dry Broadleaf, also generate water masks of an unacceptable quality (Fig. 3.6b).

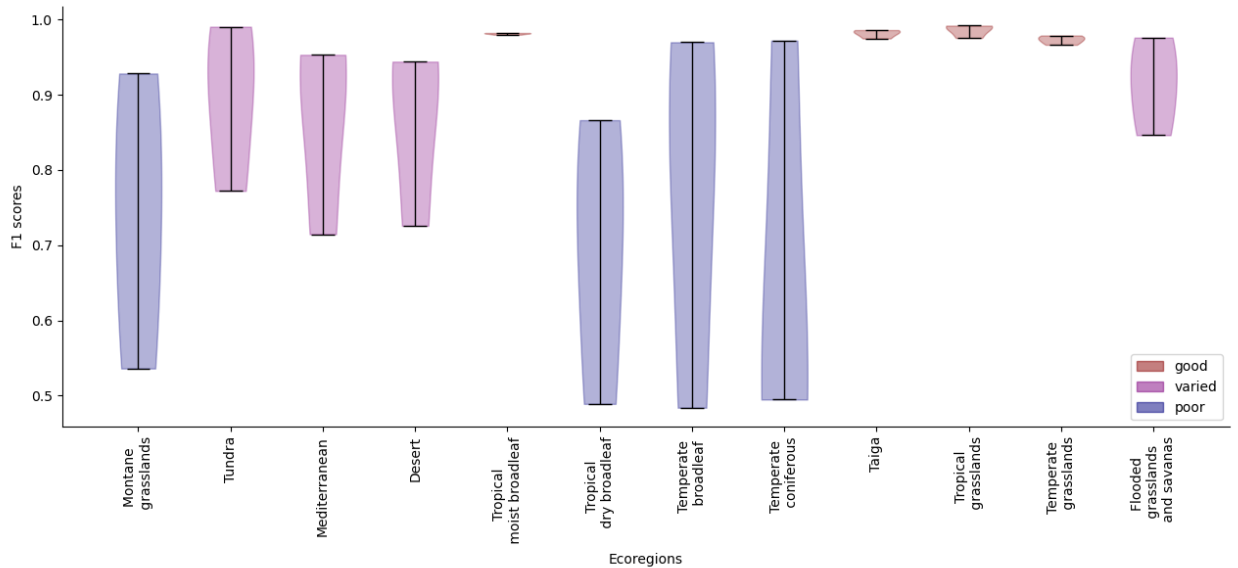


Figure. 3.5: Within region F1 scores for biomes predicted by M20. Based on these results, biome predictability was classified as good, varied, or poor.

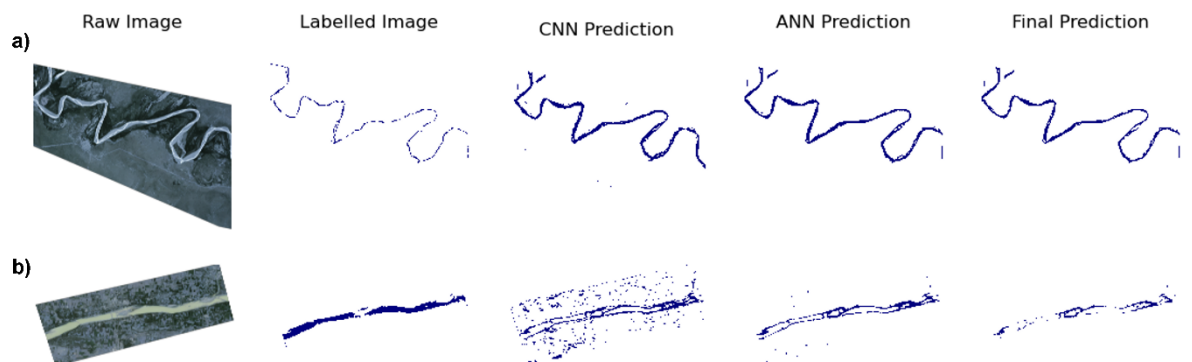


Figure. 3.6: Comparison of CSC predictive workflows for well and poorly predicted images in the poor performing biomes. Despite narrow sinuous channels, the Vaal River in South Africa, from the Tropical Dry Broadleaf biome, scored an F1 score of 0.86 (a). Other images in the same biome struggled with issues such as sand bars and urban areas, including the Narmada River in India (b) with an F1 score of 0.72. It is clear that if the CNN prediction is particularly poor, then despite the predictive improvements made by the ANN section, the final prediction will suffer.

Descriptive statistics of underlying imagery components were tested against F1 scores to understand the causes of the variable results (Fig. 3.7). While no significant relationship was found between F1 score and the range of any of the spectral bands, any of the metadata characteristics provided by PlanetScope, or any of the physical river characteristics visible from the imagery ( $p > 0.05$  in all cases), a moderately significant trend was observed between log-transformed river width and F1 score ( $r^2 = 0.34$ ,  $p < 0.01$ ) which is consistent regardless of biome, indicating that this control (i.e., width) is a local, rather than regional, driver of differences in F1 score.

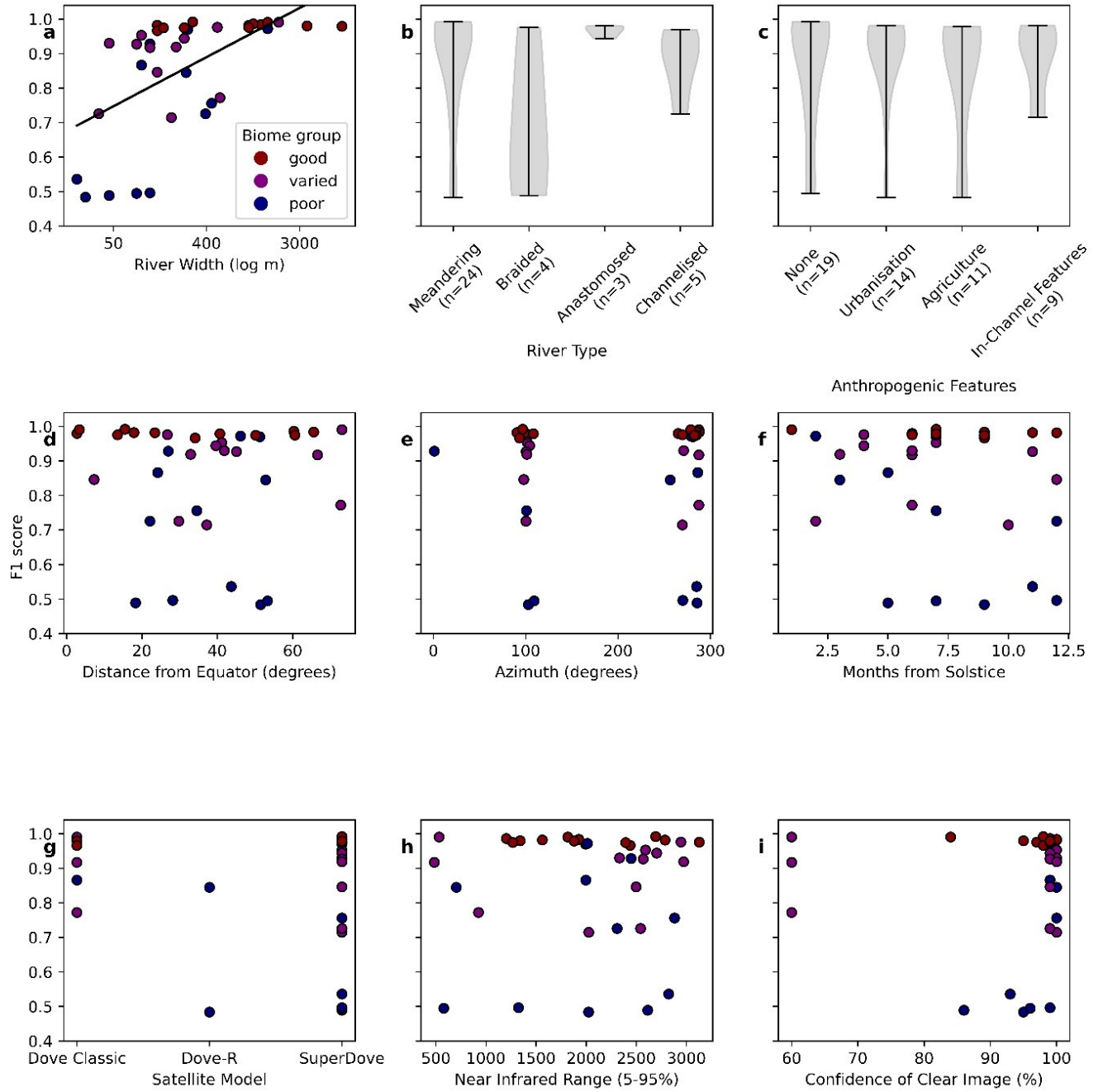


Figure 3.7: F1 score as function of variability in external (e.g., physical river characteristics) and internal (image metadata) properties. Log transformed width correlates significantly to F1 score ( $r^2=0.34$ ,  $p<0.01$ ), which is to be expected due to the greater importance of differences in smaller river widths, as opposed to differences in the widths of larger rivers. No other variables were found to be significantly correlated.

Nine poorly predicted images were isolated, with F1 scores ranging from 0.48 to 0.85 (see supplementary materials). Visual inspection of these images identified three issues common to these locations that could have contributed to the low F1 scores yielded by these data: 1. braided river types without a dominant main channel, 2. land-use types that are unclear even to a human operator (i.e., where colour/textural differences between water and non-water pixels are difficult to discriminate), and c) the presence of bridges or instream features (e.g., boats). These issues all appeared to cause issues for model predictions at the first CNN phase, which were then propagated through the MLP to the final result. Additional potential causes of error result from the presence of cloud or ice in imagery. For example, despite choosing cloud-free images from the PlanetScope database, some images still included small amounts of cloud (Fig. 3.8.a). Where there was a limited amount of ice and snow in an image the model still performed well (Fig. 3.8.b), but this was not the case with deep shadow covering parts of the image (Fig. 3.8.c).

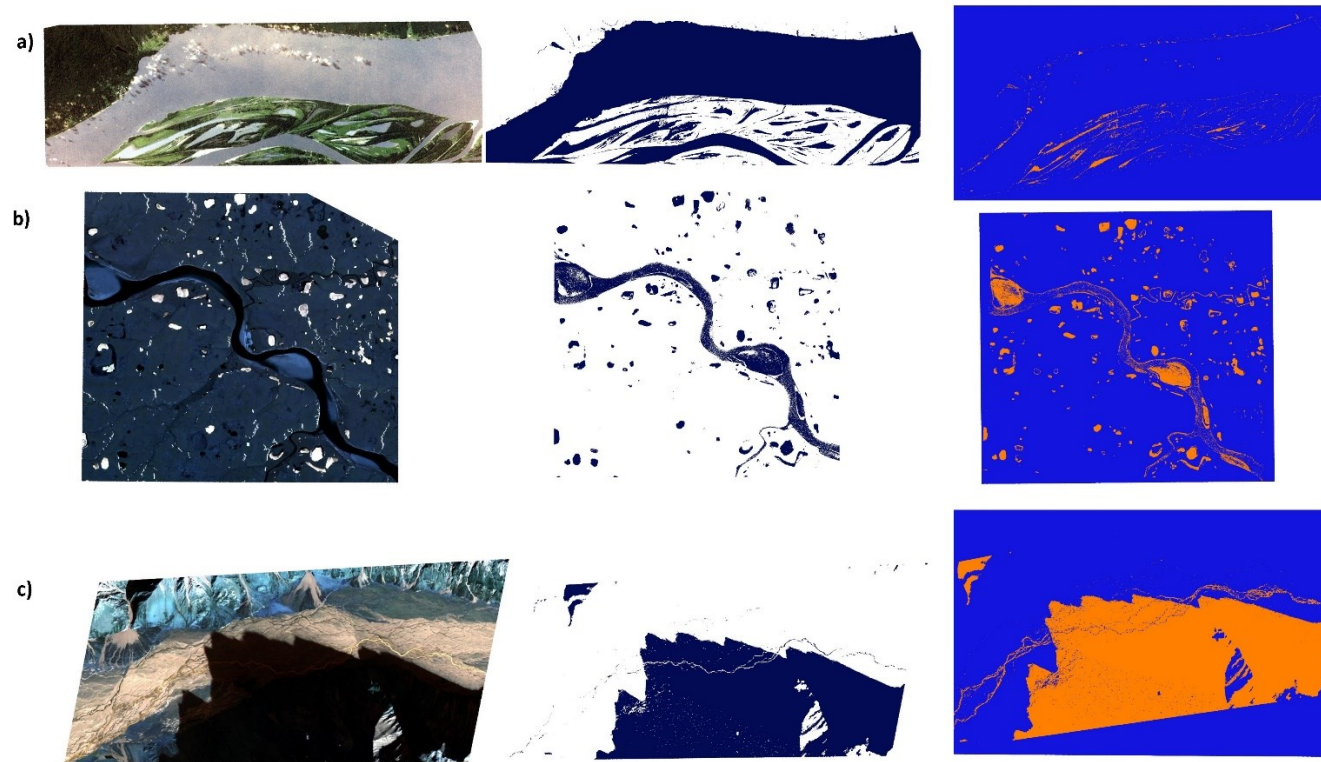


Figure. 3.8: Examples highlighting where the M20 CSC model coped or struggled with more difficult images. The first column displays the original satellite image, the second displays the prediction, and the third shows correct predictions in blue and incorrect predictions in red. a: Amazon, Brazil with unprocessed cloud. b: Popigay, Russia with snow covered frozen pools. c: Ahuri, New Zealand, deep shade which resulted in a poor prediction. However, further research is needed because the model still separated the river in both shaded and unshaded sections of the image. Example c was not included in the analysis when selecting hold out images but was added as an additional test image to see how the model coped with more extreme examples.

### 3.3.3 Fine tuning

M20 produced acceptable F1 scores on the Ottawa River test images. As with results in the original holdout images, there was a tendency towards successful predictions with 9 images predicted with a F1 score over 0.9, 1 had a score of 0.85, and 5 had scores below 0.55 producing an overall median of 0.97. After the inclusion of the additional ‘human-in-the-loop’ fine tuning labels there was only a marginal increase in median to 0.98. However, improvements were found to be focused on the images which performed worst without fine tuning. This caused the mean F1 score to increase from 0.81 to 0.90 after this fine tuning. The increase was found to be significant after Box-Cox transformation to remove skew ( $n=15$ ,  $t=8.4$ ,  $p<0.01$ ). There was some variation in F1 scores with a number of images producing marginally lower score in the fine-tuned run, in comparison to the base M20 model. However, three of the most poorly performing images saw greater improvement from  $< 0.7$  to  $> 0.95$  (Fig. 3.9). Two images still performed poorly, one likely due to the presence of a dam and the other due to an unexplained, red-coloured artefact potentially caused by shallow water (both factors potentially lacking in the training data; see supplementary material). The original test dataset (all images, all biomes) was then re-predicted using this fine-tuned model to test if the increase in the Ottawa River-specific training data had reduced its generalizability. Results show no impact on median F1 score but a minor (but significant) decrease in overall mean F1 score (0.83 to 0.81), indicating a slight reduction in the classification model’s generalisability, at the expense of improved classification results for the Ottawa River.

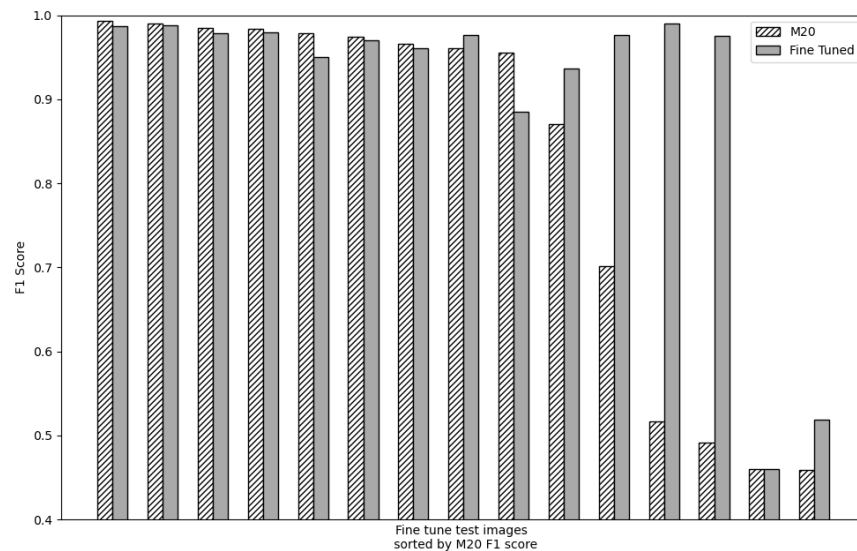


*Figure. 3.9: Difference in F1 scores between images predicted by the M20 model and after 5 images from the same river were included in the training data to fine tune it. Improvements are not universal but are dramatically better for the worst performing images.*

## 3.4 Discussion

### 3.4.1 Applicability of the CSC model

The CSC models developed here successfully produced water masks from highly diverse satellite images, from rivers across a gradient of biomes and seasons. The novel use of the CSC architecture with a CubeSat constellation highlights the potential for the incorporation of daily PlanetScope satellite imagery in studies relating to dynamic river systems. The inclusion of a fine-tuning step (section 4.5) adds further capacity to refine the model on the sites of most importance and interest for a user, allowing the generation of highly accurate water masks with minimal labour or expertise required. The median F1 score of M20 (0.93) is a particularly notable given that the approach is effectively an automated system being tested across multiple global domains, and in some biomes the approach performs extremely well scoring over >0.95 F1 on all test images. Although it is acknowledged that the lack of field data prevented formal ground validation, the global nature of this study precludes such an approach. Instead, more manually intensive labelling methods were used for the assembly of validation data that also come with their own associated error which inherently prevents perfect F1 scores (see Moortgat et al., 2022 for further discussion). Therefore, the high F1 scores are encouraging given the limitations of the labelled data these test images were compared against.

The method proposed here is not intended to compete with the GRWL water masks (Allen and Pavelsky, 2018) or similar products, which are employed regularly in satellite studies of river systems (Lin et al., 2019, Rosentreter et al., 2021, Yang et al., 2020). Rather, the approach is intended as a method for developing water masks in dynamic environments at (up to) daily frequency, as opposed to using a static product. I propose that a continuation of the method developed here could refine existing GRWL RivWidth predictions, which require a binary water mask as input (Pavelsky and Smith, 2008). Placing the model developed here in a similar cloud computing pipeline (Yang et al., 2019) may encourage users to adopt concurrent development of water masks rather than use static, assumed bankfull datasets such as the GRWL (Allen and Pavelsky, 2018). Adaptive water masks could push remote sensing breakthroughs in temporally sensitive aspects of river systems such as flow dynamics and large-scale variations in water quality across a range of discharges. The method also provides water masks and therefore river widths at a higher resolution than the GRWL. The GRWL application is limited to rivers  $\geq 90$  m wide (Allen and Pavelsky, 2018) which could be overcome with the  $20 \times 20$  3 m pixel cells used here, enabling 60 m rivers and sometimes smaller to be fed into RivWidth. This ability to monitor smaller rivers, especially at a higher temporal resolution, would vastly increase the applicability of these methods for studying flooding scenarios where water progressively accumulates downstream into larger rivers.

### 3.4.2 Constraints on model success

Despite the success of the M20 model, Median F1 scores in the investigation are not as high as those in similar AI-driven water mask studies (e.g., Moortgat et al., 2022, Carbonneau et al., 2020, Qayyum et al., 2020). These studies differ from ours in a variety of key ways because of constraints that had to be placed on this model to work with PlanetScope imagery. Therefore, the very fact that the accuracy of the M20 model approaches these other studies, in spite of these limitations, makes us consider it effective.

All satellites represent a trade-off between spatial resolution and frequency which directly relates to the quality of water mask predictions which can be achieved with their imagery. CubeSats are released at a relatively low altitude which decays further over time (Planet, 2018), enabling them to acquire medium-high resolution imagery. Having a constellation of CubeSats facilitates daily return period imagery at this 3 m resolution, which is vital for the task of monitoring river systems. This means the spatial resolution achieved for the resulting water masks is superior to models focusing solely on 'conventional' EO satellites (e.g., Landsat, Sentinel). Conversely, proprietary satellites such as Worldview or China's GF-2 produce imagery with a resolution many times finer than PlanetScope is capable of (Moortgat et al., 2022, Li et al., 2021). The same can be found of aerial imagery where the proximity to the target results in very high-resolution data. Water mask classification models produced using these data understandably perform very well because each CNN tile is able to include more pixels for the same ground area enabling better characterisation of water or land structures (Carbonneau et al., 2020, Moortgat et al., 2022, Li et al., 2021). While these high- and hyperspatial resolution data capture methods have potential to produce better results than those presented here, it is not practically or financially feasible to obtain the temporal frequency of imagery required for generation of dynamic water masks. PlanetScope is thus the only system I am aware of that provides both relatively high temporal *and* spatial resolution. While it is acknowledged that PlanetScope is proprietary, it is less expensive than other high-resolution satellite or airborne imagery (Cornebise et al., 2022). Furthermore, PlanetScope offers 5,000 km<sup>2</sup> a month of free imagery for individuals/groups affiliated with an educational institution under their Education and Research Programme, meaning that the techniques developed here will be open and useable by a large academic community. Additionally, it is currently available for free for some NGOs and Government employees through ESAs third party mission scheme (ESA, 2023) and NASAs Commercial Smallsat Data Acquisition program (Maskey et al., 2021).

A trade-off of the high return period provided by CubeSats is their much lower radiometric quality, an issue that this classification model would not have had to contend with if developed with data from other satellite sources. Larger, high quality sensor

systems used in these other platforms create radiometrically stable data with a much higher signal-to-noise ratio and therefore less erroneous values for the model to cope with (Ling et al., 2019, Yin et al., 2021, Isikdogan et al., 2017). Similarly, 'conventional' aerial imagery is largely immune from the disruptive effects of the atmosphere (Smith et al., 2021), with the resulting image quality being several orders of magnitude higher. Conversely, with PlanetScope, each platform, each sensor on the platform, and the calibration of these sensors differs as a result of the sheer quantity of satellites and their limited payload capacity (Frazier and Hemingway, 2021). Although the metadata provided by Planet does show no correlation with F1 score (Fig. 3.7), unreported differences in illumination conditions and weather conditions add additional complexities. The intricacy of hosting this assemblage of satellites means that, despite proprietary corrections made by PlanetScope (Kington and Collison, 2022) to normalise for radiometric variability between satellites, differences in absolute radiometric values still abound (Wilson et al., 2017). This in part may be the cause of the lack of correlation between F1 score and NIR band metrics. This aligns with findings that CNN models can delineate water masks relatively well using just panchromatic imagery (Moortgat et al., 2022) when NIR values would otherwise normally be expected to be the chief determinate of ability to depict water from 4-band imagery (McFeeters, 1996). Based on these factors, a relatively simple classification model might ostensibly be considered unviable, but the M20 CSC method nevertheless appears to be able to adequately handle these complexities. These findings are particularly interesting because CubeSats are increasingly common in the EO sector (De et al., 2022). If CNNs (and by extension, CSC) can produce accurate classifications despite this variation in CubeSat image quality, then they could be applicable to a wide variety of cases beyond water masking.

By comparison, the much poorer performance of the comparator state-of-the art Tiramisu FCN may come as a surprise. However, work using FCNs generally involves much higher quality (i.e., radiometrically stable) imagery (Moortgat et al., 2022, Carboneau and Bizzi, 2023) than PlanetScope, meaning that strong radiometric differences (which the CSC approach is robust to) are not accounted for by the FCN model architecture. The FCN requires considerably larger tile sizes than CSC, and while these tiles can be mixed (water and land), the requirement for larger tiles makes it more difficult to balance water and land pixels, even with a focal loss function "punishing" the model more for errors in water predictions. Trying to predict directly to the pixel level requires a large training set (Jégou et al., 2017), which is also inherently difficult with larger tile sizes (i.e., fewer training tiles per image). This necessitated the use of augmentation to gain more training tiles, potentially biasing the model to expect images of similar radiometric variability to this relatively narrow training base of 72 images. It is hypothesised that this meant that when predicting hold-out images, the model was subsequently unable to cope with the extreme radiometric differences between these

‘unseen’ PlanetScope images. The additional complexity of the semantic segmentation thus led the FCN to perform poorer than the CSC which, through the inclusion of the secondary ANN stage, was able to achieve high quality semantic segmentation for the image quality directly related to the input image.

### **3.4.3 Model structural and testing choices**

Our classification model is reasonably robust to levels of internal sensor noise and poor radiometric quality, but testing the model globally introduced further external variability. Many methodological studies into the use of EO for mapping river characteristics constrain their datasets to single regions and limited numbers of images (Feng et al., 2019, Junqueira et al., 2021, Moortgat et al., 2022, Qayyum et al., 2020). This limits the image variability resulting from different climates, vegetation, and river types (Thoms and Sheldon, 2019, Malhi et al., 2022). As a result, when site-specific classification methods are expanded globally, they are generally ineffective (Foody et al., 2003). A large part of the lower overall accuracy found here, in comparison to similar studies (e.g., Moortgat et al. 2022, Marochov et al 2020), is explained by the inclusion of rivers from across different biomes. It is important to reiterate that this model was not intended nor expected to work universally and without adaption.

To maximise potential operational use of the model, structural decisions were made which could have impacted prediction scores. Spatial resolution and the associated tile size used in different models is key to understanding how structural differences have impacted the relative performance of models. Increasing tile size facilitates higher per-tile information content, allowing the CNN phase of the CSC to better learn contextual features such as texture and geometry (Carbonneau et al., 2020); the improved training metrics on a random allocation of test tiles in each epoch (0.87 accuracy and 0.31 loss for M32 compared to 0.84 and 0.36 for M10) thus fit with what is known about increasing tile size (Reina et al., 2020). This enables a better prediction for images with a higher range of different pixel brightness values. However, these improved accuracy and loss metrics in training did not correspond to increased F1 scores on hold out images (Table 1). Due to the resolution of this imagery, the larger the tile size, the more difficult it is to pick out enough pure-water tiles when predicting an image. This in turn leads to a poorly trained MLP and a poorer final CSC outcome. Therefore, there is clearly a balance between information and resolution for choosing the best tile size. Higher resolution imagery can increase pixels in a tile whilst maintaining the tile’s footprint and therefore, ability to predict narrow streams whilst also increasing F1 scores (Carbonneau et al., 2020, Moortgat et al., 2022).

It might be surprising that a model structure often considered universally useful such as VGG16 (Theckedath and Sedamkar, 2020), did not perform well here. VGG16 requires

a minimum tile size of 32 due to the number of max pooling layers in the architecture (Simonyan and Zisserman, 2014). In part, the lack of success here might be attributable to this balance between tile size, resolution, and river size. However, the depth and complexity of the VGG16 could also be too large for the quantity of training data available and the binary classification task. VGG16 was created with 1000 classes and 138 million parameters which can lead it to very easily overfit with practical (in this case binary) tasks and relatively small training data sets (Wu et al., 2017), which explains why it was limited in value here.

#### **3.4.4 Ecoregion differences**

Median F1 scores are shown to obscure considerable variation within the results for different biomes (Fig. 3.5). This is a common trend in image classification, with potential for individual results to be considerably worse than their aggregated scores (Carbonneau et al., 2020, Buscombe and Ritchie, 2018). A selection of smaller rivers simply did not have enough pixels for the CNN step to be effective, which results in unsuccessful predictions. However, there is a large degree of variation in some results from rivers with widths of ~60 m. It is hypothesised that these rivers are large enough to have 'disruptive' features (e.g., large islands and bridges), which impact model accuracy, yet they lack sufficient pure water pixels required for the model to overcome these errors, weakening the correlation between river width and F1 score.

Braided streams were found to produce lower F1 scores, which was especially the case within the worst performing biome (Tropical Dry Broadleaf). Despite the overall quantity of pure water pixels across the theoretical bankfull area, individual stretches of water were often too narrow for the CNN phase to pick out. Seasonality therefore effects these narrow channels, which would only be measurable when flows are high enough to increase the water surface area to the minimum requirements of the model (Ashmore et al., 2011). Therefore, although the model produced here may not be viable for average discharge measurements in these braided streams, the return period of PlanetScope makes it a viable to still be an important flood monitoring tool (Feng et al., 2019).

Some conditions were not accounted for in the training data, but separate test images were included for these (see supplementary material). Snow, ice, and frozen river systems proved problematic for the model, although further research is needed to determine if and how the model should delineate frozen watercourses. Encouragingly, however, the model does not appear to be disrupted by winter conditions on the banks such as snow-covered land in the Taiga biome (Fig. 3.8.b). Similarly, the model appears able to cope with artefacts relating to minor cloud or shadow, which could negatively impact F1 scores but not to a great extent (Fig. 3.8.a). The model was not trained for

these specifically, yet when applied to extreme cases of each it was still able to function to some degree. In one heavily shaded image, the model delineates dark mountain shadow and land as different classes, yet in each the river is considered different from the surrounding land type (Fig. 3.8.c). This shadow issue is present in other studies of PlanetScope classification in mountains (Qayyum et al., 2020) and should be investigated further but nonetheless clearly shows that the CNN phase is based on more information content than simply pixel values.

Other conditions where the model was expected to struggle did not lead to catastrophic failure. For example, results from the Temperate Broadleaf biome were lower than several other biomes but still around  $F1 \approx 0.8$ . Upon inspecting images associated with these F1 scores, it became clear that they comprised urban areas, such as central London. It might be expected that the model would struggle in these areas due to the conflicting NIR reflectance values from other urban land use types (Xu, 2006). However, the model coped fairly well barring errors around bridges and watercraft. This is promising because it suggests that limited additional specific test data could improve urban results dramatically.

The categorisation of the different biomes into good, variable, and poor is clearly simplistic for the task at hand but could be useful. These categories highlight characteristics that the model struggles with. For example, Montane Grasslands often have braided streams due to the high gradient environment (Montgomery and Buffington, 1998), more ice and snow, and smaller first order streams (Strahler, 1957). These lead to fewer seasons in which the model can be applied because it is expected to produce poorer results when low angle sun hits steep valley sides, low flow confines braided streams to separate small channels, or snow covers banks. This provides useful information for river managers on the model's applicability. However, when the 'flashy' nature of upland hydrological cycles limits other forms of flood monitoring, these braided streams would combine to become wide enough for the method to identify and produce robust river masks. This means that while the model might be sub-optimal for braided streams during particularly low flows, it is likely to work effectively during large flood events when other remote sensing methods cannot be deployed as rapidly (Ballesteros-Cánovas et al., 2015).

### **3.4.5 Fine tuning**

Where and when M20 is likely to work best has been shown but it is intended to be considered as a 'base' model, to be further fine-tuned to the region or task required. This will enable users to save vast amounts of time when creating water masks for rivers, by allowing them to achieve highly accurate classification results with the labelling of only a handful of images. The main strength of the CSC method is that the

base CNN has learnt to smooth the difficulties and differences associated with CubeSat data. Therefore, with minimum effort individuals can operationalise the high spatial and temporal resolution of PlanetScope to process water masks.

‘Interventional model training’ can be used to bias the model towards the biome in question whilst adding to the overall learning and generalizability of the model (Wu et al., 2022). Here this is used to integrate human knowledge and experience to keep humans ‘in the loop’ of model training and usage (Wu et al., 2022, Nunes et al., 2015). The training data pipeline used in this study only required the drawing of simple polygons enabling “no data” classifications (see [https://github.com/SamValman/Public\\_RiverTwin](https://github.com/SamValman/Public_RiverTwin) for a step-by-step guide). Increasing the speed and ease of labelling thus encourages practitioners to invest the time to use and improve the classification model (through the creation of additional labels). This simplification step during training could have inhibited the model in comparison to similar studies with more complex methods of creating training data (Moortgat et al., 2022). This was especially the case with the FCN comparison attempted here, which in turn required considerably more training data and pixel level classifications, which required the use of semi-automatic classifiers, sometimes with multiple iterations to obtain sufficient quality water masks. The simple polygon-based labelling method of CSC enables model training to be targeted to capture the right information at the right place and time, which in turn necessitates non-experts to develop additional training data (Rabaey, 2020).

Testing of the theory that these models could be improved with limited additional training data was carried out on the Ottawa River, situated in the Taiga biome. Although the Taiga was the best performing biome, the Ottawa River was not one of the initial 36 rivers in the study. Therefore, some of the characteristics that make up the Ottawa River could have been learnt by the model from other similar rivers, but it will not have explicitly seen this river. Despite this, the M20 model first predicted the majority of the 15 Ottawa River test images well (Fig. 3.9). However, fine-tuning M20 with 5 additional training images from the Ottawa River significantly improved predictions on these same 15 hold-out images. This is an important demonstration of just how little user input is required to create useful water mask predictions once the initial global model has been improved.

In this study, it was chosen to retrain the model from scratch whilst including the fine-tuned images. This was done to prevent ‘catastrophic forgetting’ whereby transfer learning causes a model to be unable to accurately make predictions of the original training task (Kirkpatrick et al., 2017). In an ideal world the methods chosen would enable ‘lifelong learning’ whereby with each user-fed fine-tuning run, the model would increase its training set (Parisi et al., 2019). This would reduce the time taken for users to update the model and allow the model to continuously improve by a concerted

community effort. Methods of overcoming this 'catastrophic forgetting' problem are beyond the scope of this paper, but bringing these methods from the computer science domains to EO and river science should be a research priority. On top of this call for an increase in community efforts to train truly global models, there need to be easier ways to access image classification models such as those used here. Cloud computing would enable access to multiple individuals with diverse site knowledge and training data (Rabaey, 2020). This is partly why the model was built using the TensorFlow API, which has good compatibility with Google Earth Engine (Gorelick et al., 2017, Abadi et al., 2016). Future work should focus on bringing this lifelong learning into the cloud to collectivise the best models for maximum benefit.

### 3.6 Conclusion

Rivers are large, dynamic systems which cannot be monitored by field measurements at the spatial and temporal scale required for management. EO has the spatial coverage to provide a potential solution to monitoring issues but traditionally used open-source satellites, such as Landsat, do not always have the spatial or temporal resolution to be useful for practical applicability. The PlanetScope constellation operates a daily return rate with 3 m spatial resolution, but it has previously been limited to localised studies due to its variable radiometric quality. The novel application of CNN-Supervised Classification (CSC) was shown to produce accurate water masks from PlanetScope imagery, overcoming the inherent radiometric issues associated with imagery from CubeSat constellations to provide automated water masking at a finer temporal resolution than any other current EO method. It was found that CNN-based architecture is a promising option to analyse the increasing quantity of images coming from CubeSat satellites with increasing numbers of bands. By being the first model to explicitly develop accurate water masks from PlanetScope data, it has created the potential for river management applications to be operationalized at a global scale with daily medium-high resolution imagery.

This model developed here was demonstrated to generalize reasonably well across different global biomes, with a median F1 score of 0.93 and max F1 scores of 0.99. Narrow anastomosed streams, deep shadow, and some urban influences were shown to limit the accuracy of model predictions. These limitations were concentrated in some biomes, but also demonstrated that the model can be fine-tuned to improve its applicability in specific locations. Indeed, the results indicate that very marginal increases in the training data can significantly improve the results of the base model in case study regions. Where it works particularly well, I also believe that the model could be extended to differentiate between different hydromorphic units such as vegetation, visible sediment, or hydraulic features. This extension would be a directly applicable management tool for environmental assessments which often request mapping of these features which might change with different discharge levels (Fryirs and Brierley, 2022). Therefore, more research is called for into making web-hosted 'lifelong learning' models that utilise the increasing availability of satellite data and the ability to continuously retrain these models, improving both their accuracy and allowing them to classify other riverine features. This would help the entire field move forwards towards the practical operationalization of this imagery.

# Chapter 4:

## Rapid revisit data from satellites for monitoring the impact of drought on the Madeira River, Amazon basin.

**Submitted to:** Science of Remote Sensing with the authors listed as S.J. Valman, D.S. Boyd, and S.J. Dugdale, January 2025.

### 4.0 Abstract

Climate change is increasing the frequency and severity of droughts on large river systems. Riverine droughts are poorly captured by traditional *in situ* measurement techniques focusing on point-measurements such as discharge, which also cannot be used to measure the associated impacts on communities living alongside these rivers. Earth observation (EO) has been shown to have the capability to measure the magnitude, frequency, and impacts of hydrological drought across large scale systems, but previous studies have relied on satellites with temporal resolutions too poor to fully capture the temporal dynamics of drought events. It is shown that the PlanetScope CubeSat constellation now provides imagery regularly enough to monitor the progression of drought in the Madeira River, Brazil (>2500 images, 1700 of which were from a single dry season over a 1000km river reach). The study mapped percentage change of in-channel exposed dry area often in the form of sand bars around vegetated river islands areas of interest (AOIs), as a tool to monitor water levels under drought. This enabled measurement of increases in exposed area at all 35 AOIs chosen of the lower Madeira River during the dry season. The results confirmed that shipping channels, relied on for >33 million tonnes per annum of agricultural transportation, significantly narrowed during the dry season by an average of 750 m. Moreover, 65% of AOIs formed isolated pools, risking aquatic life and fish strandings in a region which relies heavily on fisheries for subsistence. Exploring the quantity and quality of available imagery in the PlanetScope archive suggests that an average of one image every 2 days is the upper limit to satellite image coverage due to cloud cover during the Amazon dry period. Thus, this approach provides the methodology, a baseline measurement,

and assessment of the potential to build a satellite-driven monitoring system of drought impacts on major river systems.

## 4.1 Introduction

With a rapidly changing climate, droughts are expected to become more common in all major river basins (Zhou et al., 2021, Balti et al., 2020). These droughts propagate from purely meteorological events into hydrological droughts that cause rivers to dry up and constrain their socio-economic benefits including hydropower, transportation, and subsistence fisheries (Arantes et al., 2022, de Jong et al., 2021, Garcia et al., 2021, Doria et al., 2018). Drought-exposed riverbeds can also contribute CO<sub>2</sub> emissions, which respond to inundation area in both extreme drought and during flooding (Almeida et al., 2017).

Proxies are frequently employed to measure riverine droughts and their wide-ranging impacts (Tomsett and Leyland, 2019, Dahlmann et al., 2022). One such proxy is the measurement of changes in 'in-channel' exposed dry area around river islands to describe the degree of riverine drought. In-channel islands exist in many large river systems and these are a key geomorphic component whose surface area increases as the river level falls due to reduced discharge (Shi et al., 2018, Sun et al., 2018, Sultana et al., 2021). Such changes can reveal the direct geomorphic impacts of droughts such as where shipping routes are constricted (Cammalleri et al., 2020, Garcia et al., 2021), where fish may be isolated from the main channel (Archdeacon et al., 2022), and where communities subsisting off the river are distanced from wetted channels (Doria et al., 2018). Anthropogenic factors can further influence the visible impacts of drought on these islands via the impact of dams on downstream hydrology and sediment (Williams and Wolman, 1984, Ayes Rivera et al., 2019, Vauchel et al., 2017, Grill et al., 2019). Therefore, monitoring exposed sediment around in-channel river islands at high temporal resolutions over large spatial scales may enable new methods of extracting anthropogenic and hydrological influences on drought.

The scale and size of river islands that grow or shrink during drought prevents traditional in-situ field monitoring approaches, especially on large rivers where change needs to be monitored over 100s of kilometres of river reaches (West et al., 2019, Lakshmi et al., 2023). One solution is to use Earth observation (EO) which has been shown to have the potential to measure drought impact across whole rivers in a diverse suite of ways (Jiao et al., 2021, West et al., 2019). To date, a limited number of studies have focused on using EO to monitor changes in river islands (Shi et al., 2018, Sun et al., 2018, Hossain et al., 2013, Nama et al., 2022, Hossain and Saha, 2024, Gao et al., 2013). This previous research demonstrated the potential of monitoring river islands to provide proxies of riverine drought dynamics and confirmed there was an inverse relationship between exposed river sediment and river discharge. However, most of these previous studies have used satellites with spatial resolutions of ~10-30 m and return periods of 5-16 days, such as NASA's Landsat programme. The relatively long return period of

open-source government-administrated satellites restricts the number of useful images of island change per year, which may have been a factor constraining earlier studies to a limited number of islands in short channel reaches. As such, previous investigations have all focused on eight or fewer islands, in reaches as short as 40 km (Gao et al., 2013, Sun et al., 2018), over long timescales using limited imagery per year (e.g., 7 images over 29 years; Shi et al., 2018). This means that there is considerable scope to scale up monitoring at increased spatio-temporal resolution to reveal finer-scale dynamics in river islands during drought. Indeed, regular satellite data acquisition would provide the “essential” continuous monitoring (Sun et al., 2018) to discern the interaction between extreme events and changes in river islands. New advances in CubeSat technology has led to the development of a constellation of 130+ PlanetScope satellites to provide daily imagery of the entire globe at ~3 m resolution (Planet, 2024a). Ordinarily, the laborious nature of semi-automated or manual land/water masking carried out in previous studies (e.g., Sun et al., 2018, Hossain and Saha, 2024) would inhibit the full potential of this new imagery for characterising in-stream island dynamics through time. However, recent progress in AI-based PlanetScope-specific automated classification techniques (e.g., Valman et al., 2024, Freitas et al., 2024) makes the large scale detection and analysis of river islands feasible over thousands of satellite images and river kilometres.

This paper presents this work in the context of the Madeira River, one of the world's largest rivers and a tributary of the Brazilian Amazon River that has a history of extreme drought (Laureanti et al., 2024). At over 1000 km long, without prohibitively expensive investment, the Madeira River requires new methods to monitor these drought impacts. The potential of CubeSats to measure the impact of the devastating drought that occurred on the Madeira River in 2023 (WWF, 2023) is demonstrated via quantifying space-time dynamics in exposure of sediment around river islands. These data subsequently facilitate comparison of this drought event to ones occurring in previous years, allowing us to test the relationship between sediment exposure and discharge at a higher frequency than that previously studied (Sun et al., 2018). The overall aim of this chapter was to explore the potential of CubeSat satellite technology to provide useful metrics of dry season river water level on river islands of the Lower Madeira River thus satisfying the second research objective of this thesis. To do this I have applied the following sub-objectives:

- 1) investigated how river island geomorphology is influenced by dry season conditions on the Madeira River.
- 2) Analysed the causes of why dry season impacts differ along the Madeira River
- 3) Evaluated the potential of EO methods to monitor long term future variability in drought impacts.

## 4.2 Methodology

### 4.2.1 Study area

The Madeira River is the second largest tributary of the Amazon River draining an area of 1.4 million km<sup>2</sup>, with an estimated mean annual discharge of 31,200 m<sup>3</sup>s<sup>-1</sup> (ANA, 2024). The study reach extends from Porto Velho, Rondônia, Brazil to the confluence between the Madeira River and the Amazon near Itacoatiara, Amazonas, Brazil (Fig. 4.1). Despite the presence of the San Antônio Dam 6 km upstream of Porto Velho and other further upstream impoundments, the Madeira River contributes up to 50% of the Amazon's sediment load (Ayes Rivera et al., 2019). This sediment contributes to the presence of at least 54 river islands in this 1000 km-long study reach. For the most part this is a single thread unconfined river channel along the reach, with bifurcations into two channels around these islands although these channels still measure in 100s metres. Both the banks and these islands are heavily vegetated with trees adapted to the wet and dry season pulse cycles; however, the upstream hydropower may be reducing the stability of this system with higher constant flows (Assahira et al., 2017). The chosen reach, free from the influence of storage reservoirs, provides an environment to demonstrate the potential for monitoring dry season changes in river island extent (and thus drought).

The choice of study reach was also driven by news reports of reduced shipping between these two cities resulting from the 2023 drought and formation of river islands (Reuters, 2023). This shipping accounts for 33.76 million tonnes of corn and soybean which is of global importance, with decreased efficiency as a result of low flows has led to CO<sub>2</sub> increases of 22% from the shipping when it is able to move (de Gomes Garcia et al., 2022). The river also supports large scale subsistence fisheries with over 1300 species recorded in the basin leading to per capita consumption being up to 167kg per annum (Doria et al., 2018). The subsistence and sale at local markets mean that any reduction in access to this fish stock may not be immediately noticed at a national scale but could have devastating effects for communities along the river.

The study site follows distinct wet and dry seasons (Li et al., 2020a), with the dry period lasting from July to October (JASO; Marengo and Espinoza, 2016, Van Oel et al., 2018). Although this is heavily influenced by El Nino Southern Oscillation which is being measured with the extreme drought here and only occurs once in the extent of this study (2016) when there is limited PlanetScope satellite data. This dry period also corresponds with decreased cloud cover enabling satellite image collection.

Selecting areas of interest (AOIs) polygons to include in the study used visual inspection of the earliest imagery available in the PlanetScope satellite imagery archive (July or August 2016) to determine where islands were present. The dimensions of these AOIs

were set at 2.5 km upstream and downstream of the ends of an island and 500 m wide on each bank. These values were chosen through trial and expert judgement of how much the islands and channel had potential to migrate over the study period. If multiple islands overlapped, they were consolidated into a single polygon and the furthest upstream and downstream islands were used to start the 2.5 km extents. This resulted in 35 AOIs labelled numerically downstream (DS) starting from DS 00 at Porto Velho to DS 34 at the confluence. The largest of these polygons was 106 km<sup>2</sup>, the smallest was 17 km<sup>2</sup>, and the mean size was found to be 48 km<sup>2</sup>. These polygons were subsequently used to define the geographic scope of PlanetScope imagery downloaded as described in section 2.2.

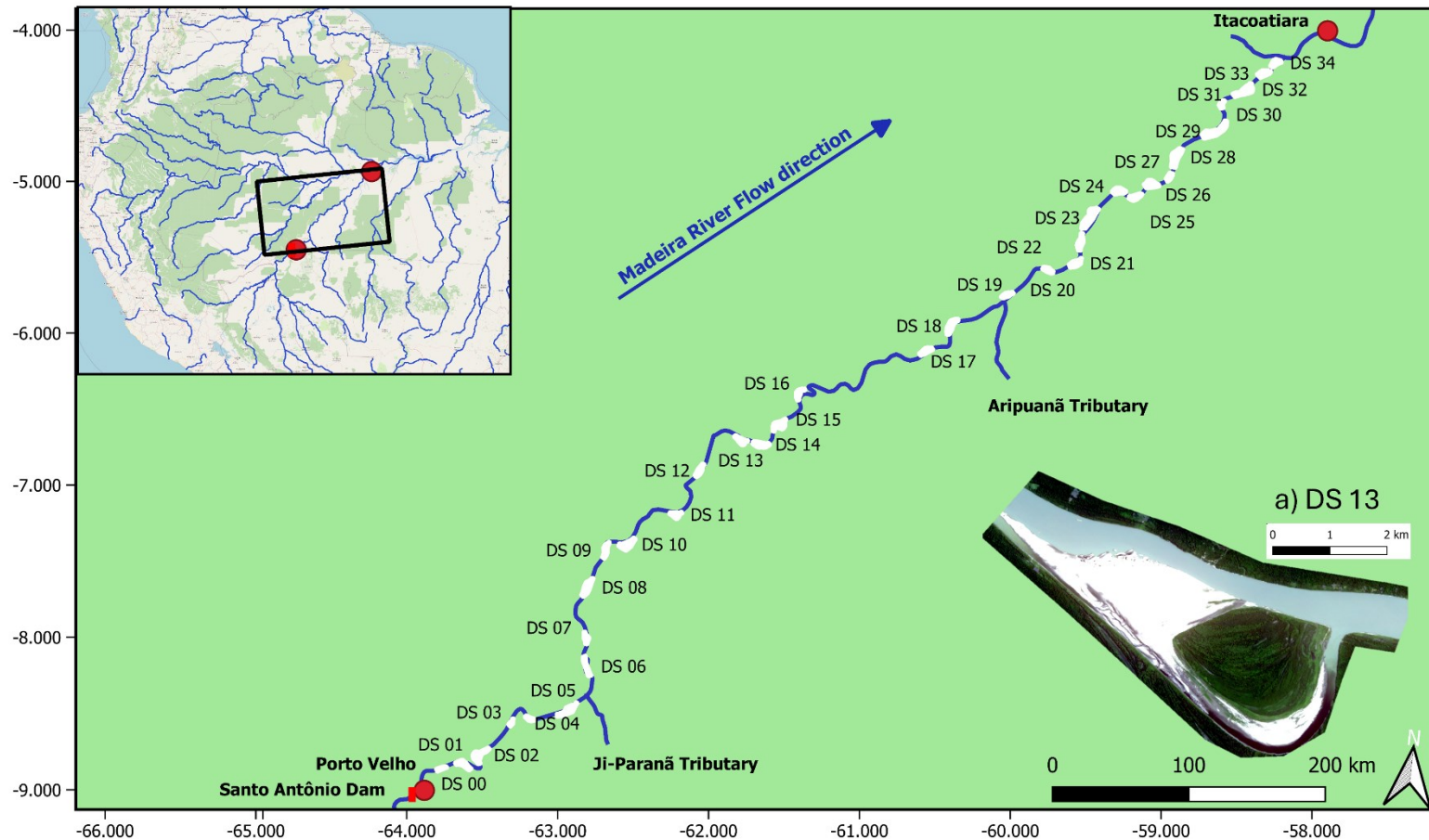


Figure. 4.1: The study areas of interest are labelled downstream (DS) from the first AOI, DS 00, at the town of Porto Velho. The Santo Antonio hydropower dam above Porto Velho may influence the activities of these islands but there are no hydropower schemes within the study area itself. The final AOI DS 34 is at the confluence with the main branch of the Amazon River. Inset a is an RGB satellite image of DS 13 typical of the island AOIs. Note the white exposed sediment and the darker secondary channel starved of river flow.

#### 4.2.2 Satellite imagery and processing

PlanetScope satellite imagery, in its “pre-processed to surface reflectance and harmonised to Sentinel 2” format (Frazier et al., 2021), which was then converted to binary water masks using a novel Convolutional Neural Network (CNN)-based semi-supervised classification technique (Valman et al., 2024). Whilst proprietary, PlanetScope is available for NGOs, government employees, and researchers through ESA’s third-party mission scheme (ESA, 2024), NASA’s commercial Smallsat data acquisition program (Maskey et al., 2021), and Planet’s own Education and Research Programme. Hence, the methods curated here are open to a wide user-base and could be realistically expanded in future research and monitoring schemes. The radiometric quality of PlanetScope imagery has been shown to be highly varied (Frazier and Hemingway, 2021; Valman et al. 2024) due to the constraints of a limited payload per miniaturised ‘CubeSat’ satellite, their different altitudes, highly variable atmospheric conditions, and sun angles that result from a constellation of 130+ satellites. These issues make automatically classifying/extracting the ‘water mask’ (i.e., a binary raster depicting water presence/absence) very difficult, which has traditionally limited the spatial or temporal extent of river studies using PlanetScope (e.g., Junqueira et al., 2021) and leading to arctic (i.e., less vegetated) rivers dominating research using these platforms (e.g., Cooley et al., 2017). This is especially difficult in areas where wet woodlands can coexist with these large river systems, making it difficult to manually or automatically classify these classes. However, recent advances in CNN approaches (Valman et al., 2024, Carbonneau et al., 2020) mean that the rapid extraction of water masks from these data is now feasible. I therefore used the CNN model developed by Valman et al. (2024) to segment the imagery, inputted as individual AOIs into the model, producing binary water masks showing the location and extent of the Madeira’s wetted river channel and also in-channel islands. All Python code used in this study is available at the project GitHub repository (<https://github.com/SamValman/RiverTwinRiverIslands>); for more details on the CNN-based algorithm used to segment images and instructions on its application, the reader is directed to Valman et al. (2024).

Images with  $\leq 10\%$  cloud cover, as defined by Planet Explorer, were included in the analyses. These images needed to be checked manually post classification, but the chosen classifier was often able to successfully segment the river channel (i.e., water mask), even when obscured by partial cloud cover, based on the semantic context of neighbouring image pixels/tiles. Thus, it was decided that the time trade-off of manually checking these images was acceptable in this study, in order to achieve the most complete dataset by maximising the number of usable images. In total, the approach rendered 2697 usable images, of which 1700 images were classified for the year 2023. Ultimately corresponding to an average of one image every two days for each AOI during the dry season. The remaining 997 images from a reduced number of AOIs,

acquired between 2016 and 2023, were subsequently classified to enable water mask extraction from previous years at lower temporal frequency (as low as 3 images in 4 months for one AOI in 2016), with a view to monitoring longer-term trends in river island formation/drought propagation. To test the accuracy of these water mask classifications, 12 images (550 km<sup>2</sup>) were selected at random and 100 pixels were selected from each, using stratified random sampling. For a dynamic variable such as water surface area over this extent it is not possible to collect ground 'truth' data therefore there are a variety of alternatives each with drawbacks (Moortgat et al., 2022). In this case, these pixels were manually assessed for accuracy in QGIS and used to calculate an overall accuracy score, which was weighted to account for class imbalances as per best practice (Olofsson et al., 2013, Olofsson et al., 2014). This validation showed the CNN model used here was able to classify imagery with an F1 accuracy score of 0.98. This was higher than the stated global ability of the classifier (0.93, Valman et al., 2024) which can be attributed to the simple planform of the Madeira River and the manual removal of the obvious erroneous results during pre-processing (e.g., assessing the classifier's ability to deal with cloud). Using supervised methods to classify over 2500 images would not be feasible for a study of this size without sacrificing accuracy.

#### **4.2.3 Processing island AOIs**

Following data download and water mask extraction, consideration needed to be given to how to separate changes in exposed sediment resulting from drought-linked increases in island size from changes in proximal terrestrial land uses such as ponds and lakes. Moreover, looking exclusively at the change in individual islands was not automatable using pixel connectivity analysis, as islands often extended to touch the banks towards the end of the dry season. Therefore, the decision was made to mask the banks (Fig. 4.2: island extraction) and thus remove proximal water sources from the study. Upon inspection of the image series, the Madeira's banks were shown to exhibit negligible movement over the course of the study period, so these were unlikely to impact results. To develop this mask for each AOI, the first available image from the 2023 dry season was used where pixel connectivity analysis was still possible due to the lack of exposed sediment connecting islands and banks. The extraction of the bank mask used pixel connectedness analysis to isolate disconnected features in an image, thus separating islands from the bank and water (Virtanen et al., 2020). These masks were then placed over every image in the series, excluding the confounding changes beyond the banks in terrestrial water sources from the analysis.

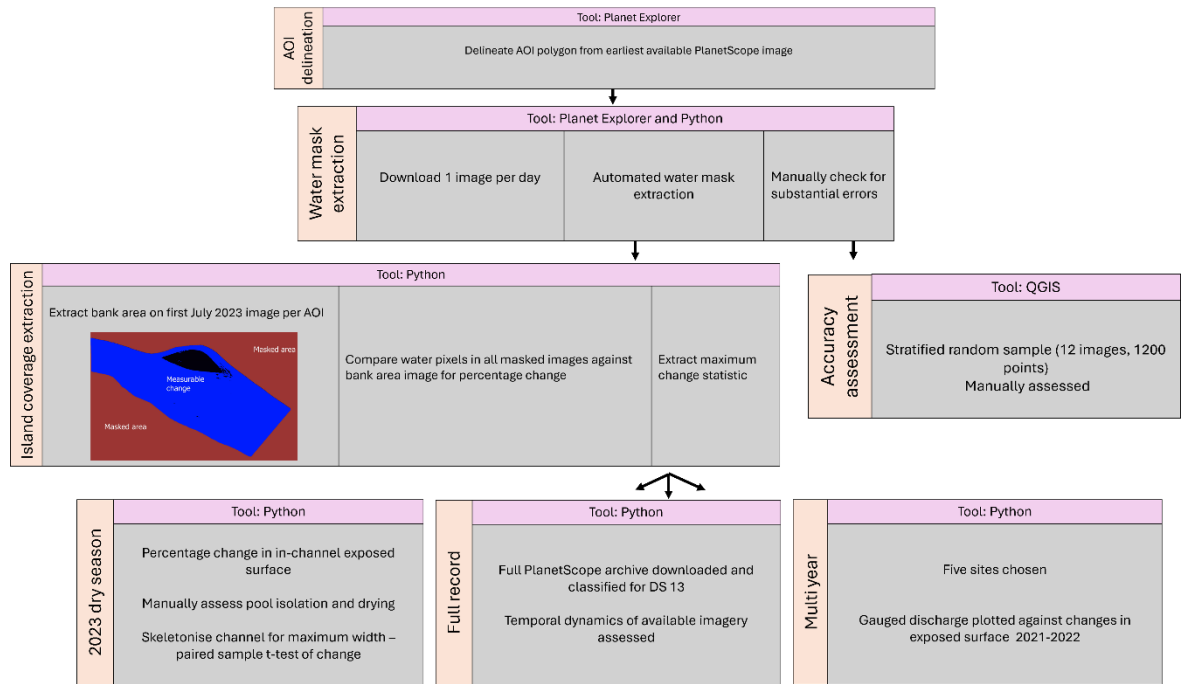


Figure. 4.2: Workflow to produce island change metrics from PlanetScope satellite imagery.

For assessing change in exposed sediment around these islands through time, the percentage of the channel that was not water was measured (rather than focusing on individual islands), hereafter referred to as *percentage exposed sediment*. This percentage change was relative to the first image in each timeseries (i.e., the first image of the dry season) and therefore dimensionless, enabling the magnitude of change in different AOIs to be compared regardless of their size.

#### 4.2.4 Relating exposed sediment to drought

##### 4.2.4.1 Investigating dry season drought with 2023 imagery

Three temporal scales of analysis were used for this study (sections 4.2.4.1 to 4.2.4.3), each relating to an objective. Firstly, to investigate the interaction between exposed sediment and progression of the dry season during 2023, island percentage change was calculated across the entire 1000 km study reach at the highest possible temporal resolution (i.e., every ~2 days) for the 2023 dry season, giving an indication of the drought's magnitude and onset speed. Temporal variability in river width as a result of drought-driven increase in island area (e.g., islands encroaching on banks and dividing channels) was also quantified, using a simplified image skeletonization approach using the RivWidthCloud algorithm (Pavelsky and Smith, 2008, Yang et al., 2019) to extract a centreline from the main and secondary channels in these water masks. The simplified version was used because the morphological operators contained within RivWidthCloud are already incorporated in the chosen image classification model (Valman et al., 2024). Width measurements were extracted along the centreline for every centre line pixel, but the primary focus was the change in maximum channel width

in each AOI (3 m resolution). This avoided comparing secondary channels, which were by default narrower than the main channel, and provided the most conservative estimate of change in the river width and thus access for shipping of the main channel. Similarly, isolated pools were also manually extracted, using connected pixel analysis to highlight these groups of pixels. The presence/absence of pools were assessed on a binary level to give some indication of how many AOIs developed isolated pools during the dry season. The maximum change in percentage exposed sediment at each 2023 AOI was plotted in a streamwise direction to explore longitudinal trends in island dynamics.

#### *4.2.4.2 Analysing causes of longitudinal drivers using imagery from 2021 to 2023*

To confirm the assumption that water level is the main driver of exposed sediment along the Madeira River, a comparison was made between exposed sediment and river discharge, using daily-averaged data supplied by the Brazilian Water Authority (ANA). Discharges from 2021 to 2023 were compared against exposed sediment computed from PlanetScope imagery for the same period at five AOIs spread along the river (DS 01, 13, 14, 24 and 34; Fig. 4.3) where these longer term records of island dynamics were collected. Hydrometric data were downloaded for the gauging station at Porto Velho (ID: 15400000) for the dates which corresponded to the image capture dates in these five AOIs.

These five AOIs also form the basis of the second scale of temporal analysis for monitoring long-term drought conditions inter-annually. All available imagery from 2021 to 2023 was collected for the five AOIs discussed (DS 01, 13, 14, 24, 34) and the same methods were adopted to calculate percentage exposed sediment change for this extended (i.e., 3-year) dataset. Due to the large quantity of images this required (802 images for the 5 AOIs alone), it was not possible to carry out the analysis with every AOI in the study, hence the decision to focus on only five AOIs.

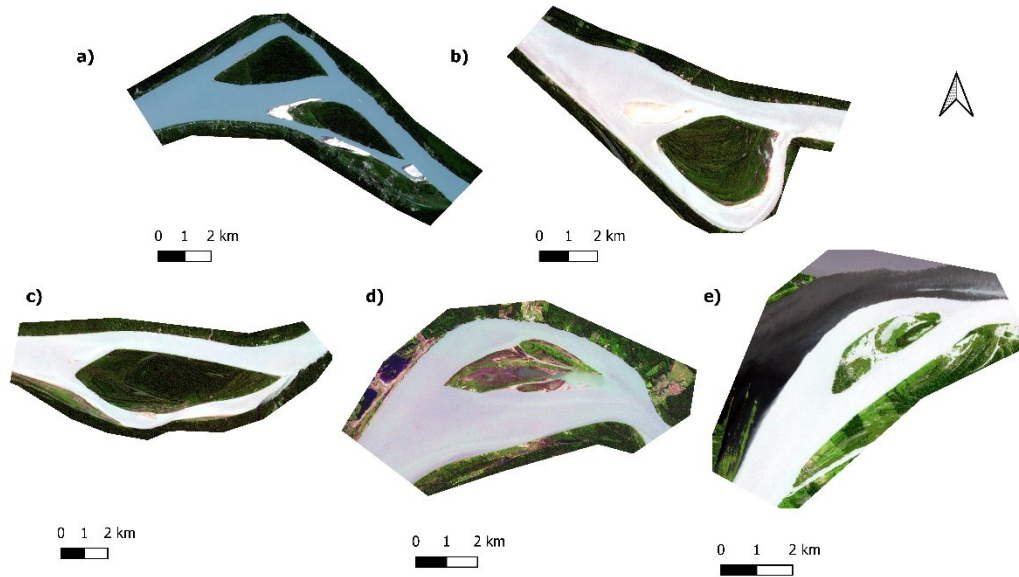


*Figure. 4.3: Example AOIs longitudinally spaced along the Madeira River and used for the 3 full annual discharge record. All images are the first RGB PlanetScope image from the 2023 dry season for each AOI. a) DS 01, b) DS 13, c) DS 14, d) DS 24, e) DS 34.*

#### 4.2.4.3 Evaluating future CubeSat potential using the PlanetScope full imagery archive

The final scale of temporal analysis explored the potential of expanding these methods to the entire PlanetScope imagery archive (i.e., as far back as 2016, when the first CubeSats in the constellation were launched). To do this, all available imagery from 2016 to 2023 during the dry season was downloaded and processed for a single mid-reach AOI (DS 13) resulting in a total of 202 images, this was too many to include other AOIs at this scale of analysis. Plotting the number of usable images per year from this analysis enabled assessment of the data and computing requirements which would have been required to carry out a full archive assessment of the whole river or extend monitoring into the future.

#### 4.2.5 Statistical analysis

All image processing and subsequent analyses were carried out in Python (version 3.10), running on a Windows PC with a 12-core Intel i7-12700K, 32 Gb RAM and a NVIDIA GeForce RTX 3070 GPU (8 Gb RAM and 5888 CUDA cores). For statistical analysis SciPy and Scikit-image packages were relied upon, with NumPy, and Pandas for data management (Van der Walt et al., 2014, Harris et al., 2020, McKinney, 2011, Virtanen et al., 2020).

A range of statistics were measured pertaining to exposed sediment around islands. To compare between AOIs of different sizes, the percentage change in exposed sediment cover against a baseline quantified from the first available 2023 image was used. Derivatives of channel change were calculated and plotted along with exposed sediment percentage data using the Matplotlib package (Hunter, 2007) to understand whether the trend in island growth was constant or whether rates and magnitudes of change varied at different points along the river channel.

Linear (Pearson's) correlation was used to assess the relationship between exposed sediment and discharge (using an alpha value of 0.05). These correlations were carried out using all images from the five separate AOIs in a single comparison. AOIs were also individually compared to discharge to investigate if some covaried more strongly with discharge than others. Changes between the maximum river width at the start of the 2023 dry season and the maximum width after four months of drought conditions were also tested, using a paired sample t-test applied to the first and last image at each AOI as a pair (following testing for the assumption for normality using a Shapiro-Wilks test).

## 4.3 Results

### 4.3.1 River island dynamics

Our PlanetScope-derived water masks of the 35 AOIs on the Maderia River reveal considerable increases in exposed river sediment in 2023 as the dry season progressed (up to 34% change), in response to decreasing water levels resulting from drought. Here, it is described how the area covered by exposed sediment, the rate of change, and the magnitude of change varied between islands. Classification of PlanetScope satellite imagery clearly displays the extent of river island coverage changing during the dry season (Fig. 4.4). Some areas of riverbed become consistently exposed for considerable periods of the dry season. Other sections of the bed are only visible for brief periods and yet can make large changes to channel width and shape when exposed. Maximum width was found to significantly narrow between the first and last dry season image at all AOIs ( $t=9.4$ ,  $p=0.004$ ) leaving channels on average 750 m narrower (Fig. 4.5).

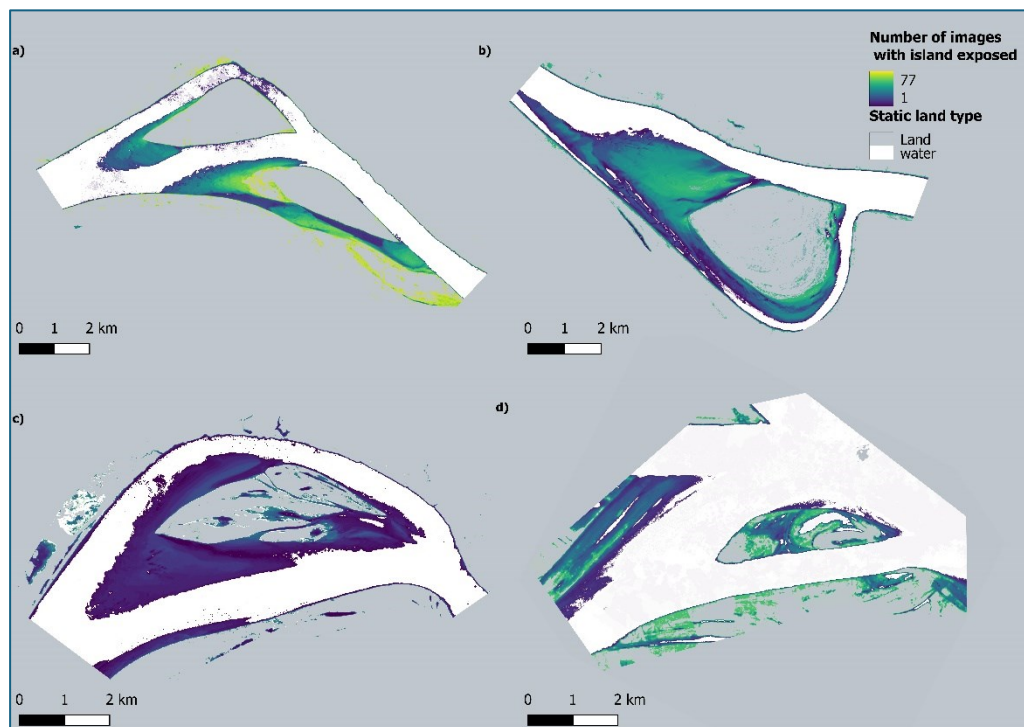


*Figure. 4.4: Exposed sediment change over 2023 dry season at AOIs (a) DS 01, (b) DS 13, (c) DS 24, and (d) DS 34. The colour scheme indicates how many of the available images show land at different points; darker blues indicate areas that were less frequently exposed, lighter yellows indicate areas of more frequently/consistently exposed sediment. Due to differences in quantity of available imagery between AOIs, the different panels should be considered individually. Pixels that are either perennially island, bank, or water have been replaced with satellite imagery.*

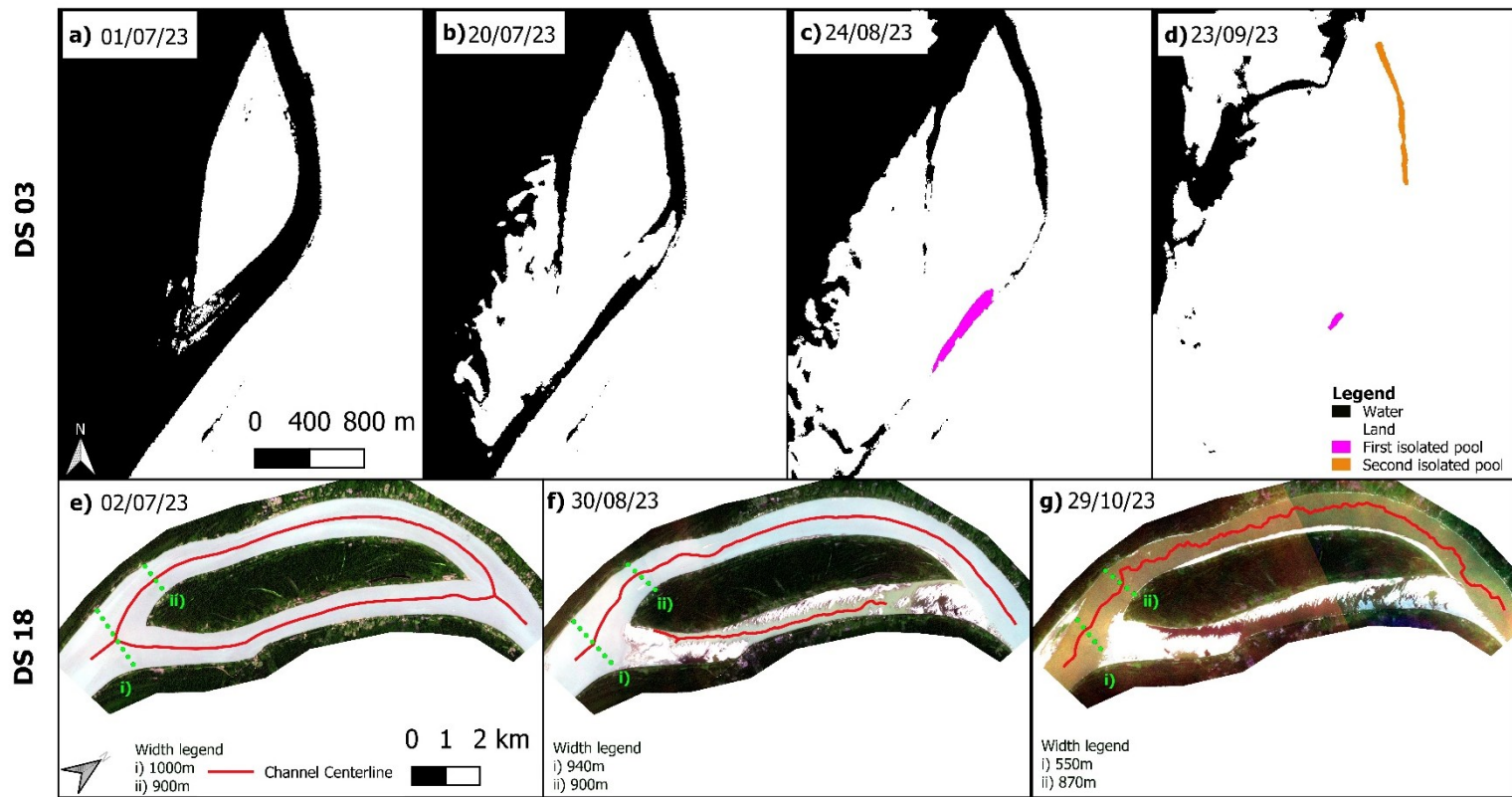


*Figure. 4.5: Satellite visualised impacts of island growth. Panels a) to d) show the isolation of pools of river water risking potential ecological damage. The surface area of the main isolated pool in c) is 16000 m<sup>2</sup> which has shrunk to 507 m<sup>2</sup> in d) with a second (14000 m<sup>2</sup>) large pool isolated. Panels e) to g) display the narrowing of shipping channels with island growth. First the river is narrowed to 1 channel (b) and then the entrance to the channel (gi) becomes narrower than the original narrow point (gii). Note the complexity of the centreline in (g) from smaller island features that shipping is also required to navigate around.*

Percentage exposed sediment for all AOIs in the 2023 dry season was observed to increase from July (start of dry season) to October (end of dry season), as might be expected from a period of drought. The maximum percentage increase in exposed sediment between the first dry period image and the last was 34 % at DS 12 and the minimum was 3.5 % at DS 08 (Fig. 4.6a). Comparing the relative magnitude of change showed a continuous overall trend of increasing exposed sediment as the dry season progressed. Despite spikes of increased rate of change in individual AOIs, the mean average change slope across all AOIs has limited fluctuation, displaying a smooth trend in increased exposed sediment (Fig. 6.5b).



Figure. 4.6: a) Percentage change in exposed sediment compared to the coverage in the first 2023 July image at each AOI. b) Derivatives of each AOI with a mean for all AOIs to show if the magnitude of change increases or is stable throughout. The AOI positional distances downstream are mapped with the colour graph to suggest if there are any clear trends based on longitudinal position.

#### **4.3.2 Longitudinal trajectories in sediment exposure**

Longitudinal (i.e., downstream) trends in the maximum seasonal increase in exposed sediment per AOI (again, in percentage compared to first dry season image) highlight alternating patterns of high and low magnitude change (Fig. 4.7). To understand why dry season impacts differ along the Madeira, the positions of large tributaries are included in Figure 4.7 to determine whether any of these low-high magnitude 'cycles' may be linked to tributaries driving inputs of sediment or discharge. However, the two large tributaries corresponded with opposing positions in these maximum exposed sediment cycles (i.e., one tributary coinciding with a large increase in exposed sediment, and one coinciding with a small increase), meaning that they are unlikely to be driving these results. Beyond this observation of high-low magnitude change 'cycles', the river does not appear to display any notable streamwise trends in exposed sediment change over the course of the dry season (i.e., as upstream degradation or downstream deposition).

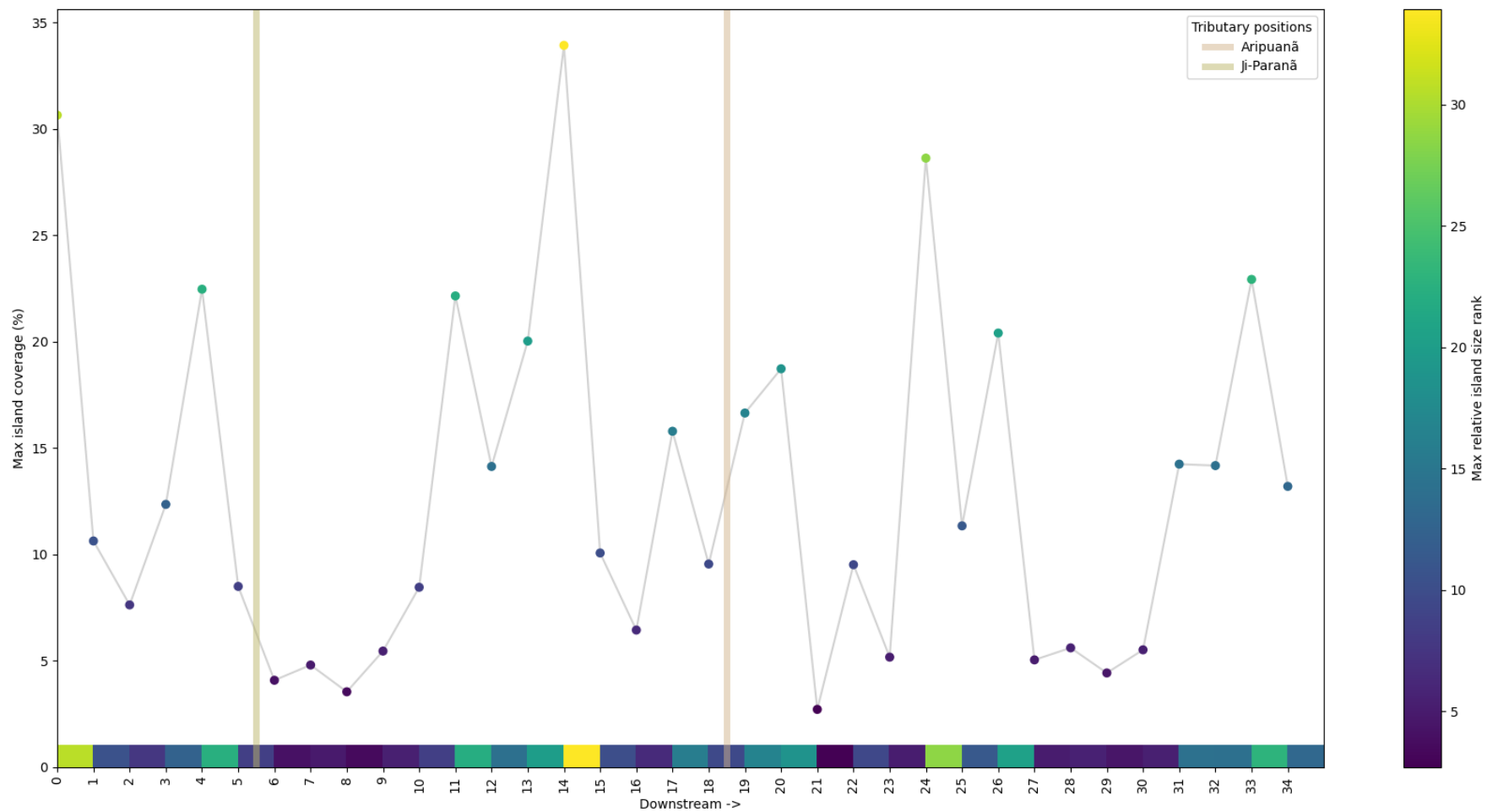


*Figure. 4.7: Longitudinal profile of maximum percentage change in exposed sediment at each AOI showing alternating patterns of high and low change; neither the upstream nor downstream portions of the reach appear to exhibit more change than the other. Two major tributaries join the Madeira in this study reach; however, these correspond to opposing magnitude trends in exposed sediment change and therefore are unlikely to be the cause of these repeating pattern.*

#### 4.3.3 Long term island change

Despite the lower number of available images in the earlier years of the PlanetScope constellation (i.e., 2016-2020), these data are still sufficient to reproduce trends in exposed sediment over time. Isolating a single AOI (DS 13) enabled me to study changes in dry season magnitude over multiple years, as inferred from percentage exposed sediment from 2016 to 2023. While reduced image availability limits the ability to elaborate on some of the potential findings, there are clear inter-annual differences (Fig. 4.8a) in the rate of change of exposed sediment as the dry season progresses. DS 03 was chosen because it was a typical example of the other islands and placed longitudinally in the middle of the river without being too close to either major tributary (Fig 4.7). These trends are echoed by the five AOIs from which a longer (but more complete) record (2021-2023) was collected. As seen in the higher spatial resolution dataset from the 2023 dry season (Fig. 4.6), the magnitudes of change are different between each AOI, but the five AOIs exhibit broadly similar inter-annual trends (Fig. 4.8b). The mean maximum percentage change in exposed sediment is higher for 2023 (21.3%) than 2021 (16.29%) and 2022 (19.7%) confirming the 2023 drought as an exceptional event (e.g., WWF, 2023). This is further echoed by the findings from the full temporal record at DS 13 where (mean maximum percentage change in sediment in 2023 again stands out from the preceding years between 7.4 and 19.1% for the period 2016 to 2019).

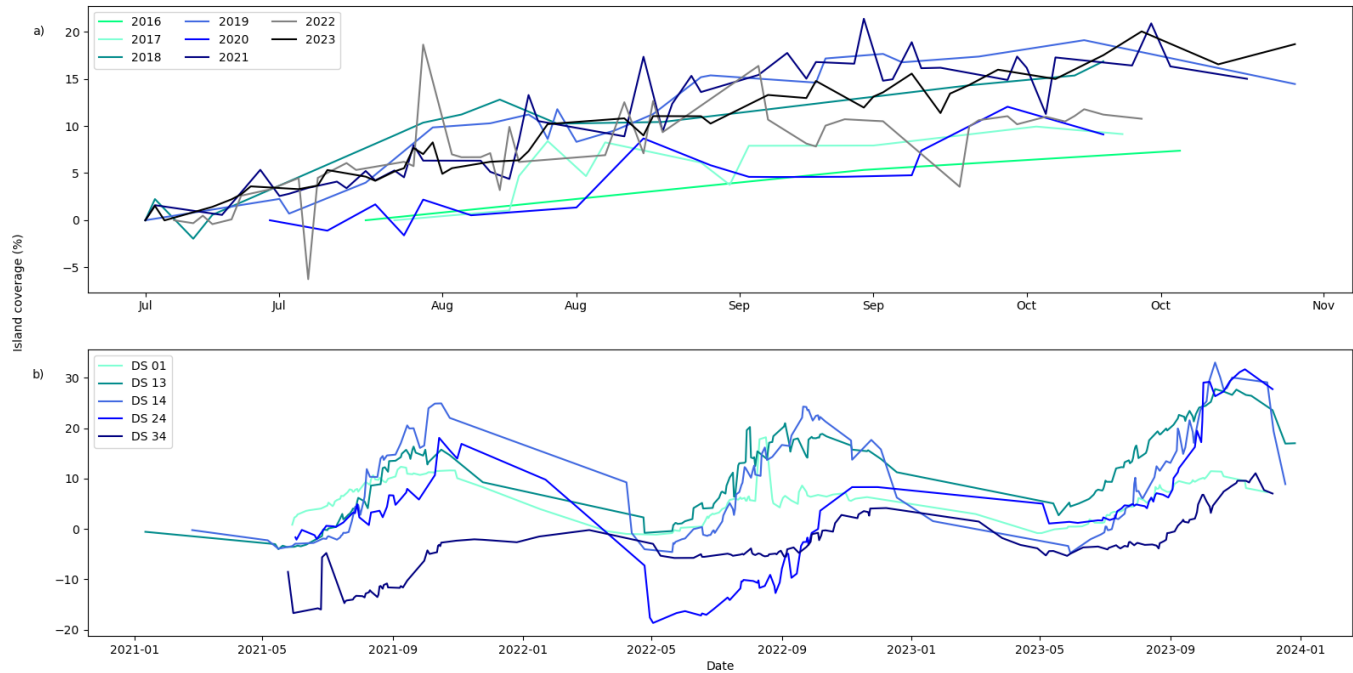


*Figure. 4.8: Percentage change in exposed sediment over multiple years. a) displays the full availability of PlanetScope usable imagery for DS 13. b) shows the five example AOIs for the years where more recent data is available. The percentage change in b is calculated at each individual AOI.*

#### 4.3.4 Linking island dynamics to river discharge

As expected, a weak but significant negative correlation was found (Fig. 4.9a) between percentage exposed sediment and discharge measured at the Porto Velho gauging station (ID: 15400000) over the period 2021-2023. However, distinct spatial patterns were found within this overall trend when inspecting the correlations for each AOI separately (Fig. 4.9b) which may indicate causes of spatial differences in island changes. While some AOIs (e.g., DS13, DS01, DS14) exhibited notably strong ( $R^2 = 0.79$  and  $0.63$ ,  $0.64$  respectively) correlations, others had weaker relationships. In particular, DS 34 was found to show no correlation with discharge ( $R^2 = 0.08$ ). This AOI is positioned on the Confluence of the Madeira and the Amazon, and local hydraulic/geomorphic drivers of exposed sediment resulting from tributary dynamics are thus likely larger drivers of sediment exposure at this location. Removing this AOI (DS 34) from the overall dataset notably improves the correlation ( $R^2=0.42$ ;  $P<0.01$ ), confirming the exposed sediment-discharge relationship, but also highlights the influence of local factors in determining streamwise trends in river channel response to drought

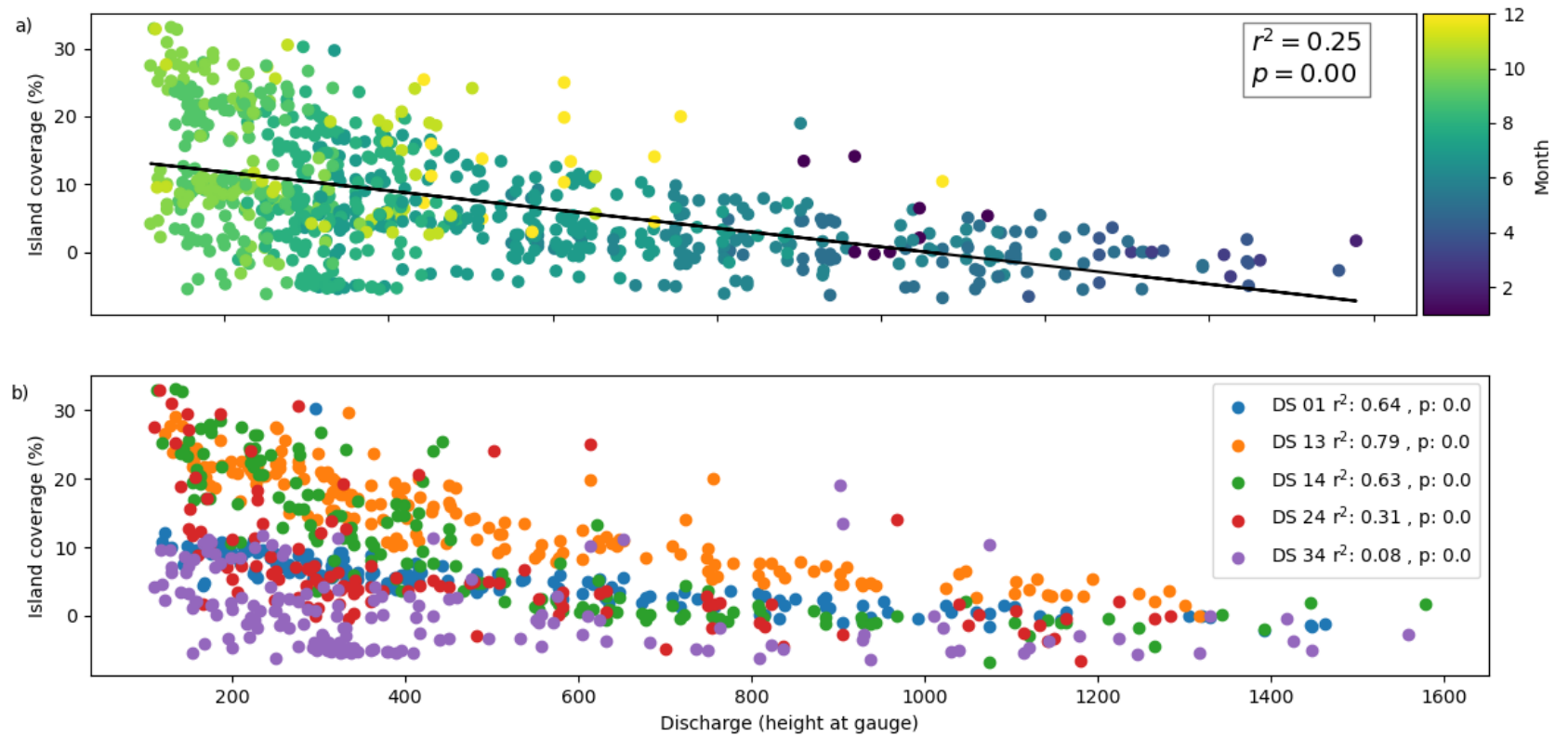


Figure. 4.9: Comparison between 2021-2023 exposed sediment percentage change and discharge at the Porto Velho Guage over the same period. As expected, there is a significant negative correlation found between sample AOIs percentage exposed sediment and the discharge measurements per timestep for each image in these samples (a). However, when these are split into individual AOIs (b) it becomes evident that the negative correlation would have been greater without DS 34 which may have alternate drivers including discharge from other rivers.

#### 4.3.5 Satellite monitoring trajectories

Measuring recent historical change in island dynamics over multiple years (rather than just 2023) was more difficult due to limitations in the availability and quality of images from PlanetScope's previous generations of 'Dove' satellites, which lack the sensor improvements featured in the newest 'Superdove' generation. However, as a proof-of-concept for future monitoring programmes, AOI DS 13 was selected as an AOI with an island that appeared to have little longitudinal migration over multiple years to illustrate changes in the availability of usable PlanetScope images as the satellite constellation size increased. To do this, all images with <10% cloud were classified, and unusable results removed (Fig. 4.10). Results show that until 2021, the number of usable images improved rapidly with the addition of PlanetScope satellites to the constellation (Fig. 4.10a), after which this number apparently stabilises.

Using these results, the five AOIs spread throughout the river system which provided annual exposed sediment comparisons for the period 2021 – 2023 (see section 2.2) were further analysed with a view to understanding which times of year yielded the most usable images. The results show that the vast majority of images came from the four-month dry season (when cloud cover was at a minimum), with only between 22.8 and 33.4 % of usable images coming from the other eight months per year (Fig. 4.10b). Taken together, these results (Figure 4.10a & b) suggest that satellite coverage during the dry season is nearing a 'saturation' point whereby satellite data availability is limited more by weather (i.e., cloud cover) than by satellite overpass/image availability. This explains the variation in wet season image numbers when the gaps in weather related obstructions to image capture are more irregular. In the interests of producing a framework for future researchers using PlanetScope it was tested whether factors in the geometry or geography of AOIs would influence image availability by analysing imagery collected for the 2023 dry season to assess which AOIs contained the most available images. There was no significant trend between AOI size or downstream position with number of available images (Fig. 4.10c).

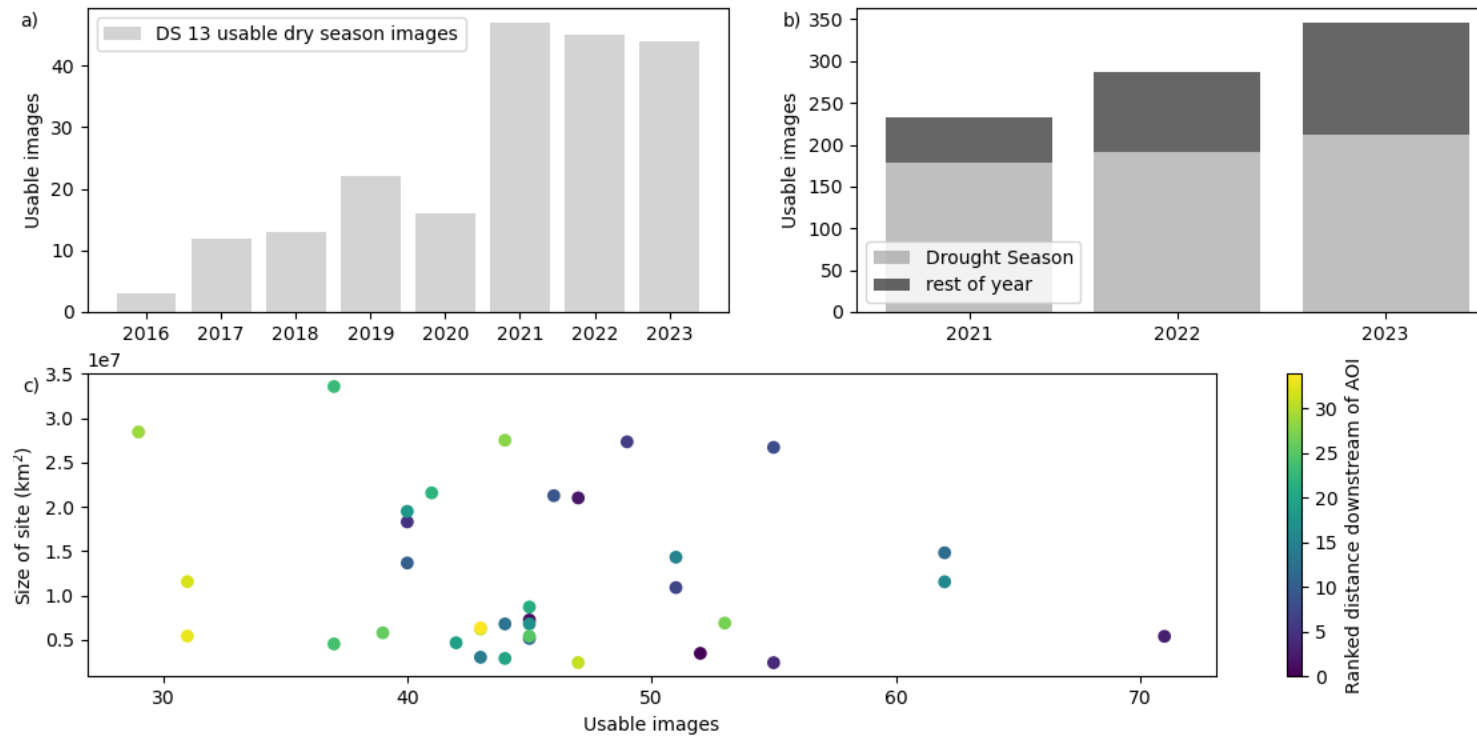


Figure. 10: Number of usable images after the water mask extraction had been carried out. a) There is a clear trend of increasing images per year at AOI DS 13 during the dry season until 2021. b) Of the 5 AOIs that were analysed in more depth, the dry season can be seen to account for the vast majority of these available images. c) Focusing solely on the 2023 dry season where the most separate AOIs were studied, there is a range of available images, but this is not significantly related to position downstream or AOI size.

## 4.4 Discussion

### 4.4.1 Drought insights from above

Analysis of the PlanetScope CubeSat imagery showed that all AOIs on the Madeira River downstream of Porto Velho experienced increases in the percentage of the previously wetted channel comprising exposed sediment as the dry season progressed. The magnitude of change in this exposed sediment varied with location and time, but the trend of increasing exposure during the dry season was consistent throughout the river system. Earth Observation is the most cost-effective and time-efficient method to adequately measure river systems of this size (Fassoni-Andrade et al., 2021), and it has been shown that PlanetScope is capable of directly measuring the spatial changes in exposed sediment associated with river islands in over 1000 km of river at high temporal frequency. I was able to make dry season estimates in exposed sediment at a frequency which equated to better than once every two days at the majority of AOIs, well beyond the 5 to 16-day return period of previous satellite-driven river island studies (Shi et al., 2018, Sun et al., 2018, Hossain et al., 2013, Nama et al., 2022). Given that the impact of cloud cover/weather on the number of usable images increases as a function of return period (i.e., the longer the return period, the longer the 'no data' period lasts), the ability to obtain data at ~2 day intervals, after cloud has been accounted for, represents a considerable advance on these previous methods (Shi et al., 2018, Sun et al., 2018, Hossain et al., 2013, Nama et al., 2022, Hossain and Saha, 2024, Gao et al., 2013). For example, Sentinel-2 can provide imagery only every ~5 days therefore a single image removed for cloud cover will lead to a ~10 day data gap. The results therefore clearly demonstrate the effectiveness of CubeSat-based river monitoring to provide information for stakeholders at scales and frequencies not previously available.

Increased exposed sediment during dry months is expected annually, as river levels change with seasonal precipitation (Vergasta et al., 2023). However, the method developed here can provide a direct indication of years in which these falling river levels, and resulting increases in exposed sediment, have reached a level indicative of a hydrological drought such as that which occurred throughout 2023 (Espinoza et al., 2024, Fraser-Baxter, 2024). In addition to traditional metric-based assessments of drought, direct visible impacts on river users could represent new supplementary methods of classifying drought as it is felt by individual stakeholders (Stahl et al., 2020, AghaKouchak et al., 2021). For example, increased exposed sediment can constrain shipping passages (Fig. 4.5; Karahalios, 2020), potentially resulting in a drought assessment targeted solely at the management of visible transport constraints (i.e., narrowing shipping lanes). These drought assessments would be provided in conjunction with primary river variables such as discharge (Fonstad and Marcus, 2010). This is key during periods of hydrological drought when observed discharge measures

become decoupled from modelled discharge estimates and reanalysis products due to the lag between meteorological drought transitioning to hydrological drought (Zhou et al., 2021).

As is clearly displayed in figure 4.4, the approach highlights potential for measuring where land is frequently inundated or where bars of sediment are exposed. This is vital for understanding where channels will close during drought, and/or which areas will become isolated (Fig. 4.5). Large pools of water became isolated in 65% of the AOIs studied in 2023, and in many cases multiple pools were isolated, reconnected, or dried up throughout the study period (Fig. 4.5a-d). This could have significant impacts on fish strandings and would likely reduce water quality in these pools when they are isolated (Van Vliet et al., 2023), risking fish die offs even if they are later reconnected. In a region reliant on fishing (Arantes et al., 2022, Pestana et al., 2022), these at-risk secondary channels are also locations that are important for launching boats, catching fish, and providing nursery/rearing habitat outside of the main flow (Goulding et al., 2019). The river is also an important source of transport both for local people and larger shipping (Garcia et al., 2021, Suedel et al., 2022). It has been shown that over the 2023 dry season, the channel significantly narrowed, but further research will be needed to understand the implications of this for affected communities, and whether this occurs annually or only in drought years. Some channels closed completely to shipping early in the dry season (Fig. 4.5f), while in others the previous widest point became the narrowest and thus represented a constraint on ship passage. The algorithm-derived channel centreline is much more irregular towards the end of the dry season (Fig. 4.5g) due to the centreline algorithm 'wandering' between narrower sections of channel bounded by small in-channel sand bars, something which shipping would also have to contend with, increasing the time and demands of travelling through a reach. The exposed sediment change maps (Fig. 4.4) also effectively provide non-dimensional 'bathymetric' insights into areas which are likely to remain shallow during the wet season (i.e., areas that are most frequently dry), something that is vital for river navigation (Kangsabanik et al., 2023). With a river system that has sediment yields as dynamic as the Madeira River, and whose bathymetry may not be surveyed as regularly as would be desired, these assessments could represent a cheap and effective way to help direct funding for more in-depth bathymetric surveys at targeted locations where the river becomes the most constrained.

#### **4.4.2 Longitudinal trends in river island dynamics**

Inspection of the 2023 longitudinal changes in exposed sediment (Fig. 4.7) indicates that there is no significant increase in exposed sediment as a function of distance downstream. These findings are in opposition to theories of "downstreamness", whereby the propagation of drought causes more extreme impacts downstream

(Dahlmann et al., 2022, Zhou et al., 2021). However, many of these drought studies pay particular attention to reservoir storage which, while significant in many rivers, does not exist in the 1000 km study reach of the Madeira River (Van Oel et al., 2018). The alternating nature of exposed sediment peaks and troughs seen in the maximum percentage change (Fig. 4.7) could be attributed to other drivers superimposed on the general trend of increasing exposed sediment during the dry season. While inspection of the location of major tributaries indicates that these are not responsible for streamwise patterns in exposed sediment, it is hypothesised that given the extremely high sediment yield of the Madeira River (Ayes Rivera et al., 2019), that sediment dynamics, rather than hydrological processes, is likely the main driver in spatial patterning in areas of high and low magnitude island change. Longitudinal profiles of river systems are directly linked to sediment dynamics (Costigan et al., 2014), but there has been little investigation into changes in island dynamics in response to this, and nothing at the ~1000 km scale of the study.

Regardless it is important to know if and how these peaks of dry season channel change may move up or downstream over time - i.e., if the areas of maximum change will maintain their location in the river over decades or shift downstream annually. Methods for quantifying similar channel changes in smaller, highly dynamic rivers have been proposed in the past (Major et al., 2019, Thorne et al., 2023) but these often rely on aerial LiDAR or in-situ measurements of channel planform change. Using the methods presented here, PlanetScope may enable continuous monitoring of these cycles of longitudinal or temporal change in large river systems over long timescales as the extensive catalogue of imagery continues to evolve. This monitoring would require more extensive river reaches encompassing the space between the AOIs used here but could enable researchers to investigate how these phenomena transfer to larger river systems without the cost and impracticality of traditional field methods.

It is worth noting that longitudinal trends in exposed sediment may result from other factors, such as island shape (Picco et al., 2015), anthropogenic influence (Long et al., 2021) or vegetation cover (Gurnell and Bertoldi, 2020). For example, AOI DS 34 is an outlier in the exposed sediment:discharge relationship; it is proposed that this was caused primarily by its distance from the discharge gauging station at Porto Velho because different discharges from each tributary may have influenced the discharge value at DS 34, but this is further compounded by the fact that this AOI is located close to the Madeira's confluence. As sediment dynamics and backwatering effects at confluences are often very different from the rest of the river (due to the multiple channels joining together in the confluence causing eddies and other features that erode and deposit sediment in ways that would not otherwise be expected (Yu et al., 2020, Li et al., 2022b)), this may account for the lack of trend at this AOI.

#### **4.4.3 Causes of decoupling exposed sediment from discharge**

In fact, the decoupling of exposed sediment from discharge is potentially very informative in itself, and one of the largest sources of useful ‘anthropocentric information’ that a study such as this can provide. In the case of DS 34, I speculate that the cause of this decoupling is principally geomorphic (i.e., due to the complex hydrodynamic behaviour of the river confluence and its onward links to sediment movement), but elsewhere when exposed sediment change is unexpectedly decoupled from discharge, this may constitute an indicator of anthropogenic influence. For example, gold mining has occurred directly within the Madeira River, via barge-dredging of river sediment (Pestana et al., 2022, Alessi et al., 2023). In many other places in the world, rivers are used for large scale sorting and extraction of sand and building materials (Gruel and Latrubesse, 2021, Hackney et al., 2021), which can have huge consequences on river sediment dynamics (Kondolf, 1994). These changes may be traditionally quantified through field methods and/or expert analysis of sediment patterns, but it is proposed that comparing expected theoretical correlations between discharge and exposed sediment change against corresponding real-world data could provide an indication of where anthropogenic influences on sediment (i.e., sediment extraction) might be occurring. Methods such as this would also be able to help indicate how far downstream the impacts of these practices propagate and thus provide support to and help define environmental impact assessments and monitoring.

Similarly, large scale engineering structures have been identified to impact the sediment dynamics and geomorphology of almost all large rivers in the world (Ayes Rivera et al., 2019, Beveridge et al., 2020b, Crosato and Mosselman, 2020). The impact of these structures will further decouple exposed sediment from discharge. This could assist studies on decreasing sediment yields in the Madeira River as a result of the upstream dams (Ayes Rivera et al., 2019, Li et al., 2020b). The current annual comparisons do not yet show decreases in the exposed sediment resulting from these dams but provides a baseline to compare future results to and monitor sediment changes over time. It would be expected that the maximum island change will decrease in magnitude due to sediment starvation (Shi et al., 2017) and the distance over which this occurs could help define the longitudinal impact of these dams (Williams and Wolman, 1984). However, there is likely to be some disruption to these signals in the mega-rivers of Brazil because their size and available stream power is able to entrain material from unprotected banks where there is limited engineered flood protection (Suedel et al., 2022). Multiple years of imagery will need to be analysed to separate the longer trend of hydropower disruption on sediment yields from more localised influences.

#### **4.4.4 Towards a continuous monitoring programme for river island dynamics**

I chose to monitor island dynamics by quantifying changes in exposed sediment because using more stringent textbook definitions of islands (i.e., non-changing vegetated in-stream land masses; Robert, 2014) would have limited the island numbers used in the study. Changes in vegetated islands are inherently slower, and the results would have missed important channel-changing aspects of dynamics in unvegetated bars which build upon these islands. However, deciding how to classify the islands was still a key constraint of the work carried out here. Connections between exposed bars are dynamic and unstable resulting in islands being difficult to define. For example, an exposed bar may impact shipping and fluvial hydraulics yet may be separated from a vegetated island by narrow wetted channels (e.g., Fig. 4.2b) prohibiting the delineation of a single island. These concerns were overcome through the use of the relative percentage sediment coverage metric, accounting for all exposed sediment in the channel. This decision limits the applicability of this method to some regions where islands have large flood defences and therefore artificially high-water levels, however these rivers are unlikely to be on the same scale as the one monitored here due to the length of bank which would need protecting and thus alternative methods could be used. This metric provides information directly relevant for ecological and anthropogenic concerns during droughts. Continued monitoring could build a long-term record of channel coverage, enabling links between climatic trends and drought impacts to be better understood.

A hypothesised continuous monitoring programme would take PlanetScope images as soon as they are available and input them to a data pipeline such as the one used here (Fig. 4.2) to produce exposed sediment metrics. This would enable alerts to be posted as soon as obstructions to shipping passages are visible in the satellite imagery and could maintain a full river record of the available width and narrow points. It would also help direct environmental regulators and government agencies towards fish strandings in backwater areas in sufficient time to provide assistance as needed. This assistance could help mitigate the impacts of drought on rare or endangered aquatic species by preventing strandings (Archdeacon et al., 2022). Individually, the methodology presented in this chapter lacks the feedback mechanisms to be an ESDT on its own. However, as stated throughout, this project aims only to build the tools for an ESDT, therefore combining discharge influencing components (e.g., hydropower management) with this methodology and temperature or transport models would allow users to feedback and obtain practical choices for their actions and the likely response to these actions. Furthermore, the length of the dry season in the Amazon basin is increasing (Espinoza et al., 2019) and with it, more extreme hydrological events, such as droughts (Molina-Carpio et al., 2017, Marengo and Espinoza, 2016). Using the proposed pipeline, long term monitoring could provide more information on climatic impacts such as those from El Niño and La Niña as they become more extreme with

climate change (Cai et al., 2021) and produce more extreme drought scenarios (Cai et al., 2020). This may be able to increase the likelihood of helping communities to be resilient to these disasters. This study only encompassed one El Niño (2023) which did appear to produce more exposed sediment as would be expected (Fig. 4.8), but more years will need to be measured before the significance of this is clear. Moreover, to measure a more continuous trend through different seasons would require a constellation approach to combine the methods here with SAR data which could collect sediment extents during the parts of the year found to have high cloud cover.

#### **4.4.5 Maximising the benefits of CubeSats**

The results of the study highlight the potential of the rapid return period of CubeSats for a variety of different riverine studies and provide insights into their benefits and limitations. The water mask extraction approach used here had the ability to be 'fine-tuned' by retraining the classification model with imagery from the target river (Valman et al., 2024). However, this was not required in this study because the main stem Amazon River was actually used in the training of the base classification model (Valman et al. 2024), meaning that the model was familiar with the spectral and spatial characteristics of the Madeira River, thus providing high quality water mask segmentation without needing additional fine-tuning. Furthermore, less than 2% of cloudless images needed to be removed from the dataset, despite the considerable radiometric quality issues associated with CubeSat imagery (Frazier and Hemingway, 2021). This can be attributed to the large channel size (Valman et al., 2024) which was relatively balanced with land pixels in each image, something that has been shown to improve predictions for Neural Network-based classifiers (Bugnon et al., 2019).

The availability of cloud-free images resulted in a high number of days yielding usable water masks (Fig. 4.10a). This contrasts strongly with other studies where cloud cover occludes the limited Landsat images altering the planned study months (Nama et al., 2022). This, coupled with the limited number of images from the other eight months of the year (i.e., the wet season, not included in these analyses), suggests that the Madeira River basin is now reaching the climatically driven upper limit for the number of cloud-free daily PlanetScope scenes. As a result, many more satellites and improvements in sensors would be needed for increasingly diminishing returns in additional imagery (Roy et al., 2021). For example, in the Amazon Basin wet season, cloud cover persists for up to 90% of each month (Collow et al., 2016) making any additional imagery unlikely. Potentially including additional satellite systems such as the Harmonised Landsat Sentinel system would provide opportunities to fill these gaps during differing overpass times (Claverie et al., 2018) or combining the approach here with radar imagery (Li et al., 2022a) where available to confirm the trends analysed here are consistent during periods of cloud cover.

Regardless, the catalogue of PlanetScope images increases with each consecutive year that the CubeSats are capturing imagery, meaning that long term, high temporal resolution trends will increasingly be available for analysis (similar to that already from Landsat's 40-year record; Shi et al., 2017). However, because of the PlanetScope constellations greatly enhanced revisit rate, drought conditions and other primary and secondary river variables such as discharge, channel change, and ecological function (Carbonneau et al., 2012, Caissie, 2006) will increasingly be accessible at a higher frequency over a larger area than had previously been possible. As other satellite providers increasingly improve sensors and move towards a constellation approach (Wu et al., 2021a), further river variables such as high-resolution river temperature (Gadal, 2023) and sediment dynamics (Gardner et al., 2021) may also become measurable with rapid revisit datasets. The methods developed here could thus be expanded upon to provide further insights for river managers and stakeholders.

## 4.5 Conclusion

Hydrological droughts are becoming increasingly common in large rivers due to climate change (Zhou et al., 2021, Balti et al., 2020). However, the difficulties in defining droughts, the discontinuity of their impacts, and the scale over which they can impact a river system makes them hard to measure with traditional primary variables such as discharge from fixed gauges. Here the potential of using PlanetScope's CubeSat constellation to measure change in river exposed sediment is explored as a proxy for drought. This provided a measure of the resulting direct impact of the dry season drought on channel morphology of the Madeira River. It was found that there was a consistent trend of increasing exposed sediment during the dry season, throughout the 1000 km study reach, resulting in the river significantly narrowing (on average by 750 m), coincident with news reports of reduced shipping (Reuters, 2023). Different years have higher or lower magnitudes of exposed sediment change over the course of the dry season, which may relate to the climatic conditions. 2023 was the first El Niño year where maximum PlanetScope constellation image capture was available and recorded the highest annual exposed sediment coverage increase over the study area. It was also found that although variability in exposed sediment significantly correlates with discharge, the strength of this correlation varies spatially. I propose that this relates to sediment dynamics in Madeira River which may explain observed downstream 'cycles' of high and low maximum dry season sediment exposure.

Building on the methods proposed in this paper would enable additional high frequency monitoring of shipping channel width, isolation of pools of water (potentially leading to fish strandings), and locations of significant geomorphic change. As the extent of the PlanetScope imagery catalogue is extended over time, trends will become clearer, allowing for research into space-time variability in channel change during drought.

# **Chapter 5:**

## **Operationalising Earth Observation technology to maximise monitoring of the thermal impacts of power generation: a constellation of constellations**

### **5.0 Abstract**

River water temperature regulates many other riverine processes giving it ecological and socio-economic importance. River water temperature is increasingly driven by climate change and anthropogenic activity such as power generation, urbanisation, and industrial effluent. Therefore, understanding and monitoring river water temperature is vital for sustainable management of these interconnected drivers. However, due to its dynamism and spatial complexity, river water temperature has proven difficult to monitor effectively. Point-based sensors lack the spatial coverage to encompass downstream effects of thermal pollution and air temperature-based models cannot identify anthropogenic thermal effluent. Satellite thermal infrared has a large body of research supporting its ability to monitor water surface temperature over large spatial scales at little cost to the end user, nevertheless adoption by river managers has been inhibited by two key limitations. Firstly, satellites with sufficient spatial resolution to monitor river systems have low temporal resolution. Secondly, 'water' pixels that contain land produce erroneous results. By applying a "constellation of constellations" approach by combining Landsat 8, 9, ASTER, and ECOSTRESS data availability was more than doubled from any single sensor (Landsat 9 providing the highest majority at 45%). PlanetScope optical CubeSats are used to tie the quasi-constellation of thermal imagery together with an independent high resolution water mask which would enable additional thermal imagery to be added in the future where static water masks were shown to inhibit TIR monitoring. This approach was applied to 100 km reaches in three

major river systems: the Rhone, Nile, and Yangtze rivers. This demonstrated the methodologies effectiveness at identifying the downstream thermal pollution effects from nuclear, coal, and hydropower generation with 2°C temperature spikes which persisted variable distances downstream based on individual facets of these river systems. It is further argued that the modular design of this framework will support future satellite launches and management requirements.

## 5.1 Introduction

River water temperature is an environmental variable with profound socio-economic implications, whereby increases in this water temperature threaten the usability of freshwater as a sustainable resource (Ficklin et al., 2023). On a local level, rivers can act as heat sinks, keeping air nearby up to 2°C cooler on unseasonably warm days thus potentially helping to mitigate the impact of heatwaves (Hathway and Sharples, 2012). Whereas regional thermal power demand (i.e., nuclear, coal and oil) requires river water to cool their systems (Raptis and Pfister, 2016, Raptis et al., 2016), therefore higher “cooling water” temperatures reduce the efficiency of these methods and result in increased power costs for the consumer (Lohrmann et al., 2019, McDermott and Nilsen, 2014, Boogert and Dupont, 2005, Hutchens et al., 2024). These increased costs from high water temperature are also reflected in wastewater treatment works, which are shut down during high temperature events to prevent costly destruction of biological cleaning methods (Hughes et al., 2021, EBS, 2024).

Water quality, controlled by river temperature, include eutrophication, waterborne disease prevalence, and damage caused by chemical pollutants (Ouellet et al., 2020, Van Vliet et al., 2023, Johnson et al., 2024). These can directly impact the usability of freshwater as a sustainable resource by damaging the potability of drinking water and leading to the proliferation of waterborne diseases (Sokolova et al., 2022). Indirectly, this decline in water quality can lead to fish die offs which impact commercial fisheries (St-Hilaire et al., 2021, Burdick et al., 2020, Roychowdhury et al., 2021) yet, damage subsistence fishing communities disproportionately more (Carothers et al., 2021). These examples show how our social and economic systems are reliant on water quality and are therefore tightly coupled to river temperature.

To ensure sustainable use of river systems, as river temperatures rise under climate change, our interactions with these rivers need to be monitored increasingly well and understood (St-Hilaire et al., 2021, Ouellet et al., 2020). It is feared that rivers are exceeding tipping points whereby they no longer cool sufficiently overnight or provide enough cool-water refuges to maintain ecological resilience (Johnson et al., 2024). Additionally, anthropogenic activities can also drive localised spikes in river temperature as both wastewater treatment works (Zhang and Chadwick, 2022) and thermal power plants discharge thermal effluent downstream (Raptis and Pfister, 2016, Raptis et al., 2016, Naimaee et al., 2024, Itsukushima et al., 2024, Zoran et al., 2012, Bonansea et al., 2021). These users do not operate in a vacuum; urbanisation has been shown to increase water temperature independently (Briciu et al., 2020, Cao et al., 2016) and also by requiring the development of these industries (Zhang and Chadwick, 2022, Wu et al., 2021c). Even typical “green” energy sources such as hydropower influence river temperature, with cool water spikes when water is released from the bottom of the

reservoir; this unseasonably cool water can cause just as many problems for aquatic life as warm water releases (Rheinheimer et al., 2015). As a result of the need to discharge thermal effluent in rivers, jurisdictions are increasingly imposing regulations on when and where power generation can occur. For example, in Europe, such regulations have increasingly led to nuclear power generation being curtailed in summer due to rising water temperatures (Guénand et al., 2023). Similarly, such regulations mean that hydropower releases may not be allowed when they are most desirable or profitable (He et al., 2023, Wang et al., 2021a).

Despite the multi-faceted importance of river temperature and potential economic benefits of maintaining records of and monitoring water temperature, there is a scarcity of available data (Hannah et al., 2011, Johnson et al., 2021, Murphy Jr et al., 2021). Continuous in-situ data loggers have become increasingly affordable (Johnson and Wilby, 2013, Hadi et al., 2020) but these can be swept away, and lack spatial coverage (Johnson et al., 2021). Conventional aerial imagery has much greater spatial coverage, yet it is prohibitively expensive for most use cases especially considering it only provides a single 'snapshot' of river water surface temperature (WST) at a point in time (Torgersen et al., 2001). This imagery measures the top 0.01 m of the water column (Torgersen et al., 2001) yet in many rivers it is representative of the river body temperature (<1°C of difference) especially in locations with consistent mixing, meaning that it can provide information on surface-level thermal pollution inputs (Fricke and Baschek, 2015). Drone-based thermal infrared sensors are increasingly used for measuring WST, partly because their ease of use allows for repeat surveys which facilitate the monitoring of spatial and temporal dynamics of WST. However, the limited battery life of these drones hinders their ability to monitor large rivers and because these data suffer from accuracy issues (Dugdale et al., 2019), this prohibits the generation of accurate space-time temperature records (Niwa, 2022).

Alternatively, Satellite-based technology has shown potential to monitor river temperature over a spatial extent well beyond that which was previously possible (Tavares et al., 2020, Al-Murib et al., 2019, Wawrzyniak et al., 2012, Despini and Teggi, 2013, Ling et al., 2017). However, longwave thermal infrared bands (TIR) are required to monitor WST and existing satellite-based TIR sensors necessitate coarser spatial resolutions (>60 m<sup>2</sup>) than most other spectral bands, because these sensors are measuring a weaker energy signal in the form of emitted thermal energy, as opposed to the higher energy returned by reflected solar radiation. (Xue et al., 2020). This coarse resolution causes satellite data to be susceptible to the 'mixed pixel' problem, whereby image pixels contain a mixture of land and water, with substantially different emissivities (the efficiency of an object at emitting thermal radiation, integral to calculations of TIR temperature) and temperatures. Using coarse imagery means it is hard to define boundaries between these water and land classes using simple indices (Xu, 2006,

Ermida et al., 2020). Static bankfull water masks, developed with more complex algorithms, are often used instead. These display an average wetted area which by default also has mixed pixels at any other flow stage (Allen and Pavelsky, 2018, Pekel et al., 2016). A second limitation of the current satellite TIR monitoring approach is a lack of appropriate return periods, resulting in inadequate data being captured to monitor river systems at a resolution appropriate for sustainable management (i.e., being able to monitor and alter power plant operations based on WST in enough rivers catchments to provide a useful tool). This is because a minimum river width of 3 pixels is required to measure WST from satellite to prevent these mixed pixels (Hori et al., 2021) therefore a 100 m pixel resolution requires a 300 m minimum river. Despite recent developments from the private sector, the only existing satellites viable for studying rivers (i.e., pixels  $<100\text{ m}^2$ ) have 16 day return periods, missing many temporal changes in river systems (Wulder et al., 2022). Therefore, any single satellite system alone, does not provide the temporal resolution necessary to capture continuous changes in WST, precluding the use of these data for monitoring WST by industries that might otherwise benefit from regular satellite-based maps of water temperature.

To address these two problems, a “constellation” approach is proposed to improve the operability of TIR satellite data for WST retrieval, focusing on increasing the scale of coverage both temporally and spatially whilst applying novel datasets to improve the accuracy of results. Firstly, in order to address issues relating to the mixed-pixel problem and therefore the requirement for dynamic water masks, the PlanetScope CubeSat constellation was used for its daily optical imagery to provide 3 m resolution water masks that capture individual islands that might otherwise cause erroneous results (Valman et al., in Review, Martí-Cardona et al., 2019). Secondly, in response to the requirement for more frequent temporal coverage, data was harnessed from as many TIR sensors as possible. These included the continuous Landsat constellation of 5, 7, 8 and 9 (Wulder et al., 2022, Masek et al., 2020, Barsi et al., 2014), the ASTER sensor on the Terra satellite (Despini and Teggi, 2013, Abrams et al., 1999), and example images from the ECOSTRESS sensor on the International Space Station (Fisher et al., 2020). This was made possible by combining an automated PlanetScope water mask method (Valman et al., 2024) with cloud computing software for the majority of the TIR imagery (Gorelick et al., 2017) to achieve a previously unprecedented scale of thermal analysis. This methodology provided the ability to test the longitudinal and temporal impact of a suite of anthropogenic power generation and land use scenarios that occur in large river systems. In doing so, I set out to achieve the following sub objectives to meet the 3<sup>rd</sup> thesis research objective; to measure anthropogenic influences of river water surface temperature using satellites:

- 1: Develop a framework to combine higher spatial resolution satellite-derived water masks with TIR satellite imagery to alleviate issues relating to the ‘mixed pixel’ problem.

2: Integrate multiple thermal sensors to determine the maximum currently achievable temporal resolution for river WST retrieval.

3: Demonstrate this approach on three major rivers to demonstrate its effectiveness for detecting anthropogenic impacts on river temperature.

By achieving these sub-objectives, this project ultimately aims to develop a semi-automated workflow to facilitate high temporal satellite WST monitoring, to enable sustainable management of river temperature in response to anthropogenic impacts as set out in the thesis research questions.

## 5.2 Methodology

### 5.2.1 Study sites

Three rivers were chosen for this study to provide an analogue of different river systems impacted by anthropogenic influences on water temperature: the Rhone, France, the Yangtze, China, and the Nile, Egypt. All three of these rivers are impacted by anthropogenic temperature change, and thus act as potential case studies highlighting where satellite-based TIR monitoring methodologies could be beneficial for tracing the impact of this thermal effluent (Fig. 5.1). All rivers were required to be 300 m wide for the majority of the year providing a 3:1 river width to pixel size ratio commonly referenced in the literature (Hori, 2021, Handcock et al., 2006). This enables pure pixels to be possible in the centre of the river channel that are unaffected by contamination from islands or the banks which have starkly different emissivity values and therefore would increase the recorded temperatures. This necessarily reduces the transferability of this methodology, yet these larger rivers have disproportionate economic importance and suffer from the greatest anthropogenic stress, making sustainable management of these rivers a priority (Best, 2019). A targeted literature review of anthropogenic activities that contribute to thermal pollution guided the selection of these study sites. Power plants emerged as substantial sources of anthropogenic thermal pollution in river systems (Raptis and Pfister, 2016). These were also an activity whose impact could be mitigated by sustainable management (Guimarães et al., 2023).

#### 5.2.1.1 *The River Rhône*

In the Rhône River, thermal pollution primarily originates from nuclear power plant cooling systems, which discharge heated water back into the river channel (Zoran et al., 2012, Wawrzyniak et al., 2014). France produces two thirds of its power from nuclear energy, more than any other country and a number of these sites are on the River Rhône, providing an exemplar river to understand how nuclear power thermal pollution could be measured by this approach. Compared to the other two rivers in the study it is relatively narrow often 3-500 m wide, providing another dimension to understanding thermal influences in different river systems. The area of interest (AOI) for each site was centred on one location identified as likely to have direct influence on river temperature (Table. 5.1). As such, for the Rhône this was Saint-Alban Nuclear Power Plant, but other influences on river temperature were taken into account for the same river reaches. One of these was hydroelectric power generation which has also been shown to influence river temperature (Kędra and Wiejaczka, 2018) even for 'run of river' hydropower (Bonacina et al., 2023) such as those that can be in the River Rhône.

Diffuse thermal pollution was also expected to occur in the River Rhône as urban land use is extensive in the upper section of the chosen reach, where the city of Lyon surrounds the first 10 km of the reach. Urban land use is linked to increased water temperature through mechanisms such as storm water runoff from heated areas, urban heat island effects, and the removal of shade (Itsukushima et al., 2024, Cao et al., 2016, Orr et al., 2015a). By incorporating point and diffuse sources of potential thermal pollution the Rhône can be considered an effective case study, with potential management benefits from applying the methodology presented here.

#### *5.2.1.2 The River Nile*

The Nile River, the longest river in the world, has some of the largest inputs of thermal pollution from energy production (Raptis et al., 2016). However, due to climatic, hydrological, and anthropogenic factors the concentrations of these power generation facilities vary considerably (Pacini and Harper, 2016). Hydropower plays a large role in the upstream management of the Nile River (Heggy et al., 2024), but the reach selected is characterised by a single run-of-river dam, the Asyut Barrage. The impact of this solitary dam on river temperature enables contrasts to be drawn between the changes in river temperature in the Nile and the multiple interlinked hydropower structures found in the River Rhône.

Much of the other anthropogenic impacts are concentrated around this barrage and the city of Asyut in the centre of the reach. These include two oil fuelled power plants which are less common globally (Byers et al., 2018) but have been shown to significantly increase river temperatures (Okwen et al., 2011). However, outside the city of Asyut there is much less urbanisation than other rivers in the study which was expected to produce different temperatures regime trends as a result.

By selecting a reach in Egypt, where there is a notably warmer climate than other rivers in this study, it is hypothesised that thermal pollutants will have correspondingly less influence here. Alternatively, high levels of water extraction in the Egyptian reaches of the Nile, for drinking and irrigation purposes (Basheer et al., 2023) may lead to diffuse impacts on thermal regimes not experienced elsewhere. These extractions can affect both the water volume and temperature, potentially leading to localized warming in areas of high demand (Booker and Whitehead, 2022). The high levels of abstraction and the multiple upstream hydropower plants on this river have changed the hydrological regime and left a single thread river which lacks much of the dynamism that enabled the foundation for ancient societies to develop where agriculture relied on floods and large changes in water levels. This diffuse impact is expected to be particularly prominent in the chosen reach, offering another unique facet to the study of thermal pollution dynamics in large river systems.

#### 5.2.1.3 *The Yangtze River*

The Yangtze River is the largest river in this chapter with a discharge of  $30,000 \text{ m}^3/\text{s}$  (Wang, 2023) and the basin stands out for the magnitude of thermal pollution occurring from power plants (Raptis and Pfister, 2016), where the largest water withdrawals for power generation are found globally, at  $12 \text{ km}^3$  annually, a third of the overall discharge (Lohrmann et al., 2019). This degree of influence has led to the Yangtze being included in this study because any improvements in such a heavily utilised system would have more influence than any other river system in the world. This is mostly from coal power stations (Raptis and Pfister, 2016, Raptis et al., 2016) which are found in large numbers across the river and its tributaries (Fig. 5.1). The Yangtze River basin is changing as China implements a coal-to-gas policy (Wang et al., 2023) a phenomenon that this study has the potential to measure. A cluster of oil and coal plants were selected as the central location of the Yangtze reach to simulate the proliferation of these power generation facilities across the river system.

The Yangtze also has the most urban land use of any of the study sites used here, this has been reported to have substantial impacts on river flow and water temperature (Best, 2019). Therefore, the Yangtze River provided an opportunity to test if the method can extract clear signals from an anthropogenically impacted catchment.

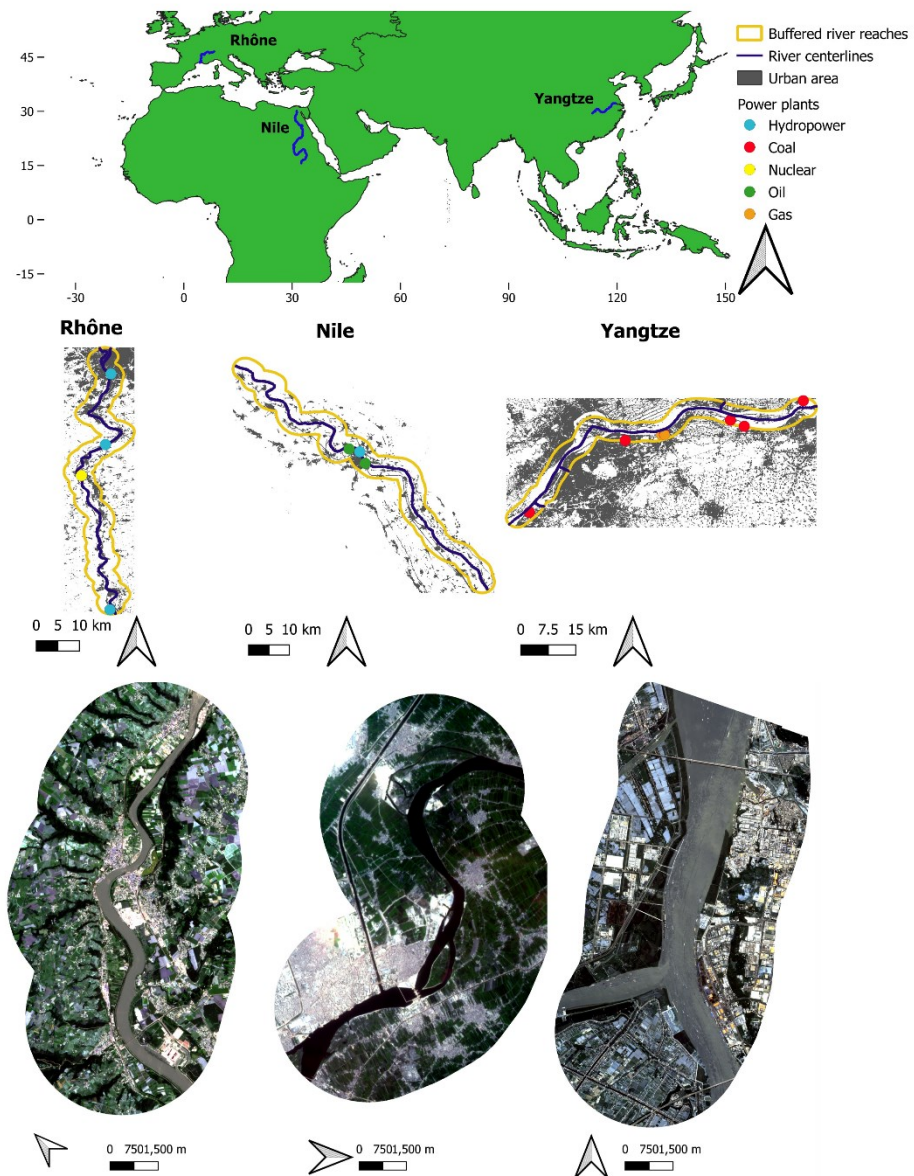


*Figure. 5.1: The 3 rivers focused on in this study. Each over 300 m wide with significant thermal power generation and/or urban areas and potential for thermal pollution.*

The Global River Width from Landsat (GRWL; Pavelsky and Smith, 2008, Yang et al., 2019) centreline for each river was then downloaded from Google Earth Engine (GEE) using a 50 km buffer around this centre point. Offline processing was then used to develop the AOI and a set of theoretical centre points along the river. Firstly, the GRWL vertices were extracted, the furthest upstream and downstream of these points were found using a convex hull algorithm. This algorithm returns the boundary points on a convex hull, which are then iterated over to find the pairwise Euclidean distance between each. Then the “travelling salesman” algorithm was used which finds the minimum path between all the GRWL vertices (Larranaga et al., 1999) starting at the

first and last points as predefined by the convex hull. On this new centreline, points were placed every 1 km as theoretical centreline points. This new theoretical centre line was trimmed so that there were 50 points upstream of the AOI (Table. 5.1) and 50 downstream, resulting in a 100 km river reach. Satellite processing also required an AOI polygon, which was developed by buffering each point by 3 km and merging these buffers together. Future users could supply their own polygons and use the code provided here to create these theoretical centre points required for further analysis.

*Table. 5.1: The catchment characteristics of the three case study rivers included in this study.*

| River Name | Continent | Central feature       | Catchment area (Km <sup>2</sup> ) | Annual average discharge (m <sup>3</sup> ) | Urban extent (%) | Population density (per km <sup>2</sup> ) |
|------------|-----------|-----------------------|-----------------------------------|--------------------------------------------|------------------|-------------------------------------------|
| Nile       | Africa    | Hydropower            | 5900                              | 1934                                       | 2                | 66.2                                      |
| Rhône      | Europe    | Nuclear power station | 330                               | 1727                                       | 5                | 111.1                                     |
| Yangtze    | Asia      | Coal power station    | 9200                              | 29656                                      | 7                | 223.9                                     |

## 5.2.2 The Constellation Approach

### 5.2.2.1 Satellite selection

Two main forms of satellite data were required for this study: optical imagery (for the generation of water masks) and TIR imagery, for the extraction of river temperature data. In terms of optical imagery, the global coverage of 3 m resolution, and almost daily return period meant that the PlanetScope constellation was chosen to provide optical imagery for developing water masks. These water masks were used to extract pure water pixels from the lower resolution thermal imagery, enabling identification of exposed islands and other features which could otherwise introduce ‘mixed pixel’ effects into the TIR pixels that were too small to be visible in other satellite water masks e.g., Landsat optical bands (30 m resolution). Having pixels that are purely water is vital because the differences in temperature and emissivity between land and water will introduce substantial error should TIR pixels contain any land, and thus return artificially high WST (Torgersen et al., 2001).

Combining multiple satellite data sources has the potential to substantially improve the quality and quantity of data available to policymakers and stakeholders. However, it

also increases the complexity of the workflow required. To the best of my knowledge, no other studies have combined multiple satellite-based TIR sensors (wavelengths 8-12 $\mu$ m) to increase the temporal resolution of remote sensing-derived river temperature. This is presumably due to fundamental differences in the necessary wavelengths and processing 'pipelines' needed to extract usable temperature data from satellite-based TIR imagery. Here, I chose to work with all available satellite datasets with a spatial resolution below 500 m to match the scale of the rivers in this study. GEE provided imagery from ASTER's Terra instrument, and Landsat 8, and 9 (currently in orbit at the time of this project), and archive imagery from Landsat 5 and 7. Data from TIR sensor, ECOSTRESS, currently flown on the International Space Station, (Hulley et al., 2017, Gustine et al., 2021, Fisher et al., 2020) is included using the NASA Earth Data system. This is an example of the potential to expand the 'constellation' using alternative systems for downloading data from scientific missions that do not continuously monitor the Earth but can fill in gaps in the WST record.

#### *5.2.2.2 Extracting pure centreline pixels*

A processing framework was developed to find pure centreline water pixels in an AOI, that could be reassessed regularly despite changes in river level, providing a repeatable method of monitoring WST every 1 km along a river (available for use at <https://github.com/SamValman/RiverTwinRiverTemperature>) An iterative process divides the input AOI into smaller 10 km river reaches, reducing the required processing power and increasing efficiency. Firstly, for the selected dates, in this case 2021 to 2023, all available TIR satellite image dates with less than 10% cloud cover are returned. Thereafter, for each 10 km reach and TIR date, the temporally closest available cloud free PlanetScope imagery is downloaded from the Planet API (Planet, 2024b). At all stages of this analysis, metadata was automatically produced for times of satellite observations and the number of days between TIR overpass and PlanetScope cloud free imagery.

These PlanetScope optical satellite images were then converted to binary water masks by applying an opensource PlanetScope specific water classification method (Valman et al., 2024). This method used a semi-supervised Artificial Intelligence based method termed Convolutional Neural Network supervised classification (Carbonneau et al., 2020, Valman et al., in review). This method was developed specifically to contend with the huge variability in PlanetScope radiometric quality resulting from a constellation of 130+ satellites, capturing imagery at different altitudes, times of day, and weather conditions (Frazier and Hemingway, 2021). The method was shown to have a median F1 accuracy score of 0.93 (Valman et al., 2024). By using this pre-trained model, the methodology did not require additional training and testing label data to be developed.

These water masks formed the basis for collecting pure water pixels by delineating small or temporary disrupting non-water features in the channel. Extracting a temporally accurate centreline therefore enabled the selection of pixels as least likely to be mixed as possible for each TIR date. The water mask was converted to a centreline through skeletonization. Next the centreline was masked to removed pixels within 100 m of 'land' pixels, this ensured purity by preventing the largest used TIR pixels used encompassing 'land' pixels and the centreline pixel.

#### *5.2.2.3 centreline pixel selection*

For every one of the 100 1 km theoretical centre pixels, extracted from the GRWL dataset for each reach (see section 2.1), the closest temporally accurate centre pixel was matched using the cKDTree distance algorithm (Narasimhulu et al., 2021). This enabled centre points to be moved with changes in river level and exposure of in-channel features yet tied them to a static location to enable longitudinal comparison of results.

At this stage, manual intervention was necessary to resolve cases where river channels diverged and instances where the GRWL centreline ran through river islands which were wider than the chosen buffer, resulting in the exclusion of the main river channel. Centre points were checked and removed manually in QGIS, as discussed in this manuscript, future iterations of the method may be able to avoid this step.

These TIR sensor independent, temporally accurate, and pure centre points were then fed into a modularised TIR extraction algorithm which collected WST for each centre points using sensor specific algorithms which could be interchanged as sensors and methodologies become available.

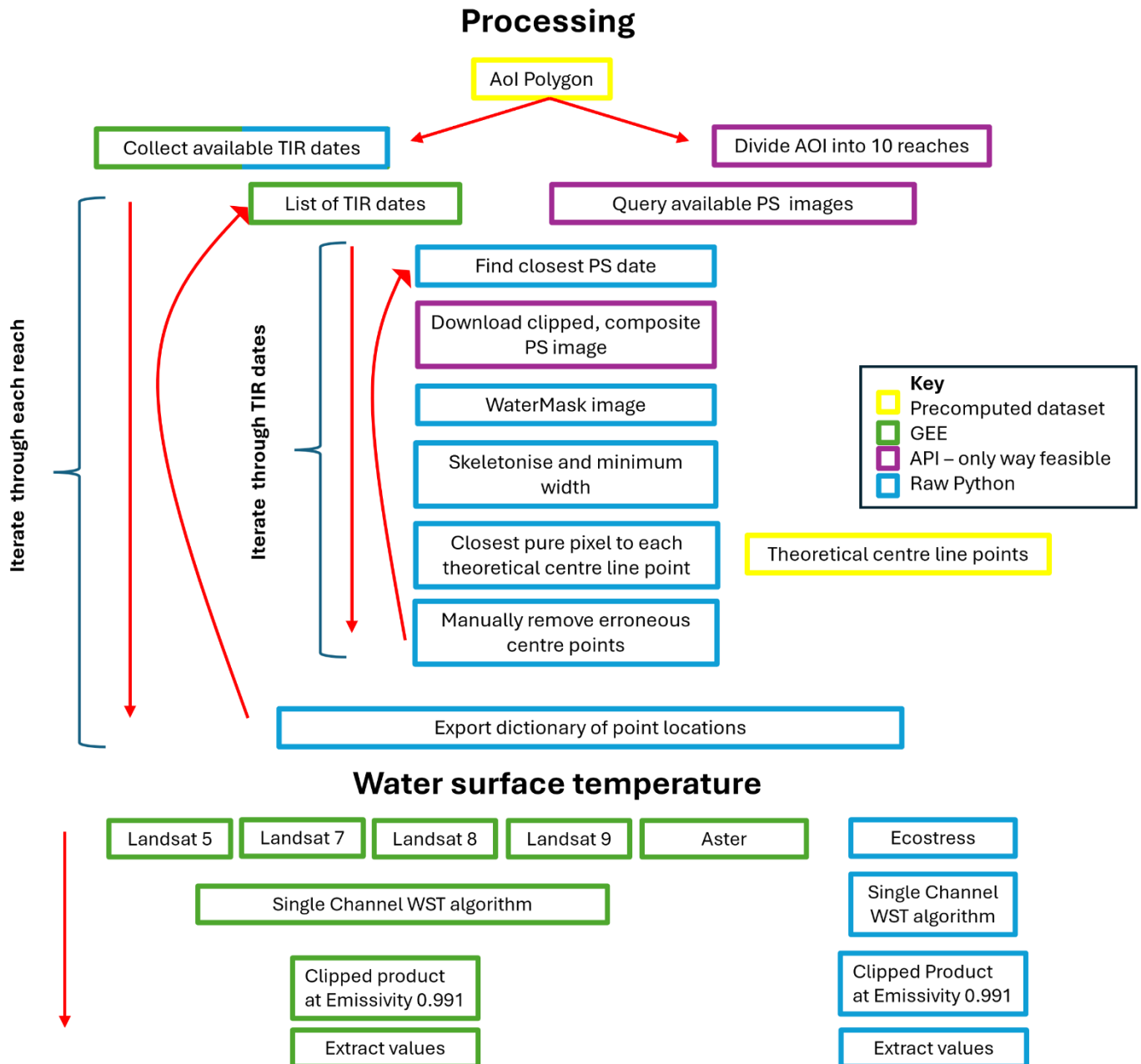


Figure. 5.2: Framework for semi-automated processing and temperature extraction using PlanetScope to provide high resolution water masks independent of TIR sensors. WST extraction from these point locations is shown for the six TIR sensors used here. These temperature algorithms are modularised to enable additional TIR sensors to be included.

### 5.2.3 Temperature extraction

Different methods can be used to extract river WST from TIR depending on the number of available bands and the corrections applied for the atmosphere (Li et al., 2023c, Jiménez-Muñoz et al., 2008, Wang et al., 2015, Barsi et al., 2014). For the Landsat and ASTER imagery, all these data were available on GEE therefore a GEE specific 'statistical mono-window' algorithm was chosen for its ease of functionality (Ermida et al., 2020). This method used a linearised version of the radiative transfer equation derived from Planck's law and used water column vapour from NCEP/NCAR reanalysis data (Kalnay et al., 1996) as a proxy for the atmospheric effects (Ermida et al., 2020). Using the statistical mono window method with coefficient values provided for ASTER TIR bands (Jiménez-Muñoz and Sobrino, 2009) enabled the same process to be repeated for ASTER band 13 which had the wavelength most similar to Landsat 8 band 10. The aspects of this method which calculated emissivity was replaced with a constant value of 0.991 (Despini and Teggi, 2013, Lamaro et al., 2013, Daigle et al., 2023) due to water having a relatively stable emissivity as a result of its proximity to a black body object (Handcock et al., 2012).

As an example of satellite imagery not available on GEE, a hard drive based TIR module was constructed for ECOSTRESS imagery. Performing atmospheric correction presents challenges due to the need to extract concurrent data from additional satellites or reanalysis products, without the ease of extracting water vapor from the GEE catalogue during analysis in the cloud as was done in the GEE modules. Therefore, the precomputed land surface temperature was extracted from ECOSTRESS (Fisher et al., 2020). The NASA Earth access module was used to download imagery directly from NASA earth data, where these images were collected between 10am and 2pm local time, before the centre points were extracted from the resulting tiffs. ECOSTRESS is based on the international space station and is a trial instrument, therefore imagery had very limited availability in some areas, such as over the Nile River basin. A substantial body of literature demonstrates a strong correspondence between in-situ and satellite-derived WST, with low bias and error metrics (Naimaee et al., 2024, Tavares et al., 2020, Daigle et al., 2023). Consequently, this study prioritizes the application of these methods rather than conducting additional validation against in-situ sensors.

### 5.2.4 Statistical analysis and comparisons

Python (version 3.10) was used for all processing and analyses on a PC with a 12-core Intel i7-12700K with 32 Gb RAM and a NVIDIA GeForce RTX 3070 GPU with 8 Gb RAM and 5888 CUDA cores. QGIS version QGIS 3.16.5 (Baghdadi et al., 2018) was used to illustrate the spatial and temporal patterns in nuclear power plant thermal effluent

plumes. Statistical analysis relied upon SciPy, Scikit-image, NumPy, and Pandas packages for data management (Van der Walt et al., 2014, Harris et al., 2020, McKinney, 2011, Virtanen et al., 2020). The top 10% of dates which had the most complete longitudinal record (i.e., those dates with the highest number of centre points covered on any single day, out of the 100 available. These number were chiefly limited by variable satellite overpass spatial characteristics and removal of erroneous centre points) were separated from the dataset for each river and plotted. In order to remove seasonality in these observations these results were normalised around the mean temperature value for each date enabling inter comparison between dates.

The extreme 2022 summer temperatures (Huang et al., 2024, Tripathy and Mishra, 2023) caused this year to be isolated for the assessment of how many days and at which locations each river surpassed dangerous river WST levels. The threshold for this assessment was set at 30°C. In French nuclear power plants this is a common regulatory limit placed on the input and output WST at which operation has to cease based on their position along the river channel and expected environmental trends (ASN, 2023). This is important for environmental assessments by regulators, financially for operators and for consumers because closure comes with a direct cost to the customer (World Nuclear Association, 2020). In the Yangtze, the Chinese water pollution prevention and control law states that ambient river temperatures cannot be increased by 1-3°C depending on the case (Quality standard: GB-3838-2002) and with summer temperatures in the yangtze at up to 28°C (Ren et al., 2024) this results in a similar threshold. Although no regulatory thresholds could be found for the Nile, its average temperature range rarely exceeds 30°C so this value was also used to show where anthropogenic influenced or substantial solar radiation was likely to have surpassed this (Abdel-Satar et al., 2017).

## 5.3 Results

### 5.3.1 Temporally accurate centreline

A skeletonization algorithm was applied to find the river centreline on a PlanetScope optical image and this was used to position channel centreline pixels. Inspection of this PlanetScope derived centreline found regular departures from the GRWL centreline, especially around in-channel islands (Fig. 5.3). Where channels bifurcated, the PlanetScope centreline was found to have often shifted between channels rather than consistently following a single channel (Fig. 5.3).

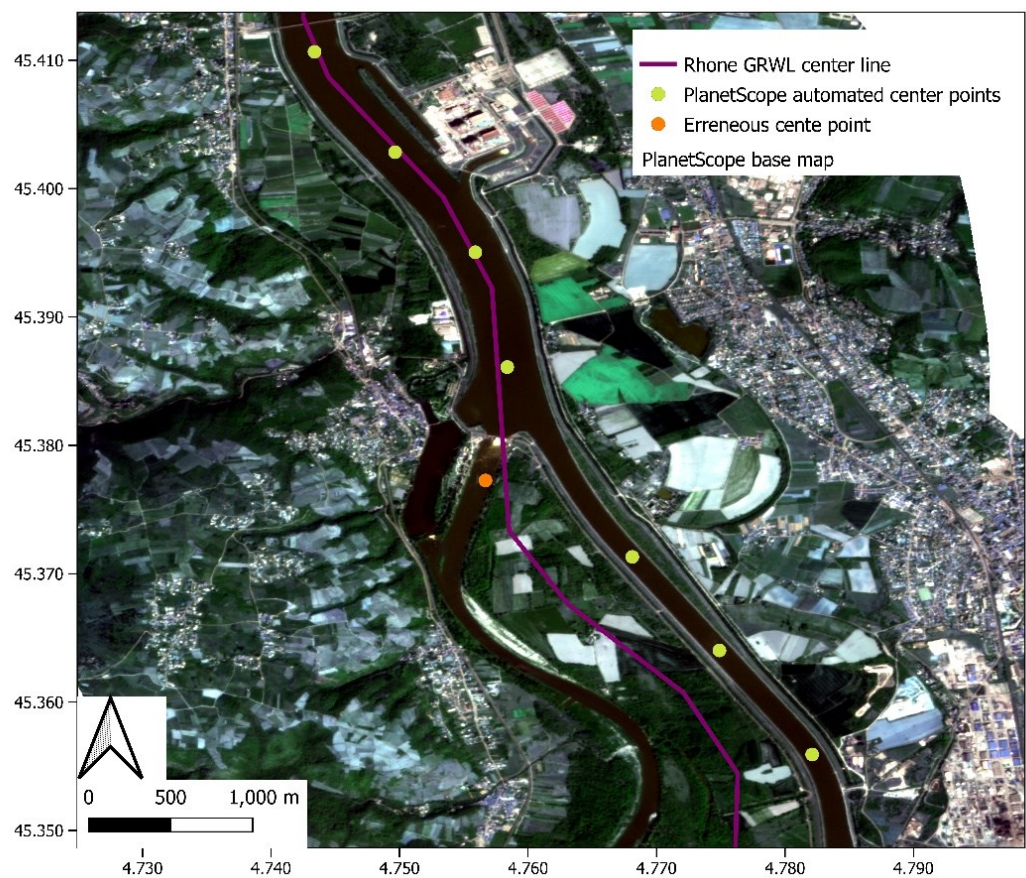


*Figure. 5.3: Example of the difficulties of using static datasets such as the GRWL centreline which is not designed for TIR WST extraction. The erroneous PlanetScope centre point in the figure also highlights the need for interaction between the operator and the method to dictate what when separate channels should be measured.*

### 5.3.2 TIR image availability

To assess the potential advantages of a constellation approach for multiple TIR satellite systems, their number of overpasses and their local time was plotted for Saint-Alban Nuclear power plant in July 2024 (Fig. 5.4). The Landsat satellites and ASTER can provide imagery in clusters but generally provide at least one image a week together.

These images are also clustered around mid-day easing comparison between temperature on different days. However, ECOSTRESS is more heavily clustered temporally over 7 days and these images have high variability in local capture time, making them more difficult to include in the “constellation” of satellites.

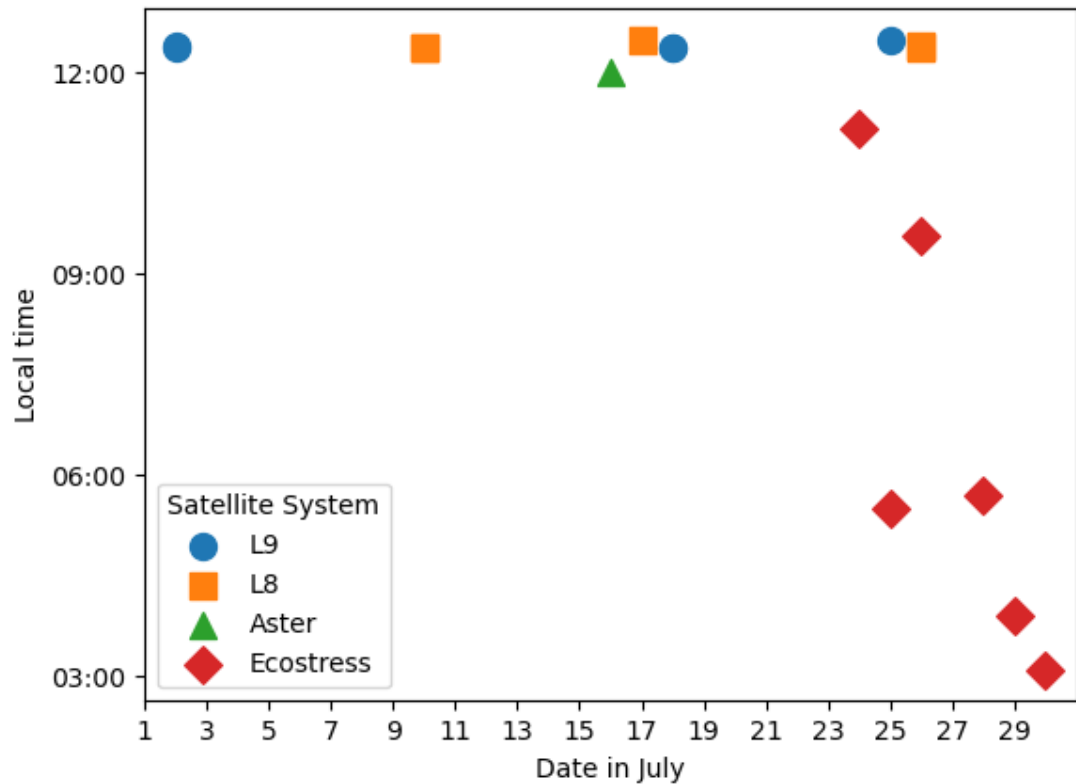


*Figure. 5.4: Comparison between the return period and local overpass time of separate TIR Satellite systems over the Saint-Alban nuclear power plant in France, during July 2024. The majority of these satellite overpasses occur around midday making them comparable, whereas ECOSTRESS covers a much wider spectrum of overpass times.*

The number of overpasses and the extent of imagery removed due to cloud contamination vary by site with 59 imagery capture days on the Rhône, 79 days on the Nile, and 43 days on the Yangtze. The proportion of these days monitored by different satellites also varies, with Landsat 8 and 9 providing the majority of available centre point TIR data, averaging 43% and 45%, respectively.

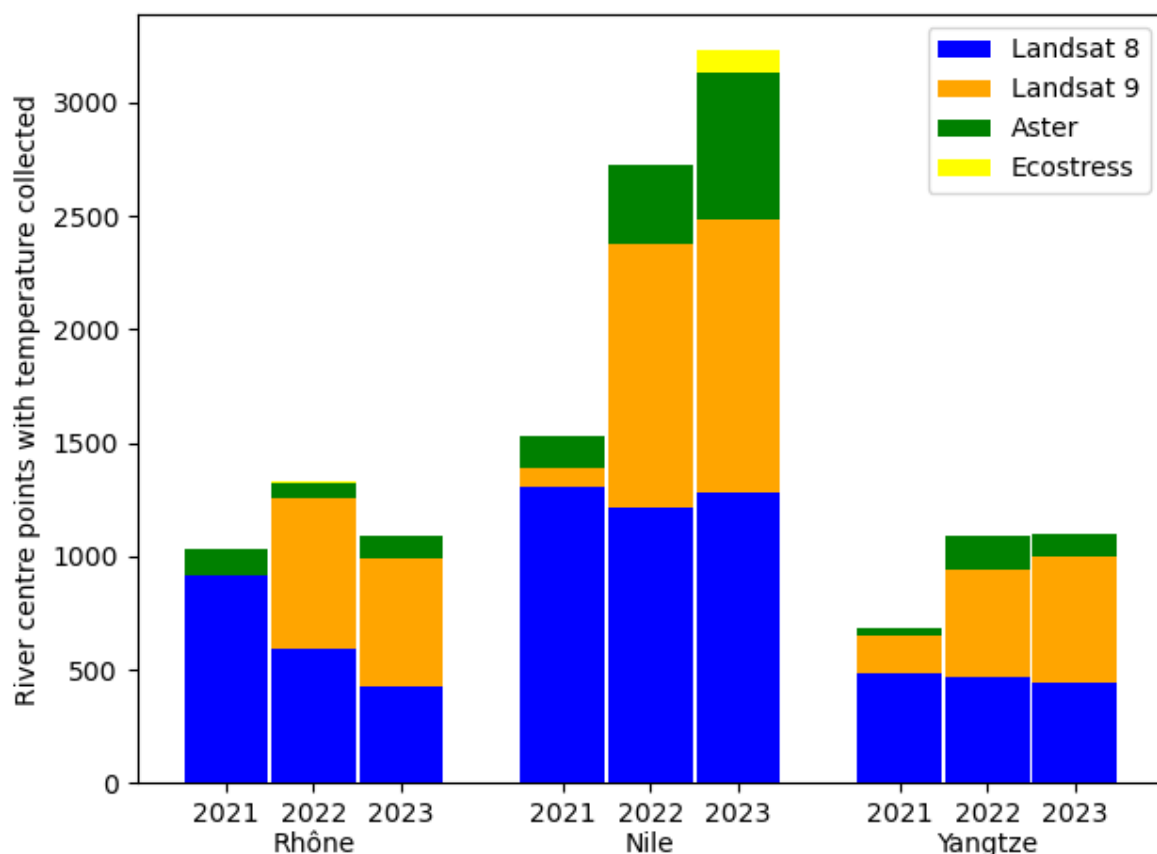


*Figure. 5.5: TIR imagery proportions from different satellites in 2021 - 2023 for the river reaches in this study, measured in centre points (every 1 km along the river) that were used in the final results. This is therefore influenced by how much coverage the rivers received, and the number of erroneous points manually removed.*

### 5.3.3 Anthropogenic cooling water impacts

Satellite imagery from Landsat 8, Landsat 9 and ASTER were clearly able to show the visible impacts of different anthropogenic power generation methods on WST. This was highlighted by temperature plumes extending from outlet channels at nuclear power stations on the River Rhône into the main channel (Fig. 5.6). These plumes were not consistent throughout the year and were harder to discern when water levels were at their highest in the summer months, and clearer in the cooler water images from March. This can be seen within the context of all available WST centre points for these rivers (Fig. 5.7) which highlights the higher average WST across the river in summer and therefore the impact small changes in WST can have.

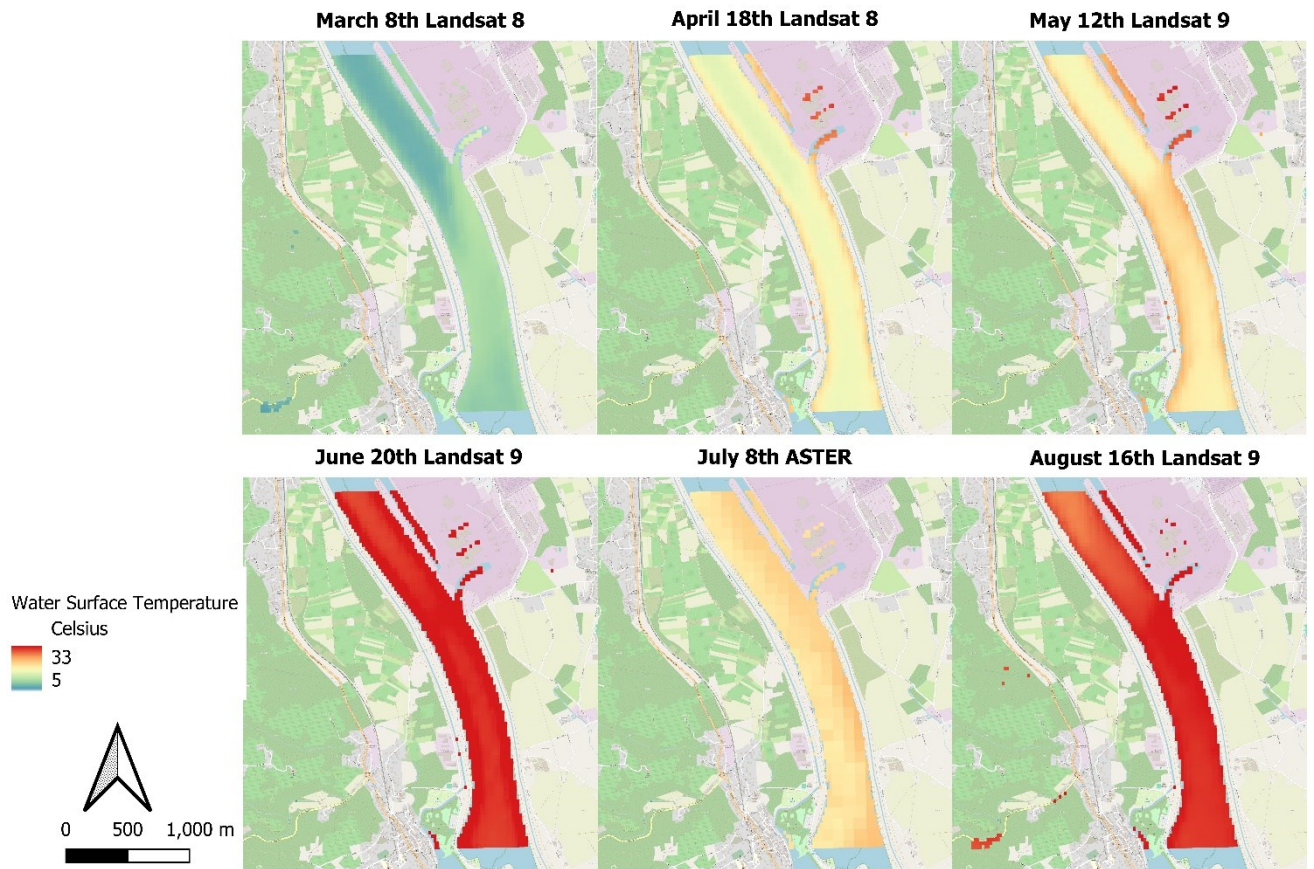


*Figure. 5.6: Long Wave TIR imagery from Landast 8, Landsat 9, and ASTER, converted into WST. These images show the different effects of thermal pollution from the Saint-Alban nuclear power plant outlet on the River Rhône, France, during different seasons.*

### 5.3.4 River temperature longitudinal profiles

These results demonstrate the effectiveness of the constellation approach in generating longitudinal temperature profiles multiple times throughout a year (Fig. 5.7). However, the resulting WST dataset reveals short, consistent gaps in these profiles at sections of these rivers where satellite-derived WST was often not viable (Fig. 5.7). Despite these limitations, the approach successfully captures clear seasonal and longitudinal trends in the form of consistent spikes and gradual reductions thereafter that influence river WST and may be linked to anthropogenic power generation (Fig. 5.8). By normalizing WST to remove seasonal variation, the increased temporal coverage provided by the constellation approach enables the detection of consistent trends and clear spikes in river WST at all sites influenced by anthropogenic activity (Fig. 5.8). The differences in appearance of these temperature spikes between rivers highlight the ability of this approach to distinguish site specific drivers.

#### *5.3.4.1 The River Rhône*

The Rhône consistently shows a major WST spike of around 2°C at km 50 of the reach, corresponding to the cooling water outlet from the Saint-Alban nuclear power plant. Despite a steady decline in temperature anomalies, this increased WST signal persists for a considerable distance downstream. This demonstrates both the capacity of the methodology to discriminate these thermal pollutants even in very complex catchments and measure their downstream impacts. Additionally, diffuse thermal pollution may be indicated by these results. In 2022 and 2023 there is a slight cooling effect in the first half of the reach which coincides with distance from the city of Lyon at the top end of the reach.

#### *5.3.4.2 The River Nile*

The Nile exhibits distinct WST differences compared to the other rivers in this study, with a higher minimum temperature, as expected given daytime satellite overpasses in a desert climate. However, the normalized WST measurements show less variability, likely reflecting the relatively few point-source anthropogenic influences in the catchment. Some temperature spikes are observed, primarily clustered around the centre of the reach, suggesting possible anthropogenic sources. The inconsistency in these spikes between surveys indicates they may be smothered by seasonality or irregular in occurrence. Notably, while Europe experienced a heat wave in 2022, WST measurements for the Nile were lower in 2022 compared to 2021 and 2023.

#### *5.3.4.3. The Yangtze River*

The Yangtze River exhibits multiple consistent spikes over 2°C throughout its normalised longitudinal profile. These spikes are corroborated by multiple temporal profiles but often occur with different magnitudes. Regardless of their magnitude, these temperature increases do not persist downstream which may reflect differences in size between the Yangtze River system and other rivers in this study. The results also present some WST anomalies (Fig. 5.7) over two dates in 2022 beyond what is seen at other sites. These two dates do not stand out on the normalised WST graphs (Fig. 5.8), which suggests that they are not anthropogenically driven.

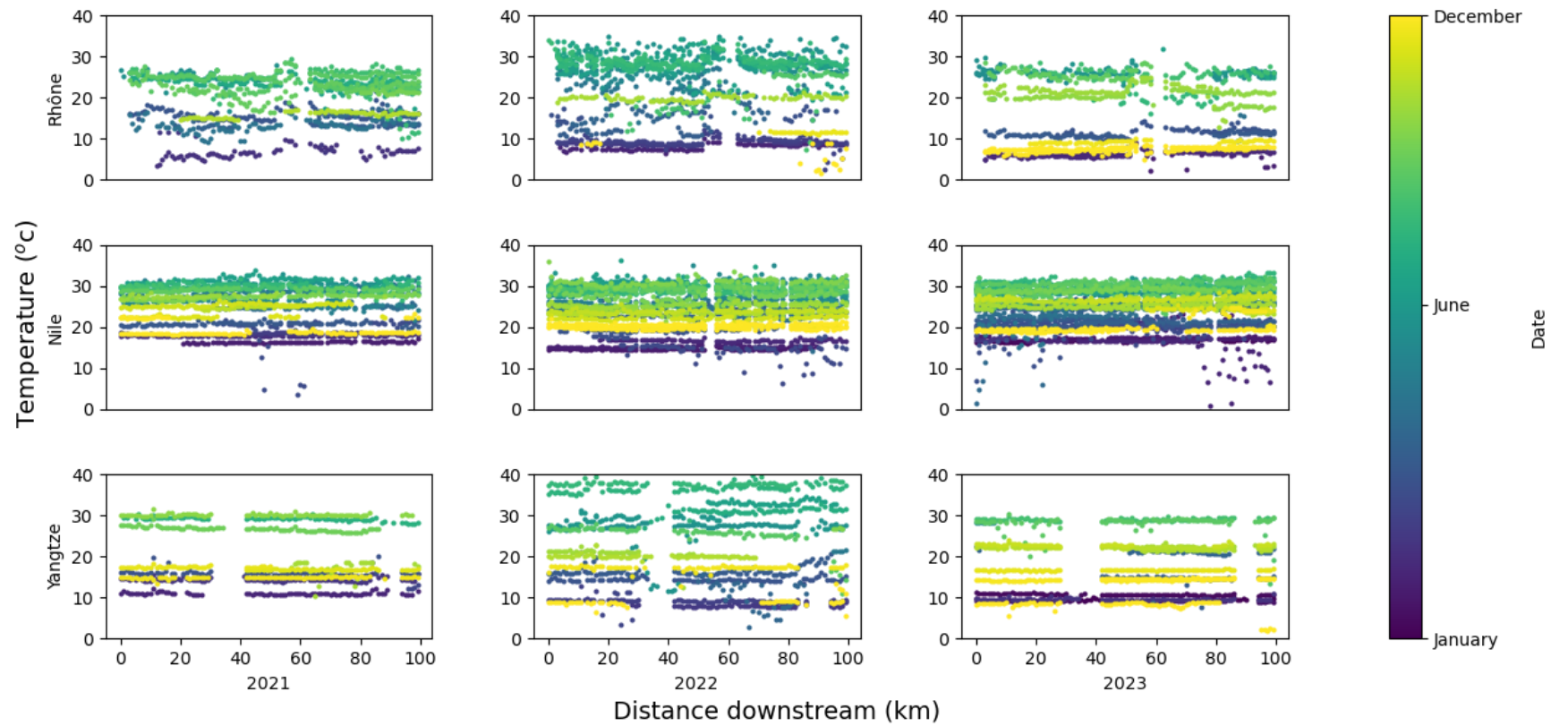


Figure. 5.7: Distribution of all centre point measurements on these river systems, displaying the seasonal and downstream changes in river WST. Note gaps in the record provide insight into where the method is harder to apply such as division into multiple smaller channels.

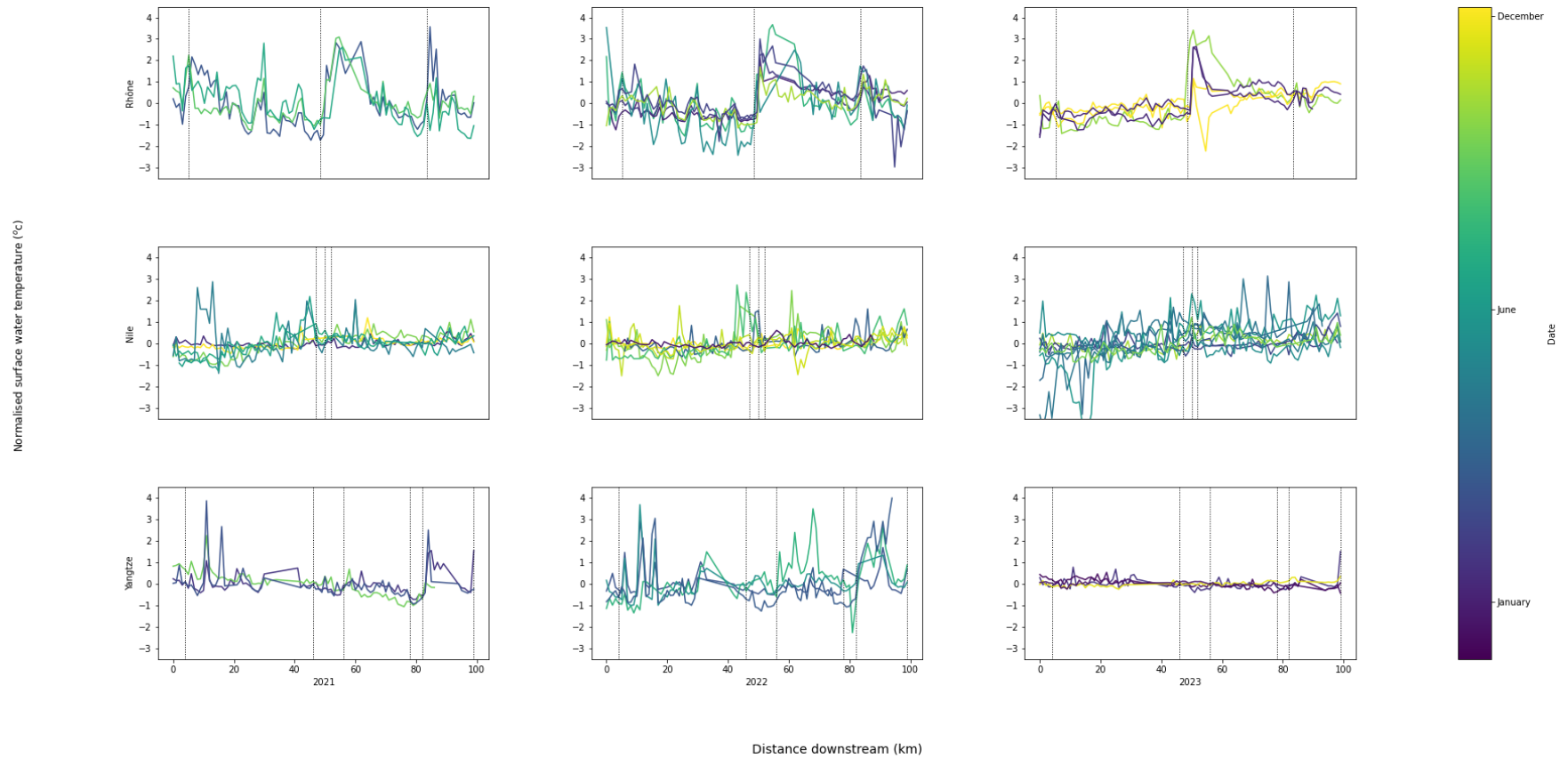


*Figure. 5.8: Daily normalised WST for the 10% most complete longitudinal WST profiles for each reach and year. The relative temperature plots the difference from the mean temperature, of each date range, for each point. Therefore, enabling comparison between seasons and highlighting the likely influences on river temperature. Such as the consistent spike at 50 km on the Rhône River, where Saint Alban nuclear power plant is located.*

### 5.3.5 Implications for regulations

These data were contextualised to provide an indication of how many days the temperature was over 30°C on the Rhône River, which is the temperature limit, set by government, that curtails power generation (Fig. 5.9). This provides much clearer indications of where WST is peaking along the system. The two main peaks are coming out of the heavily urbanised city of Lyon in the early river kms and the expected peak in the centre of the river reach, as the reach was centred on Saint-Alban nuclear power plant.

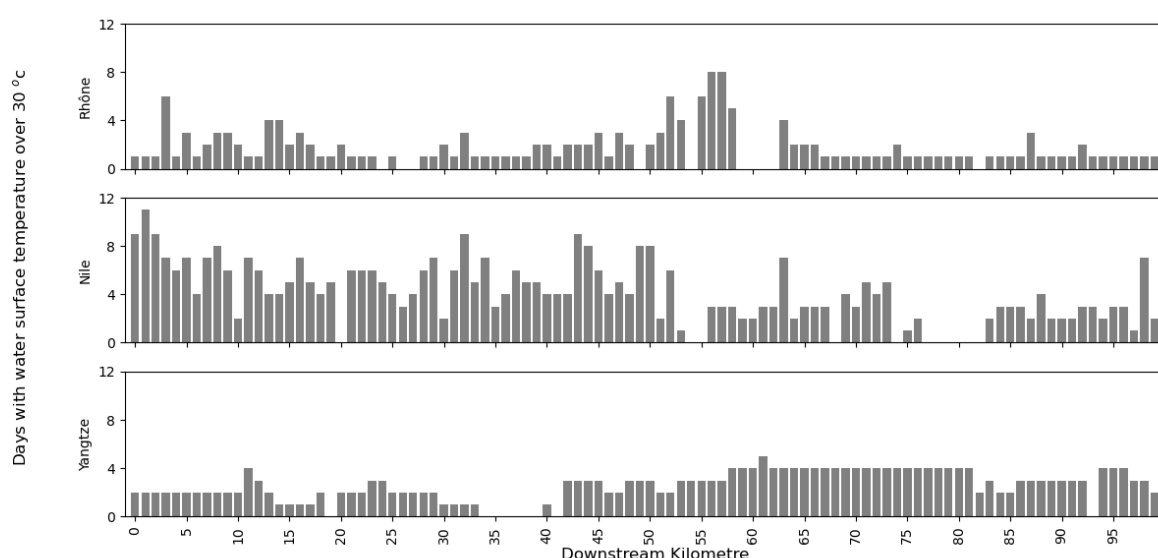


*Figure. 5.9: Days over 30°C again centred around the 50 km marker and upstream section of the Rhône River, upstream for the Nile River and consistent along the Yangtze River reach. 30°C is an environmental limit set by the French government with similar regulations in the other two rivers, however in both the heavily urbanised areas and around power plants, these thresholds are reached multiple times a year.*

## 5.4 Discussion

While the GRWL centreline was integral for this analysis, on inspection it was found to regularly depart from the PlanetScope channel centreline at different water levels. The GRWL centreline was also found to divide in-channel islands which would have led to erroneous temperature readings (Fig. 5.3). Although every effort was made to automate the process carried out here, there was still the need for some manual decision making where the river divides around these islands or is canalised, often for power generation. This requires the user to define erroneous centre points based on the phenomena they wish to measure (Fig. 5.3). Errors were found with some PlanetScope water masks where image quality or cloud caused the model to fail.

However, there are clear gaps in the river profiles, these highlight areas where manual assistance is required to provide satellite river temperature methods (Fig. 5.7). In some cases, these are where the river is divided into multiple channels too small to measure with satellite imagery, in others it is an example of the size of these river channels and the choice of buffer zone being too small where the GRWL is disconnected from the main channel (Fig. 5.3). In the latter case, the entire buffer zone can be briefly contained within one river island on the Yangtze River.

### 5.4.1 Water masks in the constellation approach

One of the key tenets this work proposes for operationalising TIR imagery from multiple different sensors is the importance of isolating the water mask from the TIR sensor. Current off the shelf models, built on GEE to be easily accessible, use normalised difference water index or the normalised difference vegetation index (e.g., Ermida et al., 2020, Wang et al., 2020b). These indices provide exceptional performance with Landsat, but have notable misclassification errors in urban areas (Chen et al., 2024), which is vital to monitoring WST, with multiple bridges and riparian urban features. The use of these indices with Landsat raises another concern, many of the features in a river channel such as bars, bridges and other factors are smaller than the 30 m<sup>2</sup> Landsat optical pixels (Tandon and Sinha, 2022). Not accurately delineating these features results in mixed-land water pixels which has the potential to induce large errors in WST readings (Martí-Cardona et al., 2019). The importance of these features is amplified within TIR measurements due to the substantial differences in emissivity values of water (a near-black body medium) and land (Handcock et al., 2012). The higher spatial resolution of PlanetScope (3 m<sup>2</sup>) provides a better likelihood of classifying small features and avoiding these mixed pixels.

The “daily” return period of PlanetScope imagery has enabled it to be used to develop these higher resolution, yet up to date, water masks. Rivers are highly dynamic systems

which change form, often unpredictably, with water level and channel change (Thoms and Sheldon, 2019). Without an up to date water mask, features such as interstitial islands may cause the same errors as if they had been undetected by a lower spatial resolution sensor. The cost of PlanetScope imagery can be partially mitigated for governmental organisations and academic institutions making it easier to incorporate (Maskey et al., 2021, Preston, 2022). Regardless, the methodology could be adapted to use non-commercial imagery such as Sentinel 2 (10 m resolution) however the return period of this imagery is much lower, and islands can evolve rapidly over time with river level and geomorphology (Valman et al., in review).

The independent water mask method also provides contingency for TIR sensors with different arrays which lack the spectral resolution to calculate these indices. Some current, and many recently announced sensors, do not have optical and near infrared bands to delineate the river channel (UP42, 2024, Li et al., 2022a) and therefore would not be usable without an independent water mask. These problems are highlighted within ASTER, where not all bands are collected for every scene therefore an independent water mask prevents loss of otherwise useful TIR information (Abrams et al., 1999, GEE, 2024). Although it is possible to use static datasets such as the GRWL centreline which has been integral to this study for delineation of the areas of interest and constraining imagery downloads, it has been shown here to not sufficiently consider river islands, hydrology, and channel change (Fig. 5.3) to enable accurate temperature extraction. Therefore, the methodology here can be argued to minimise potential error whilst maximising the number of available TIR sensors to provide the temporal resolution required for monitoring and warning systems.

#### **5.4.2 TIR satellites for WST**

There have been a multitude of studies showing that TIR satellites can produce accurate WST readings for pure pixels (Zoran et al., 2012, Bonansea et al., 2021, Das et al., 2022, Despini and Teggi, 2013, Wawrzyniak et al., 2012). This WST correlates strongly with the average temperature of the water column with the magnitude of the difference dependent on the degree of turbulence present (Dugdale, 2016, Torgersen et al., 2001). Therefore, while the use of satellite derived WST needs to be considered in the context of its use case, it can be considered a useful measure of river temperature (Handcock et al., 2012). Some of these papers discuss the need for pure water pixels (Tavares et al., 2020, Al-Murib et al., 2019, Ling et al., 2017) and the difficulty of doing so when Landsat imagery has had its resolution 'improved' (Martí-Cardona et al., 2019). However, a surprising number do not mention these issues or do so with static methods, especially in regard to Landsat's resampling issues (e.g., Naimaee et al., 2024, Zoran et al., 2012). Therefore, the work carried out here does not focus on the accuracy of the satellite TIR imagery which is backed by the literature but focuses instead on how it can

be operationalised by maximising imagery availability and purity assurance through the novel combination of TIR satellites with a dynamic independent water mask. Due to the scope of this study, it is recommended to reduce the issues with Landsat imagery by focusing on the centre line pixels on rivers wide enough to permit the selection of pixels far enough from exposed land to be pure, regardless of the position of the true Landsat pixel captured. The difference in the purity of these pixels is highlighted by the increased WST displayed at the river channel margins (Fig. 5.6), where mixed pixels are likely due to differences in the exact position of the TIR pixels in relation to the water mask. There is disagreement over the minimum river width for satellite WST measurements, earlier studies suggested a minimum viable width of 180 m (Handcock et al., 2006), with additional processing some might be 120 m (Martí-Cardona et al., 2019), and as low as 60 m (Despini and Teggi, 2013). By choosing a minimum width of 300 m and selecting the centreline pixel it was hoped to negate these issues for this study, although future work may be able to decrease this minimum viable width using additional modules to ensure pixel purity (e.g., Martí-Cardona et al., 2019).

ASTER imagery has the same reported return period as Landsat (16 days; Abrams et al., 1999) yet there was markedly less ASTER imagery available for this study than expected (Fig. 5.5), the cause for which is unclear. Although ASTER and ECOSTRESS contribute a small proportion of the data, they are important because without them, there would be an absence of WST data for the dates these satellites cover. Regardless, this data scarcity is balanced against imagery being captured at a concurrent time of day to Landsat making their results comparable without additional modelling to account for differences resulting from solar heating throughout the day (Orr et al., 2015b). The importance of this regular monitoring is that it is less likely to miss peaks in WST, where these peaks surpass thresholds (e.g., Fig. 9). These thresholds are disproportionately important for aquatic life and the sustainability of any anthropogenic activity interacting with water temperatures (Zhang and Chadwick, 2022, Van Vliet et al., 2023, Richter and Kolmes, 2005). These findings align with Earth Systems Digital Twins, remote sensing driven interactive monitoring programs, for river systems where the timing and processing is vital (Tarpanelli et al., 2023). As such it is important to include any additional data available, such as the ECOSTRESS imagery trialled here, despite requiring images to be downloaded to the hard drive and having varying times of data capture in the diurnal cycle (Fig. 5.4). While this means much of the ECOSTRESS data is not interoperable with ASTER and Landsat, it may provide the opportunity to test other impacts of river temperature at different times of day in the future, potentially when the data noise from solar and anthropogenic influences is lessened (Gustine et al., 2021).

The inclusion of ECOSTRESS using offline processing demonstrates the success of a modular TIR methodology which could enable operators to vastly increase their

available temperature data. All the TIR satellite imagery used in this study was provided by open access agreements from the United States Geological Survey which provides the foundation for a monitoring system. However, this could be supplemented with commercial TIR sensors, especially for high-risk times of year such as the summer when it has been shown that the potential to unsustainably surpass regulatory limits is higher (Fig. 5.9). Current commercial TIR satellites include the Chinese-owned Ziyuan-1 02E with 16 m spatial resolution (Zhao et al., 2024, Bingen et al., 2024) although there are planned launches for TIR small satellite constellations with the potential for higher spatial and temporal resolutions (Satellite Vu, 2022). However, it should be noted, some of these systems operate in the medium wave thermal wavelengths (3-5  $\mu\text{m}$ ), which suffer from disruption from atmospheric water vapor and lower alignment between the emission peak and the typical WST which may limit their accuracy (Dugdale, 2016). More government funded long wave TIR satellites are also scheduled such as ESAs LSTM (Koetz et al., 2018), NASAs SBG (Hook, 2023), and TRISHNA from France and India (Charvet et al., 2023). Increasing the number of TIR satellites, in a methodology such as this, increases the potential to move beyond academic studies with as few as four TIR images (e.g., Naimaee et al., 2024) towards operational monitoring of WST by satellite for sustainability and power generation optimisation.

#### **5.4.3 Monitoring implications for energy production in case study rivers**

All three rivers studied here are exemplars of regions where WST is at the forefront of policy decisions due to WST stressors from anthropogenic population pressure including water extraction, sewage treatment, nuclear, coal, hydro, and oil power generation. Operation and management of these drivers needs to be balanced with the ecological and downstream effects of these processes on WST.

##### **5.4.3.1 The River Rhône**

The spikes in WST around the Saint-Alban nuclear power plant (Fig. 5.6) correspond well with other satellite TIR studies suggesting that there are plumes of thermal effluent up to 1.5-2°C warmer than the surrounding WST (Zoran et al., 2012). Anthropogenic power generation, in a highly disturbed aquatic environment (Capra et al., 2012) increases the complexity of the thermal profile of the River Rhône, which may contribute to its departure from a downstream warming trend often expected in many large rivers (Daniels and Danner, 2020, Fullerton et al., 2015). Instead WST spikes at the nuclear power plant and then steadily returns to near average values over time (Fig. 5.8; Wawrzyniak et al., 2012). The results show changes in WST downstream that would not be picked up by sensors required at the inlet and outlets of these power plants (ASN, 2023). Moreover, as the efficiency of these plants corresponds to increased inlet temperatures (Bourqui et al., 2011), monitoring of WST further upstream would provide options for managers to adapt operating procedures for a succession of power plants on the same river, especially in regions where these WST trends are not monitored in-situ.

Each French nuclear power plant has a regulatory limit at which operation has to cease (ASN, 2023), effecting environmental assessments, operating costs, and consumers whose electricity costs are directly linked to closures (World Nuclear Association, 2020). The 30°C limit presented here (Fig. 5.9) was relaxed in the 2022 heat wave, wherein the need to maintain power supplies was considered greater than the potential environmental harm (ASN, 2023). This is reflected by these findings with the multiple days where river temperature surpasses the 30°C mark, focused around the nuclear power plant (Fig. 5.9). This will become a common occurrence with climate change (Johnson et al., 2024), threatening environmental sustainability of water use and power generation. The influence of this thermal water effluent was found to be more pronounced in the cooler months (Fig. 5.6). Yet summer WST has a higher baseline, closer to the 30°C limit, so that small temperature changes will exceed prescribed regulations. This has implications for how these rivers are assessed, since changes in WST can impact ecology just as much in winter (Ouellet et al., 2020). Interestingly, despite curtailing power generation, WST concerns are neglected in studies of the sustainability of nuclear power in France (Pata and Samour, 2022, Zhao et al., 2023).

#### *5.4.3.2 The Nile*

Although peak WST in the River Nile did not reach the levels of the other rivers in this study, there are many more instances around 30°C (Fig. 5.9). There are two explanations for this, firstly is simply the considerably higher data availability for the AOI (Fig. 5.5), meaning that more periods of warmer weather were captured. The second, explanation is climatic differences. The reach chosen is surrounded by desert and as the lack of cloud suggests has strong solar forcings potentially increasing WST. The absence of peak WST values is likely due to lower average surface air temperatures in Egypt during 2022, unlike the heat waves observed at other sites (World Bank, 2025). However, there was also less variability found in normalised WST, in comparison to other sites. This may result from the corresponding lack of point source power generation in this reach. The main source of power generation was a run-of-river hydropower structure, which have been shown to have limited potential reduced WST in comparison to larger hydropower features (Heggenes et al., 2018). However, some individual dates show spikes in WST and it is proposed that future studies assess whether operational changes in this run-of-river structure correspond to these spikes in WST.

#### *5.4.3.3 The Yangtze River*

In 2021 and 2022, the Yangtze River had the most, and most consistent, temperature spikes along the river course (Fig. 5.8). It is proposed that these are the result of numerous coal plants depositing thermal effluent into the river system (Raptis and Pfister, 2016, Xia et al., 2023). However, unlike other sites, these results do not show

that these spikes persist downstream from their origin. This may be a result of the size of the Yangtze River which is an order of magnitude higher than the other two rivers in the study (Table. 5.1), potentially leading to more mixing and dissipation of the WST signal (Nguyen-Dang et al., 2023). These spikes do not appear in the 2023 normalised data, which although there is limited information available on the closure of coal plants, may be linked to China's move towards gas and renewable energy over coal (Wang et al., 2023, Yang and Lo, 2024).

The Yangtze River basin had a record-breaking heat wave in 2022, with extreme river temperatures recorded in-situ (Liao et al., 2024, Hua et al., 2023, Huang et al., 2024). This could explain the two dates with high WST ( $>35^{\circ}\text{C}$ ) consistent longitudinally along the river reach (Fig. 5.7). With extreme air temperatures, it is likely that thermal stratification occurred on a river of this size leading to excessively high WST (Nguyen-Dang et al., 2023). Periods of high WST such as this may have contributed to the collapse of fisheries (Zhang et al., 2020) and exemplify the need to monitor WST along the entire reach to disentangle the causes of these high WST values for sustainable basin scale management (Jin et al., 2022).

#### **5.4.4 Furthering Operationalization of WST from satellite**

The work here should be considered a step towards using satellite TIR imagery as a monitoring tool, to support the development of warning systems for high WST. Whilst the methodology is designed to support river, environmental, or power station managers, they will also have to interact with the framework to improve its performance in their realms of interest. The gaps in the temperature profiles are generally situated around two key limitations. Firstly, around many power stations, large rivers are divided into multiple channels to control in and out flows (Bonacina et al., 2023) these channels are sometimes too small to be monitored by satellite which led to manual removal of centre points. The results highlight these areas as locations for in situ loggers, thus allowing the use of loggers to only be targeted where they are most important. However, the ability to monitor longitudinal trends across these rivers beyond where the loggers would reasonably be placed in a financially robust monitoring programme, means that satellite TIR is an invaluable tool. Secondly, managers can provide local knowledge of a river system by knowing where to target satellite WST measurements if the method is to be used repeatedly for a single river. This is a key part of our interactions with new big data technologies and sensors by providing feedback between the technology and the operators of that technology (Jones et al., 2020).

Cloud computing could be used to complete the operationalisation of satellite-based WST extraction and monitoring. One of the most time-consuming steps was the downloading PlanetScope imagery from the Planet API and then running through the

water mask model. Running this entirely on a cloud server, especially with the assistance of Planet, would substantially reduce processing time. Moreover, should the task be to continuously monitor for rises in river temperature and anomalies, the process would be carried out almost daily. Therefore, this would take considerably less time once the archive of historical imagery was complete and only a few images needed assessing as they become available. The additional speed in downloading PlanetScope images would enable future iterations of this workflow to be able to build more redundancy by using alternative PlanetScope images if the water mask model did not provide sufficient results. The modular fashion of the satellite WST pipeline presented here, lends itself to being developed towards the available sensors, end products, and computing software that different managers have available or required.

In the future, the full framework developed here could be integrated into the cloud facilitating products such as GEE apps (GEE, 2021). This would enable a dashboard system to be used for the dissemination of these WST readings to both the specific stakeholders but also the general public. Using georeferenced satellite imagery to form the basis of a dashboard like this would require fewer steps and be much more adaptable than a similar system relying on in-situ measurements which would need to be manually connected. That is not to say that future studies could not use the work here as a foundation to combine with in-situ sensors for specific user requirements.

## 5.5 Conclusion

Anthropogenic development and power generation has been observed to alter river WST which can have considerable negative impacts on the environment and society. While sustainable management can mitigate these impacts, the spatial scale and continuous nature of river systems presents challenges for monitoring and assessing WST trends. Satellite-based methods can address spatial monitoring limitations, yet in the past low temporal resolution and mixed pixel problems have restricted their use. These limitations were addressed using a novel framework, using high temporal resolution CubeSats to generate independent water masks to enable the integration of multiple TIR satellites to maximise the temporal resolution of WST monitoring. The 3 m resolution, near-daily return period, PlanetScope imagery resolved mixed pixels errors, whereby lower resolution methods may have missed interstitial islands, water level changes, and channel shifts that introduce error into WST measurements. A case study approach illustrated the frameworks' ability to measure the WST influences of power plant thermal effluent. In the three rivers, all the tested satellites consistently displayed similar temperature spikes around power generation sources. While WST trends varied across river systems, the signal from extreme heat waves was evident in the results, regardless of direct anthropogenic impacts.

These findings demonstrate how a continuous satellite constellation approach can provide additional data to support regulatory compliance, sustainable operation of power generation, and management of these river systems. By operationalising this method of WST retrieval in a modular, adaptable format, the study provides a tool to utilise future planned TIR satellite launches. This tool has the potential to be developed further into a fully cloud-based dashboard format that could be integrated with in-situ data to provide real-world actionable insights.

# Chapter 6: Synthesis

## 6.1: Introduction

The analysis chapters in this thesis (Chapters 3-5) have each focused on individual potential ESDT components in isolation, defining the success of these chapters on their ability to harness high resolution satellite imagery to provide insight into these real-world problems. However, when integrated together the individual chapters complement each other to enable greater remotely sensed coverage of the characteristics of large river systems. This has been demonstrated within the progression of these chapters, whereby findings and methods informed and shaped the direction of later chapters. The benefits of the interconnections of these components reveal how they collectively enhance our ability to use satellite data for monitoring river systems. The thesis was designed to enable the three components, each presented in an individual chapter, to be modular—capable of being monitored independent of each other and used without the ESDT context. Yet these components were methodologically and conceptually interconnected, using the combination of water surface extent, river stage, and river temperature to provide the maximum monitoring ability of river systems possible within this thesis.

This chapter synthesises the findings of these chapters, assessing how the previous chapters have advanced both the development of the foundations for an ESDT and the ability of high spatio-temporal satellite EO to monitor different river systems and processes. The chapter also considers how these insights may shape future research directions, how different optical satellite systems are used, and potential data analysis methodologies. In doing so, the common limitations across the three analysis chapters have been identified. In turn, potential solutions for these limitations through further research are presented, whilst other limitations are inherent to satellite EO and have been highlighted to assist the understanding and use of an ESDT by future managers and researchers. Recognising these limitations is crucial to the fourth objective of this thesis, evaluating challenges to the further implementation of an ESDT for sustainable use and management of river systems developed here.

Synthesising these chapters and demonstrating how they can be connected was required to achieve the overarching aim of this thesis: to construct the framework for an ESDT for large river systems to facilitate the use of EO satellite data for real-world engineering and sustainable management. This synthesis chapter evaluates to what extent these management challenges have been addressed through the datasets and methodologies developed in this thesis, and which challenges require further attention. In doing so, I have highlighted the considerable amount of EO satellite imagery that is

freely available (Gorelick et al., 2017, Hemati et al., 2021) or relatively affordable (Planet, 2024a) yet is being underutilised by practitioners. This research has aimed to bridge the gap, making EO data more accessible and actionable for river management, facilitating real-world applications beyond academic research. To do so, recurring challenges such as data resolution, computational constraints, and the accessibility of satellite imagery were addressed throughout this thesis. The degree to which these factors impact the operationalization of an ESDT and may be mitigated or improved upon are evaluated in this chapter. As such this chapter aims to synthesize the results of the research chapters, highlighting their collective contribution to the overarching goal of providing the foundation for the future development of an ESDT for large river systems. To do so it will answer the following three questions:

- To what extent do the integrated findings meet the thesis objectives?
- What gaps remain in operationalizing the ESDT framework?
- How do these findings shape the future of satellite-based river monitoring?

## **6.2: Integration of first order variables**

### **6.2.1. From individual components to complete first order understanding**

This thesis was an attempt to build the foundational components required for an ESDT to assist management of large river systems. By focusing on the following first order river variables (Carbonneau et al., 2012, Webb, 1996, Fausch et al., 2002): dynamic water extent, channel change proxies for hydrology, and river water temperature, it has created the potential to build a platform of components from which different aspects of the river system can be derived without the need to first characterise every potential component. If second order components had been selected instead, these would have likely provided less assistance in adding additional components and use cases in the future.

The first analysis chapter (3) used AI in the form of a novel convolutional neural network-based supervised classification (CSC) model. This efficient design enabled this model to be scaled to handle the daily revisit rate of PlanetScope, which was vital to monitor these first order variables in highly dynamic large river systems. The classification model was then applied to multiple global biomes, land uses, and river types providing direction as to where it performed best and so which locations the following analysis chapters focused on.

The second analysis chapter (4) builds on top of theories developed in the first chapter, i.e., that reducing the complexity of monitoring procedures may provide more operational methodologies. Therefore, to derive a first order hydrological variable (namely stage/discharge) from EO data, the decision was made not to take a 'conventional' approach attempting to relate discharge to river width, in absence of

many of the other controlling variables such as depth, channel shape, and channel roughness (Feng et al., 2019). Methodological advances from the first chapter were scaled up to be applicable to use more satellite imagery than any other riverine study previously carried out using PlanetScope.

Chapter 5 develops a data pipeline to maximise the amount of EO imagery available for the monitoring of river WST, making use of the PlanetScope and NASA Earthdata APIs (Planet, 2024b), along with GEE cloud computing (Gorelick et al., 2017) to maximise the temporal availability of satellite TIR imagery. Using this high temporal resolution water mask enabled multiple satellites to be used in conjunction accurately even when these satellites lacked optical bands needed to develop water masks. The third component focuses on power generation as a potential area of conflict for sustainable management of large river systems, but often these managers have to balance water quantity and its influence on governing water quality aspects together (Ellis et al., 2024, Webb, 1996), something that these first order components could be used together for.

### **6.2.2 Cumulative guidance for development of further components**

Each analysis chapter cumulatively furthered the methodological framework in this thesis, which provided results pertinent to wider applications of satellite EO remote sensing. These findings can be applied to future satellite launches, different data sources, and direct further EO research. CubeSats, in particular, provide the increased spatio-temporal resolution upon which this research hinges, yet regardless of their quality, flying them in large constellations will degrade radiometric accuracy (Frazier and Hemingway, 2021). This radiometric error inhibits the use of both deep learning and spectral index-based classification methods built for traditional large satellite systems. However, I've found that specific CSC based methods can be used to combat the accuracy issues inherent in CubeSats, a finding that should be studied further in different contexts as CubeSats make up an increasing proportion of EO imagery (de Sousa, 2023).

The 'quasi-constellation' approach, using a modular framework to combine multiple satellites together for increased spatio-temporal resolution, is another outcome which can be applied beyond a river system ESDT. This framework positions the research well to take advantage of the SBG, TRISHNA, and LSTM satellite launches, which together will provide daily TIR satellite coverage. The inclusion of PlanetScope in this framework provides a case study into how additional imagery might be included: the model was developed (Chapter 3), scaled up into a framework (Chapter 4), and modularised to be included in the constellation approach (Chapter 5), enhancing the use of other satellites included at this stage of the framework. This approach will

becoming increasingly advantageous for monitoring systems as the number and diversity of EO systems continues to increase (Davoli et al., 2019, De et al., 2022). As such, the methodological developments presented in this thesis should be used to derive actionable insights from broader EO applications.

## 6.3: Evaluating the Research Against ESDT Criteria

### 6.3.1 Achieving the key tenets

Each method used to monitor a riverine variable in this thesis was termed a component on the basis that these were developed to fit into an ESDT. In order for these ESDT components to be used as a foundation for a future ESDT a list of tenets were set out that each chapter needed to adhere to in order to be flexible enough for inclusion in an ESDT.

#### 6.3.1.1 The ESDT component must be transferable between different river basins.

These ESDT components needed to be transferrable between different river systems so they could be incorporated into different ESDTs. There will be a limit to which this is possible due to the diversity of river types, management, and land use and this has been discussed throughout the thesis, in some cases other techniques such as SAR will be more appropriate and can be included within the same ESDTs. The three chapters clearly expressed this within a variety of rivers in different biomes and a range of economically developed countries. While chapter 4 is more specific to large rivers with islands (a not uncommon landform) this is perhaps less transferable than the water mask and temperature extraction methods/findings of chapters 4 and 5. However, instead, this chapter helped to raise the question of components measuring river variables by their impact, a methodology which could be developed in a variety of catchments. The project was constrained to only large rivers (>100m) which does affect the usability of some data sources and the ability to maximise use in these rivers. However, to some extent, this thesis has built resolution agnostic methods where findings and methodology can be expanded as future sensors become available (as discussed in the literature review section 2.3.4).

#### 6.3.1.2 The ESDT component should use freely available software and data where possible. If this is not possible data should be accessible for NGOs/Governmental environment groups and academics, and the ways in which this is possible should be highlighted.

The thesis stuck to this tenet, using majority open-sourced data, coding languages, and software with the exception of PlanetScope imagery which formed the backbone of much of this research. However, I emphasise throughout that PlanetScope data is available as a third-party mission for ESA, through NASA for US government employees, and has an academic free use licence. As such the components could be implemented by the majority of user groups into an ESDT regardless of availability.

#### 6.3.1.3 The ESDT components should not require ground/*in-situ* data for the foundational elements to function, thus making them available to more users, especially in developing nations.

None of these ESDT components used ground or in-situ data for their development which makes them accessible under a variety of budget ESDT options. In some cases, ground data was used to advance or test the results (see section 4.3.4) which provides a prime example of how it should be integrated when available to improve river management which would never ignore useful datasets if they were available.

6.3.1.4 The ESDT components should strive to be automated where possible and require limited specialist knowledge to operate.

Each chapter made collective progress to reducing this need for specialist EO knowledge through methodological findings. These included the ability to fine tune water mask models with very coarse manual masks, as opposed to multistep processes requiring implementation of indices such as NDWI with morphological operators, Chapter 4's focus on the visual impacts of river level reductions, and the use of an automated multi-sensor method for Chapter 5. These all fall short of fully meeting this tenet in the form of an ESDT, as the lack of dashboard or code free operation means that running the files and choosing the river system extents is primarily a manual process. However, overcoming this can be considered a software limitation rather than a problem which further research would be required to solve.

6.3.1.5 Finally, it should be operationalized for active use in decision-making to as great a degree as possible.

This can be considered the most difficult tenet to conform to, due to the different needs of decision makers. In such a way, I believe that each ESDT component has been operationalized to the highest degree possible in a research thesis, in that they produce end-products in a format readily useable in a river management perspective. For example, where water is or is not (i.e., water masks) or the temperature at consecutive downstream locations (thermal longitudinal profiles). In order to fully operationalize these components requires the completion of an ESDT with dashboards or end user modules directly related to the user decisions, something that cannot be achieved without input from stakeholders. The further requirements for a full ESDT that are not met here are expanded upon in 6.3.2.

### **6.3.2. Forming the foundational for a future ESDT**

This research project constructed the components that form the basis upon which a river-oriented ESDT could be built but it lacks three fundamental factors that would be needed for creation of the ESDT. First, the three first order components chosen here (i.e., water masks, stage/discharge proxies and water temperature) control or reflect changes in most other riverine characteristics. To transfer this potential into an ESDT would require a user interface from which these insights and predictions could be carried out, much like a traditional GIS system that practitioners are used to working with (Agnew and Fryirs, 2022). However, unlike a GIS system with a static basemap, the components developed here are able to dynamically update as satellite imagery is

captured. Once incorporated into an ESDT, the foundation built here provides sufficient fidelity for further iterations to build more specific components to the desired needs of the user.

Second, by using a case study approach, this research addresses research objective 4 with regards to developing an ESDT for rivers that can be used by river managers and stakeholders. For example, anthropogenic point sources of WST are shown to be measurable, yet these are also influenced by water levels (Johnson et al., 2024) which can be concurrently monitored with the other components developed here. However, the use of this case study approach which enables new scientific research into possibilities of these sensors and what they measure does not cover how an ESDT should be operated. For example, the choice of reach, the extent of available imagery, the functionality of issues such as APIs which will come down to commercial interests and research based on the end users of these ESDTs.

Third, these end users and the outputs they require are the final reason the current thesis cannot in itself be considered an ESDT. Whilst I have shown that different anthropogenic factors can influence river temperature or that certain sites can become exposed by drought, these are not end user modules, which is by design. An end user module may ignore physical riverine changes instead propose actions for the user. For example, a thermal power plant operator needs to know whether they should reduce power generation or not rather than needing to know the causes for this decision, which should be available when called upon. These end modules very specific to different management roles and while the foundation for them has been provided by this research, it will require industry and management uptake to decide how these are implemented.

Part of specifying these findings to individual users has been made possible by providing the open-source framework developed (see GitHub repositories in individual chapters) allows for the testing of internal parameters. For example, interchangeable modules in satellite WST extraction can use alternative atmospheric correction methods to maintain scientific relevance. Similarly, as exemplified by chapter 4, the methodology can be applied in different contexts to archive to localised insights. These components were constructed to be future proof for an ESDT system by providing the ability to include additional satellite systems when available such as the future launches described in section 2.3.4 and for the models to be updated in accordance with improvements within the PlanetScope satellites that make up the constellation.

### **6.3.3 Challenge that have been overcome in preventing construction of a river system ESDT**

ESDTs are data hungry which is amplified by the continuity in spatial and temporal dynamics in river systems which is why traditional point-source methods have not been appropriate in the past. This thesis has repeatedly highlighted that for many river processes, satellite EO is the best solution to provide the scale and repeatability of monitoring required to assist sustainable management. However, the largest barrier to doing so has been the temporal availability of satellite imagery. The research carried out here has operationalised the daily PlanetScope imagery to provide the highest temporal resolution currently possible. With the inclusion of the constellation approach in Chapter 5, it has been possible to achieve as close to real time data capture as possible for components of a potential ESDT.

The primary challenge to overcome was to operationalise methodologies in all three analysis chapters to reduce the need for a priori EO knowledge to access satellite data for river monitoring and management. The PlanetScope water mask model was designed to decrease manual delineation to the extent that the model was designed to work without complex training data requirements. Moreover, Stage/discharge relationships were used in chapter 4 to highlight the simplicity of directly monitoring impacts of water level change by removing intermediary discharge monitoring steps. Finally, the WST framework further operationalised these PlanetScope water masks, independent from any TIR sensor, by using them to reduce processing steps which would otherwise be dependent on the optical bands of individual TIR satellites collected into a constellation.

## **6.4: Limitations in the application of components**

The findings of this thesis acknowledge some limitations as to where and how these components could be integrated into an ESDT. No combination of components will be able to produce an ESDT that can monitor every watershed and potential application, but understanding the limitations of the components presented will assist users to understand whether building an ESDT would be viable for their use cases. The components developed here were trained and tested in a variety of locations and river systems providing an indication of which of these river systems would be unsuitable for an ESDT using these components. For example, the water mask method was tested on 12 biomes with factors such as topographical shadow and lack of larger wetted channel areas ( $>90 \text{ m}^2$ ) reduce the applicability of this method river systems such as montane braided rivers. Manual interrogating optical imagery also provided indicators of phenomena which could prevent the successful application of these methodologies

for sustainable management. River channel confluences were found to produce outliers on river stage measurements (Chapter 4) whilst shallow static water was found to have higher WST, hypothesised to be the result of solar heating and lack of water column mixing (Chapter 5). These findings do not limit the methodology from being applied as long as practitioners are cognisant of them and consider potential local influences in the river systems of interest.

User feedback is considered integral to integrate remote sensing methodologies with existing river management (Fryirs et al., 2019) which can be facilitated through the construction of an ESDT (Le Moigne, 2023). This study highlights feedback from local practitioners is required in each individual component, yet it is often simple constraints that are required from the user. This is most apparent where channel form is complex and anthropogenically influenced, requiring users to select which channels and areas are of importance to their needs. Similarly, the components studied here often rely on additional datasets to form the basis for satellite analysis, such as the GRWL. In very large rivers these may not appropriately characterise the river, such as where the selected buffers do not encompass channels either side of large islands on the Yangtze River.

One aspect of these systems that local experts are unlikely to have an influence on, at least in the short term, is the design of the satellite systems and the selection of their orbits. TIR satellites represent a conflict between their overpass time and the WST factors they can monitor. At the study sites in chapter 5, Landsat passes between late morning and mid-day, representing the applications it was designed for, including the monitoring of maximum daily land surface temperatures. However, for sustainable management this does not encompass the evenings when power plants are more likely to be operating at capacity and thermally polluting waterbodies (Smith et al., 2022). Similarly, scientific experimental instruments such as ECOSTRESS collect data at multiple times of day allowing the investigation of various phenomena, such as when polluting events are most influential. However, this imagery is irregular inhibiting the constant monitoring which would most benefit a component for an ESDT. Acknowledging these limitations is important to planning which use cases these components could be used for in an ESDT.

## **6.5: Future research directions**

The main challenges preventing an ESDT being used in sustainable management comes from a traditional design and software sustainability standpoint. At the moment despite designing the back-end methodology to be as easy to use as possible, a true ESDT would combine these components into a dashboard that can be accessed without programming knowledge. A lot of this work would have to focus on isolating coding structures so that future changes to modules and structures would not change the

applicability of these methods. While the code created for the execution of this thesis has illustrated potential for the assembly/extraction of the ESDT components discussed herein, further investment and development likely beyond the scope of a PhD thesis, would be required to combine these components within a user interface to create an ESDT ready to 'ship for purchase'. As discussed under the ability of these components to meet the ESDT tenets set out in the literature review, they have been built with as much open-source data as possible. However, both this and the proprietary data rely on APIs maintained by governing bodies such as the USGS and companies such as Planet. To fully implement an ESDT approach agreements would have to be drawn up to future proof these APIs and data sources for the specific application. Getting a working open-source ESDT into operation would hopefully encourage other scientists and managers to build tools specifically for these systems to collaboratively take advantage of these and future findings rather than position their work as separate alternative options due to the lack of compatibility can occur from different groups working as silos.

Beyond the technical improvements, which to some degree are not scientific questions but software improvements, to make an ESDT there are future research priorities to better understand how this should be done, including the practical application of these components in real-world monitoring and decision making, providing benefits and understanding flaws that cannot be seen through research alone before undertaking further refinements and improvements. To do so would require the construction of an ESDT from the foundational components developed here. The first step in doing so would be to develop a dashboard interface which aligns with the findings that have focused on reducing the computing expertise required to train and use these components. By first focusing on operationalising these components, local experts and practitioners would be able to provide their input about how the system might work, and which additional components and predictive capabilities, such as water quality metrics or combined air-water temperature forecasting would be most desired. Including practitioners would also allow testing of the responsiveness of these components to operational procedures including the quantity, temperature, and timing of water discharge from industries which is otherwise difficult to obtain. Finally, the early application of these methods in an ESDT would start to outline precisely how and where this research could be supported by local experts and in-situ data collection.

In conjunction with applying the findings to regular monitoring and management, some potential future research avenues have the potential to advance all three components simultaneously. As with all optical imagery, cloud cover has the potential to inhibit accurate EO monitoring. One solution is to include active satellites such as SWOT (Domeneghetti et al., 2024) which can penetrate cloud cover. The limitations of these systems have been discussed in the Chapter 2, yet these radar data could be combined

with the components delivered here to cover gaps in the optical record. Unfortunately, radar cannot measure WST therefore the only solution for this would be the inclusion of more TIR sensors to increase the temporal resolution and assist with capturing gaps in the cloud cover. This cloud cover often occurs when river systems are of most interest (Langhorst et al., 2024), such as during flood events, therefore, to maximise imagery when gaps are available requires accurate cloud masking algorithms. There has been considerable development in this field of research, using deep learning to assist with cloud masking (e.g., Xie et al., 2023), with some methods specific to sensors such as PlanetScope (Wang et al., 2021b). The design of the framework presented here enables these cloud algorithms to be included and tested by including them as separate callable modules.

If additional deep learning modules are to be employed, along with a user-friendly dashboard and the desire to regularly monitor chosen large river systems, the computing power required will increase considerably. As such the final suggestion for future research on a river ESDT would be to construct an ESDT from this framework entirely using cloud architecture. This would enable the computing power to be vastly increased whilst removing the onus from the user to have the infrastructure for to carry out this computing. However, there are costs associated with cloud computing which would have to be balanced in order for NGOs, academic organisations and many practitioners to access such an ESDT.

Each chapter has alluded to the wider implications of the findings which have been presented here, and these are not limited to river systems as a subject area. A lot of the findings and concepts, especially the five tenets chosen to align each component, could be of use in all ESDT research. Moreover, the dynamic temporal and spatial extent of the natural world is relatively unique which means that many of the findings here can be applied to other aspects of the earth system prone to similar problems and/or monitoring difficulties, including classification with radiometrically poor sensors, managing natural catastrophe monitoring using impact based proxies rather than cause based, and studying the spatial scale of point sources of environmental pollution to understand how far reaching these might actually be.

## **6.6 Closing remarks**

This thesis contributes to a body of research to provide the tools and insight needed to manage large river systems amid growing pressure from increased demand on riverine ecosystem services, catchment modifications, and climatic change. Throughout the literature review and analysis chapters I have argued that being able to monitor river systems and identify the location, occurrence, and magnitude of external influences is vital for supporting sustainable management of these rivers. Focusing on three first

order components to provide the foundation for a future ESDT has maximised the management scenarios that such an ESDT could be applied to.

Until recently, it has not been possible to monitor these dynamic systems at the spatial or temporal scale required for management. I have outlined how for each component in this study, in-situ methods lack the spatial scale to capture much of the change whilst traditional satellite EO lacks the spatial and temporal resolution to identify many of these events. However, by taking advantage of technological advances including CubeSat constellations, cloud infrastructure, and deep learning this research has been able to produce novel high spatio-temporal methods through the integration of multiple optical and TIR EO satellites. One thing that is key to recognise is that ESDTs themselves do not provide any fundamentally new data for river managers but what they do enable is a platform for which to centre novel, applied, and operationalised methodologies around. By focusing on how these methodologies could be implemented in an ESDT, this thesis has had the structure to develop research that can be used by river managers to make change.

As the pressure on river systems is only likely to become more severe, a diverse range of expertise will be needed to protect and manage large river systems. Therefore, a large part of this research has focused on automating or simplifying the procedures required by the end user. Insofar as an understanding of EO is required to understand the limitations of the component methodologies developed here, the research has minimised the expertise required to use these tools to apply them to management. Thus, meaning that more managers may need to have a basic understanding of EO data to manage at the catchment scale, but it will provide the ability for experts from a variety of dimensions to include their knowledge in these ESDT systems.

The number of planned EO launches is encouraging for the continued monitoring of large river systems and research should focus on integrating these satellites into the findings of this thesis. The work carried here successfully demonstrated the foundation for a river system ESDT. It is now necessary to construct an ESDT, using datasets as near real-time as possible from these additional satellites, to realise the sustainable management potential of the methodologies that have been developed.

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# Supplementary material

*Supplementary Table. 3.1: List of images used as test and training data in chapter 3. These data cannot be supplied due to their proprietary nature. However, the images can be downloaded using the information provided here, and the method can be tested using the source code ([https://github.com/SamValman/Public\\_RiverTwin](https://github.com/SamValman/Public_RiverTwin)). A quota of free Planet imagery is available for researchers should you wish to download these images (<https://www.planet.com/markets/education-and-research>).*

| River Name | Country    | Biome                           | Training/ test | Date acquired | Planet Image ID         |
|------------|------------|---------------------------------|----------------|---------------|-------------------------|
| Amazon     | Brazil     | Tropical Moist Broadleaf forest | Train          | 2022-07-06    | 20220706_125524_75_2445 |
| Amazon     | Brazil     | Tropical Moist Broadleaf forest | Train          | 2022-07-16    | 20220716_131542_78_2464 |
| Amazon     | Brazil     | Tropical Moist Broadleaf forest | Test           | 2021-11-05    | 20211105_111447_1054    |
| Xi         | China      | Tropical Moist Broadleaf forest | Train          | 2022-04-09    | 20220409_030306_34_227c |
| Xi         | China      | Tropical Moist Broadleaf forest | Train          | 2021-01-19    | 20210119_023111_86_227e |
| Xi         | China      | Tropical Moist Broadleaf forest | Test           | 2021-12-07    | 20211207_022020_30_2453 |
| Betsiboka  | Madagascar | Tropical Moist Broadleaf forest | Train          | 2022-06-17    | 20220617_064055_64_24a4 |
| Betsiboka  | Madagascar | Tropical Moist Broadleaf forest | Train          | 2021-11-11    | 20211111_070200_06_240c |
| Betsiboka  | Madagascar | Tropical Moist Broadleaf forest | Test           | 2022-04-17    | 20220417_064234_00_249e |
| Bermejo    | Argentina  | Tropical Dry Broadleaf forest   | Train          | 2022-07-25    | 20220725_135140_27_24a4 |

|            |           |                               |       |            |                         |
|------------|-----------|-------------------------------|-------|------------|-------------------------|
| Bermejo    | Argentina | Tropical Dry Broadleaf forest | Train | 2022-01-17 | 20220117_132552_66_2431 |
| Bermejo    | Argentina | Tropical Dry Broadleaf forest | Test  | 2021-10-31 | 20211031_135636_10_34   |
| Rio Grande | Bolivia   | Tropical Dry Broadleaf forest | Train | 2022-07-26 | 20220726_132712_26_2429 |
| Rio Grande | Bolivia   | Tropical Dry Broadleaf forest | Train | 2022-02-07 | 20220207_133047_86_2434 |
| Rio Grande | Bolivia   | Tropical Dry Broadleaf forest | Test  | 2021-10-21 | 20211021_133611_20_242d |
| Narmad a   | India     | Tropical Dry Broadleaf forest | Train | 2022-06-23 | 20220623_051040_51_2477 |
| Narmad a   | India     | Tropical Dry Broadleaf forest | Train | 2022-04-05 | 20220405_044004_89_2429 |
| Narmad a   | India     | Tropical Dry Broadleaf forest | Test  | 2021-12-20 | 20211220_052711_57_227b |
| San Miguel | Bolivia   | Tropical Dry Broadleaf forest | Test  | 2022-07-26 | 20220726_132656_20_2429 |
| Rhine      | Germany   | Temperate Broadleaf forest    | Train | 2022-07-22 | 20220722_100205_98_249b |
| Rhine      | Germany   | Temperate Broadleaf forest    | Train | 2021-03-07 | 20210307_095519_0e_0f   |
| Rhine      | Germany   | Temperate Broadleaf forest    | Test  | 2022-07-18 | 20220718_093952_58_2465 |
| Thames     | UK        | Temperate Broadleaf forest    | Train | 2021-11-25 | 20211125_100804_19_2465 |
| Thames     | UK        | Temperate Broadleaf forest    | Train | 2022-07-17 | 20220717_104938_61_227a |
| Thames     | UK        | Temperate Broadleaf forest    | Test  | 2021-03-09 | 20210309_111845_70_1057 |
| Trent      | UK        | Temperate Broadleaf forest    | Train | 2022-06-21 | 20220621_101140_08_242b |

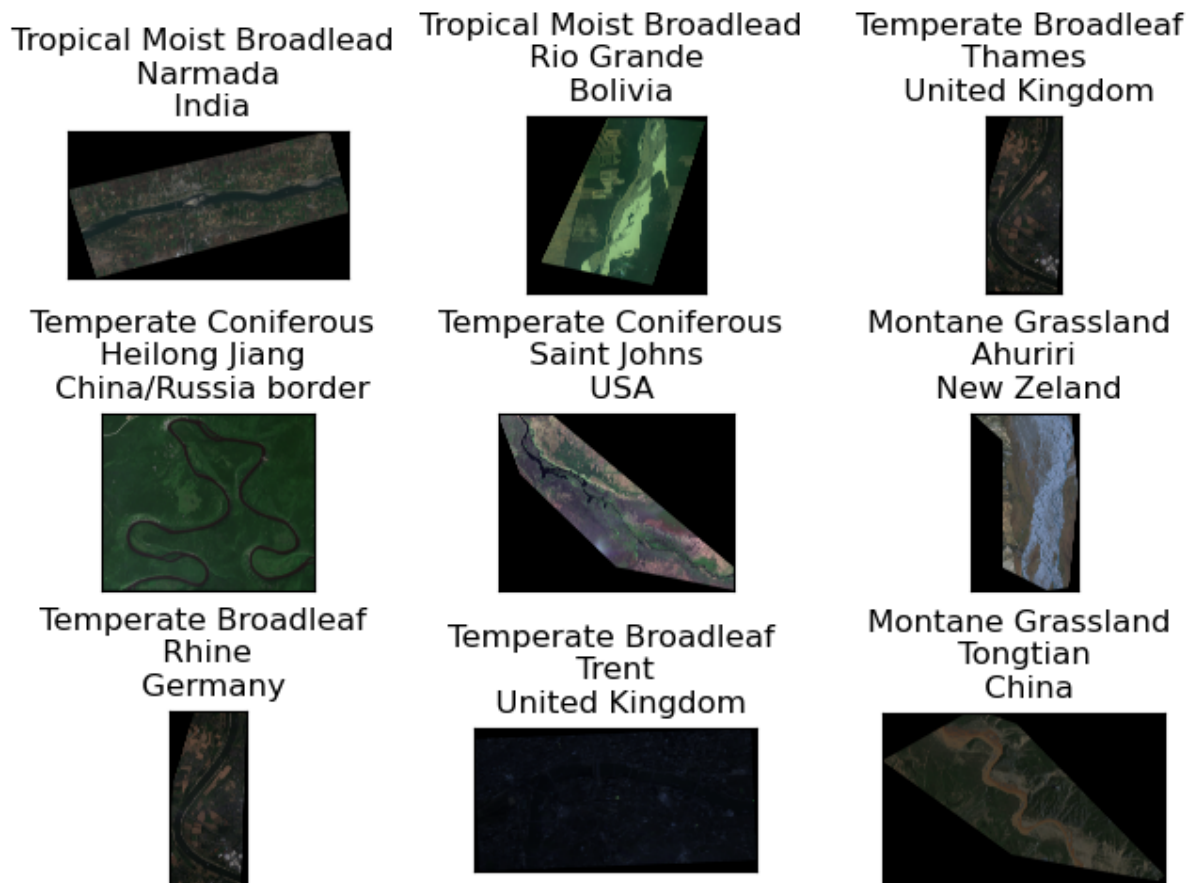
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|---------------|---------------------|-----------------------------|-------|------------|-------------------------|
| Trent         | UK                  | Temperate Broadleaf forest  | Train | 2022-07-19 | 20220719_101243_08_2451 |
| Trent         | UK                  | Temperate Broadleaf forest  | Test  | 2019-09-19 | 20190919_103841_03_106a |
| Columbia      | USA                 | Temperate Coniferous forest | Train | 2017-10-16 | 20171016_181958_0f35    |
| Columbia      | USA                 | Temperate Coniferous forest | Train | 2022-07-25 | 20220725_184659_98_2424 |
| Columbia      | USA                 | Temperate Coniferous forest | Test  | 2022-02-11 | 20220211_181759_66_2421 |
| Heilong Jiang | China/Russia border | Temperate Coniferous forest | Train | 2022-07-01 | 20220701_014731_26_2455 |
| Heilong Jiang | China/Russia border | Temperate Coniferous forest | Train | 2021-08-15 | 20210815_020257_04_2262 |
| Heilong Jiang | China/Russia border | Temperate Coniferous forest | Test  | 2022-07-12 | 20220712_022715_18_2483 |
| Heilong Jiang | China/Russia border | Temperate Coniferous forest | Test  | 2022-07-14 | 20220714_155105_59_2274 |
| Saint Johns   | USA                 | Temperate Coniferous forest | Train | 2021-03-07 | 20210307_151418_31_245d |
| Saint Johns   | USA                 | Temperate Coniferous forest | Train | 2021-12-24 | 20211224_155921_71_227c |
| Saint Johns   | USA                 | Temperate Coniferous forest | Test  | 2022-02-18 | 20220218_015311_70_2439 |
| Mackenzie     | Canada              | Taiga                       | Train | 2022-07-07 | 20220707_202018_41_2274 |
| Mackenzie     | Canada              | Taiga                       | Train | 2022-07-24 | 20220724_194947_23_2482 |
| Mackenzie     | Canada              | Taiga                       | Test  | 2021-09-01 | 20210901_191800_13_245d |
| Slave         | Canada              | Taiga                       | Train | 2022-05-30 | 20220530_181855_14_2477 |
| Slave         | Canada              | Taiga                       | Train | 2022-07-23 | 20220723_175248_45_2420 |
| Slave         | Canada              | Taiga                       | Test  | 2022-07-15 | 20220715_182609_05_2473 |
| Thlewiza      | Canada              | Taiga                       | Train | 2022-06-17 | 20220617_164423_37_2435 |
| Thlewiza      | Canada              | Taiga                       | Train | 2022-07-16 | 20220716_173515_86_2426 |
| Thlewiza      | Canada              | Taiga                       | Test  | 2022-07-12 | 20220712_172951_37_248f |
| Thlewiza      | Canada              | Taiga                       | Test  | 2022-05-27 | 20220527_164907_13_2431 |

|           |           |                      |       |            |                         |
|-----------|-----------|----------------------|-------|------------|-------------------------|
| Congo     | DRC       | Tropical Grasslands  | Train | 20220610   | 20220610_085239_31_248b |
| Congo     | DRC       | Tropical Grasslands  | Train | 2021-04-05 | 20210405_093343_75_1063 |
| Congo     | DRC       | Tropical Grasslands  | Test  | 2022-06-20 | 20220620_082133_49_2453 |
| Niger     | Mali      | Tropical Grasslands  | Train | 2022-07-19 | 20220719_104504_31_2414 |
| Niger     | Mali      | Tropical Grasslands  | Train | 2022-01-30 | 20220130_100330_57_2458 |
| Niger     | Mali      | Tropical Grasslands  | Test  | 2022-06-24 | 20220624_104805_35_2414 |
| Victoria  | Australia | Tropical Grasslands  | Train | 2022-07-23 | 20220723_010321_62_2231 |
| Victoria  | Australia | Tropical Grasslands  | Train | 2021-12-29 | 20211229_004331_22_2458 |
| Victoria  | Australia | Tropical Grasslands  | Test  | 2021-12-30 | 20211230_012938_55_2405 |
| Murray    | Australia | Temperate Grasslands | Train | 2022-07-06 | 20220706_233834_92_2435 |
| Murray    | Australia | Temperate Grasslands | Train | 2022-07-16 | 20220716_001310_54_247b |
| Murray    | Australia | Temperate Grasslands | Test  | 2022-02-23 | 20220223_001223_10_35   |
| Volga     | Russia    | Temperate Grasslands | Train | 2022-07-11 | 20220711_073248_94_248c |
| Volga     | Russia    | Temperate Grasslands | Train | 2022-04-08 | 20220408_071508_16_2251 |
| Volga     | Russia    | Temperate Grasslands | Test  | 2022-07-12 | 20220712_070053_61_2434 |
| Rio Negro | Argentina | Temperate Grasslands | Train | 2022-07-10 | 20220710_133544_12_2262 |
| Rio Negro | Argentina | Temperate Grasslands | Train | 2022-07-11 | 20220711_135404_73_2479 |
| Rio Negro | Argentina | Temperate Grasslands | Test  | 2022-02-08 | 20220208_131957_43_2430 |
| Nile      | Egypt     | Flooded Grasslands   | Train | 2022-07-24 | 20220724_073602_36_245c |
| Nile      | Egypt     | Flooded Grasslands   | Train | 2022-03-31 | 20220331_075137_37_2262 |

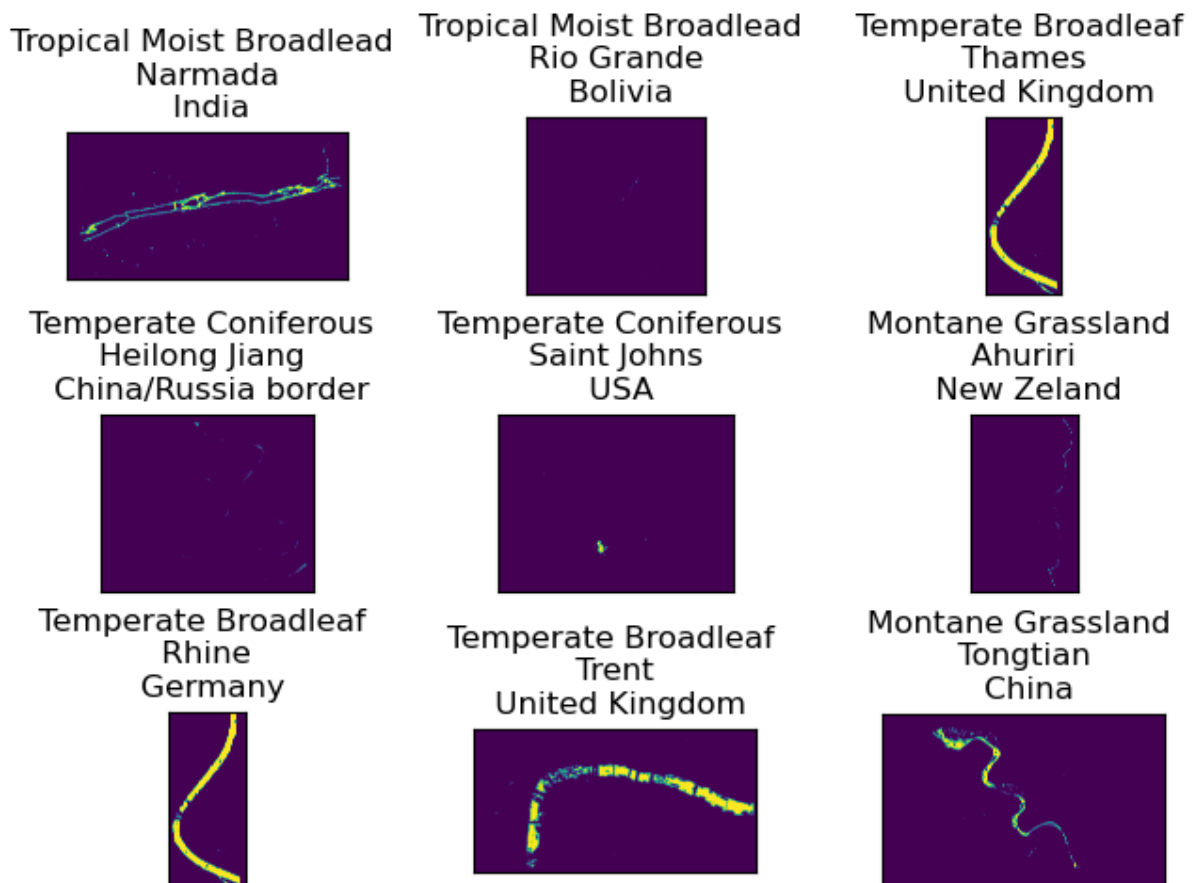
|               |              |                    |       |            |                         |
|---------------|--------------|--------------------|-------|------------|-------------------------|
|               |              |                    |       |            |                         |
| Nile          | Egypt        | Flooded Grasslands | Test  | 2022-04-05 | 20220405_080717_65_2478 |
| Bahr El Jebel | South Sudan  | Flooded Grasslands | Train | 2022-07-06 | 20220706_082021_71_2426 |
| Bahr El Jebel | South Sudan  | Flooded Grasslands | Train | 2021-10-24 | 20211024_073405_47_2451 |
| Bahr El Jebel | South Sudan  | Flooded Grasslands | Test  | 2021-12-23 | 20211223_081903_29_227c |
| Tigris        | Iraq         | Flooded Grasslands | Train | 2022-07-16 | 20220716_073503_17_2402 |
| Tigris        | Iraq         | Flooded Grasslands | Train | 2022-02-08 | 20220208_073230_97_2307 |
| Tigris        | Iraq         | Flooded Grasslands | Test  | 2022-03-29 | 20220329_064915_23_242d |
| Tongtian      | China        | Montane Grasslands | Train | 2022-07-20 | 20220720_032418_16_2427 |
| Tongtian      | China        | Montane Grasslands | Train | 2022-04-08 | 20220408_035750_13_2477 |
| Tongtian      | China        | Montane Grasslands | Test  | 2022-07-20 | 20220720_032551_72_2430 |
| Ahuriri       | New Zealand  | Montane Grasslands | Train | 2022-01-15 | 20220115_215234_09_2262 |
| Ahuriri       | New Zealand  | Montane Grasslands | Train | 2021-11-08 | 20211108_223115_40_240a |
| Ahuriri       | New Zealand  | Montane Grasslands | Test  | 2022-04-14 | 20220414_214014_57_2458 |
| Ahuriri       | New Zealand  | Montane Grasslands | Test  | 2022-07-25 | 20220725_075546_96_247e |
| Vaal          | South Africa | Montane Grasslands | Train | 2022-02-22 | 20220222_075850_36_249c |
| Vaal          | South Africa | Montane Grasslands | Train | 2021-11-19 | 20211119_072949_13_241f |
| Vaal          | South Africa | Montane Grasslands | Test  | 2021-12-10 | 20211210_081521_04_2416 |
| Vaal          | South Africa | Montane Grasslands | Test  | 2022-05-02 | 20220502_213534_99_2435 |
| Pyasina       | Russia       | Tundra             | Train | 2022-07-13 | 20220713_045717_09_2427 |
| Pyasina       | Russia       | Tundra             | Train | 2022-07-15 | 20220715_142742_00_2485 |

|            |                           |               |       |            |                         |
|------------|---------------------------|---------------|-------|------------|-------------------------|
| Pyasina    | Russia                    | Tundra        | Test  | 2022-07-17 | 20220717_052622_28_2458 |
| Popigay    | Russia                    | Tundra        | Train | 2021-07-06 | 20210706_224530_10_4a   |
| Popigay    | Russia                    | Tundra        | Train | 2021-08-03 | 20210803_035151_34_2465 |
| Popigay    | Russia                    | Tundra        | Test  | 2022-06-23 | 20220623_035535_81_241f |
| Burnside   | Canada                    | Tundra        | Train | 2022-07-11 | 20220711_182806_57_2483 |
| Burnside   | Canada                    | Tundra        | Train | 2022-07-10 | 20220710_181416_84_2251 |
| Burnside   | Canada                    | Tundra        | Test  | 2020-06-19 | 20200619_183133_10_09   |
| Ebro       | Spain                     | Mediterranean | Train | 2022-04-18 | 20220418_103813_73_2403 |
| Ebro       | Spain                     | Mediterranean | Train | 2021-10-24 | 20211024_111931_21_105d |
| Ebro       | Spain                     | Mediterranean | Test  | 2022-07-26 | 20220726_103902_88_2402 |
| Tevere     | Italy                     | Mediterranean | Train | 2022-07-24 | 20220724_092104_12_2276 |
| Tevere     | Italy                     | Mediterranean | Train | 2022-01-29 | 20220129_093254_10_11   |
| Tevere     | Italy                     | Mediterranean | Test  | 2022-06-30 | 20220630_093746_78_2488 |
| Ceyhan     | Turkey                    | Mediterranean | Train | 2022-07-26 | 20220726_080140_19_2484 |
| Ceyhan     | Turkey                    | Mediterranean | Train | 2021-12-24 | 20211224_072800_71_2420 |
| Ceyhan     | Turkey                    | Mediterranean | Test  | 2021-10-10 | 20211010_081830_73_2254 |
| Amu Darya  | Uzbekistan / Turkmenistan | Desert        | Train | 2022-07-25 | 20220725_053752_55_241e |
| Amu Darya  | Uzbekistan / Turkmenistan | Desert        | Train | 2022-03-03 | 20220303_061045_47_2495 |
| Amu Darya  | Uzbekistan / Turkmenistan | Desert        | Test  | 2022-04-12 | 20220412_053946_15_2457 |
| Syr Darya  | Kazakhstan                | Desert        | Train | 2022-07-26 | 20220726_054111_09_2435 |
| Syr Darya  | Kazakhstan                | Desert        | Train | 2022-05-22 | 20220522_061420_42_24a5 |
| Syr Darya  | Kazakhstan                | Desert        | Test  | 2021-11-26 | 20211126_063258_42_227c |
| Syr Darya  | Kazakhstan                | Desert        | Test  | 2022-02-21 | 20220221_054227_30_245d |
| Rio Grande | Mexico                    | Desert        | Train | 2022-07-06 | 20220706_162417_43_2430 |
| Rio Grande | Mexico                    | Desert        | Train | 2022-03-29 | 20220329_171715_45_2407 |
| Rio Grande | Mexico                    | Desert        | Test  | 2022-02-17 | 20220217_163226_45_2435 |

| Fine tuning images |        |       |       |            |                         |
|--------------------|--------|-------|-------|------------|-------------------------|
| Ottawa             | Canada | Taiga | Train | 2022-10-23 | 20221023_152737_75_247b |
| Ottawa             | Canada | Taiga | Train | 2022-09-08 | 20220908_153330_63_24a4 |
| Ottawa             | Canada | Taiga | Train | 2022-04-30 | 20220430_153703_03_2478 |
| Ottawa             | Canada | Taiga | Train | 2022-10-11 | 20221011_153825_10_2478 |
| Ottawa             | Canada | Taiga | Train | 2022-06-18 | 20220618_154454_04_247b |
| Ottawa             | Canada | Taiga | Test  | 2022-12-08 | 20221208_154626_85_2413 |
| Ottawa             | Canada | Taiga | Test  | 2022-11-03 | 20221103_152940_35_247c |
| Ottawa             | Canada | Taiga | Test  | 2022-08-06 | 20220806_153204_93_2477 |
| Ottawa             | Canada | Taiga | Test  | 2022-07-22 | 20220722_150150_58_2420 |
| Ottawa             | Canada | Taiga | Test  | 2022-06-25 | 20220625_153845_41_2495 |
| Ottawa             | Canada | Taiga | Test  | 2022-05-13 | 20220513_153508_86_247c |
| Ottawa             | Canada | Taiga | Test  | 2022-10-29 | 20221029_153811_44_2461 |
| Ottawa             | Canada | Taiga | Test  | 2022-10-11 | 20221011_153825_10_2478 |
| Ottawa             | Canada | Taiga | Test  | 2022-08-10 | 20220810_155545_45_2426 |
| Ottawa             | Canada | Taiga | Test  | 2022-05-18 | 20220518_154513_99_2473 |
| Ottawa             | Canada | Taiga | Test  | 2022-11-08 | 20221108_154357_63_247c |
| Ottawa             | Canada | Taiga | Test  | 2022-10-24 | 20221024_152838_39_2251 |
| Ottawa             | Canada | Taiga | Test  | 2022-10-24 | 20221024_155832_66_241c |
| Ottawa             | Canada | Taiga | Test  | 2022-11-08 | 20221108_154357_63_247c |
| Ottawa             | Canada | Taiga | Test  | 2022-10-30 | 20221030_154953_91_247a |



*Supplementary Figure. 3.1: The nine isolated images that make up some of the worst performing images in the study. These are the raw satellite images.*



*Supplementary Figure. 3.2: The predictions of these worst images made by the M20 model. There are clear issues in these images, and some are not predicted at all.*



*Supplementary Figure. 3.3: Some more difficult images which we expected the model to struggle with, were downloaded to test the limits of the model. These included: shadow, increased snow and clear sensor issues.*