REMOTELY SENSED SOLUTIONS FOR PLANT DIVERSITY CONSERVATION

Susana Baena Gallo

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Supervisors: Dr Doreen Boyd, Professor Giles Foody

Internal examiner: Dr Sarah Jewitt

PhD. University of Nottingham

Royal Botanic Gardens Kew

The University of Nottingham

UNITED KINGDOM · CHINA · MALAYSIA

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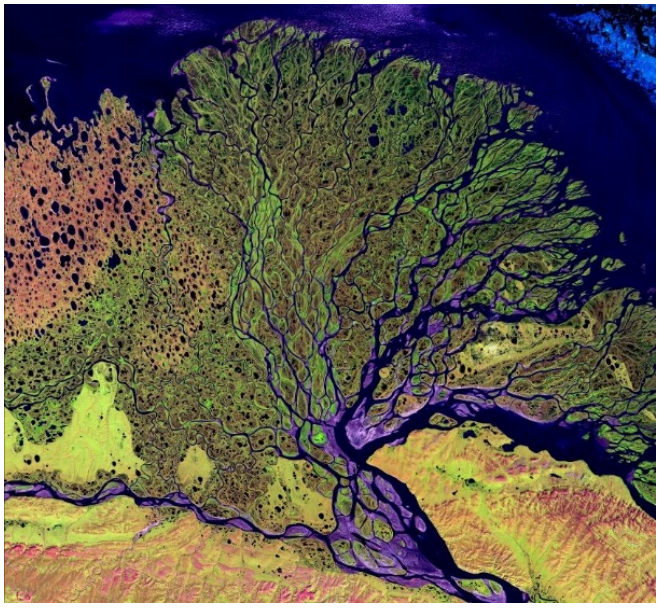
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Abstract

Global change is happening at a staggering pace and the impact that change is having in the loss of plant biodiversity is unprecedented. The latest reports on the state of the world's plants indicate that they face intensifying threats and biodiversity loss on a global scale. However, this rapid global change is also bringing extraordinary technological developments to all scientific fields. Earth Observation by Remote Sensing is undergoing a fast expansion and its capacity to monitor and analyse global environmental changes and their impact in biodiversity is ever growing.

This research analyses the current and potential role of Earth Observation in the conservation of plant diversity, identifying the latest technological developments with the greatest potential use in this field. Looking into a plant conservation organisation and through a series of case studies covering a range of spatial and temporal scales, this research brings the latest Remote Sensing technology to the plant conservation community. From collecting and processing very high resolution data for local conservation projects to help determine conservation status of a country's unique ecosystem to tracking and reporting on global plant conservation targets this research demonstrates that Remote Sensing is instrumental for addressing the observation needs of the plant conservation community.



Earth as Art – Lena Delta

List of Abbreviations

UAV	Unmanned Aerial Vehicle
CBD	Convention on Biological Diversity
CCI	Cambridge Conservation Initiative
CCSFA	Comunidad Campesina de San Francisco de Asis
CEOS	Committee on Earth Observation Satellites
CHM	Canopy height model
CMIP	Coupled Model Intercomparison Project
DEM	Digital Elevation Model
DSM	Digital Surface Model
EBV	Essential Biodiversity Variables
ENSO	El Niño–Southern Oscillation
EO	Earth Observation
GCMs	General Circulation Models
GEDI	Global Ecosystem Dynamics Investigation
GEO-BON	Group on Earth Observations – Biodiversity Observation Network
GLS	Global Land Survey
GSPC	Global Strategy for Plant Conservation
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for the Conservation of Nature
JRC	Joint Research Centre
LiDAR	Light Detection and Ranging
MAF	Moist Afromontane Forest
RBG Kew	Royal Botanic Gardens, Kew
RLI	Red List Index
RS	Remote Sensing
SDM	species distribution models
SRLI	Sampled Red List Index
SRTM	Shuttle Radar Topography Mission
SVM	Support vector machine
TRF	Transitional Rain Forest
VGI	Volunteered Geographic Information
VGs	Virtual Globes
WCRP's	World Climate Research Programme's

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A. Extended Abstract

1. Background

We live in an era of rapid global change. Habitat loss and degradation, overexploitation, climate change, spread of invasive species are some of the threats faced by many species struggling to adapt to the rapid rate of environmental change (Pereira et al., 2013). Many plants are amongst the most vulnerable species to these threats and without plants, there is no life. The functioning of the planet, and our survival, depends on them (Sharrock et al., 2014). But it is also an era of rapid technological developments. Earth Observation is undergoing fast expansion: from Google Earth to cube satellite, UAV's and major satellite missions. The first satellite with a global land-cover observing capacity was launched in 1972 (Landsat), and since then nearly 200 more such satellites have been launched (Belward and Skøien, 2015). Data continuity has been maintained and even enhanced with the opening of data archives (Wulder and Coops, 2014). Remote sensing is indeed an ever expanding field, with an exponential increase in both data availability and supporting techniques for data analysis. With this increase, our capacity to monitor and analyse global environmental changes and their impact in biodiversity also grows. Furthermore, the analysis of the ever increasing Earth Observation data acquired by Remote Sensing provides the tools to analyse the spatial and temporal nature of vegetation and ecosystems which is essential to understand plant diversity. Understanding this diversity and its threats is key to guide appropriate conservation practices.

In addition, there is recent recognition of the crucial role that these technologies play to monitor biodiversity, which goes from novel high impact research on how Remote Sensing can contribute to support biodiversity conservation (Bush et al., 2017) to global calls to use Earth Observation data to monitor biodiversity (Skidmore et al., 2015). Abundant recent literature highlights the potential for modern sensors to monitor different levels of biodiversity across a range of spatial and temporal scales (Gillespie et al., 2008; Pettorelli et al., 2014a, 2014b; Turner et al., 2003) from monitoring individual

species (Bradley and Mustard, 2006) to global environmental variables (Pettorelli et al., 2016a).

However Remote Sensing is still greatly underused by the conservation community (Turner et al., 2015). In various fora, workshops and surveys (Green et al., 2011) the conservation community itself has articulated that they are not taking advantage of the full potential of the Earth Observation data from Remote Sensing (Buchanan et al., 2015) although its use could represent a major step forward for conservation-related sciences. My research sits in that niche, exploring the opportunities provided by Earth Observation data and Remote Sensing techniques, developing tools and novel applications, aiming to unravel its full potential for the analysis and conservation of global plant diversity.

Plant diversity at different scales is very much influenced by the spatial distribution of ecosystems and the environment. The Remote Sensing contribution to enhance this geographical knowledge is critical and as such, this research naturally lies within the discipline of Geography.

2. Research objectives

The aim of this research is to explore the opportunities provided by Earth Observation data and Remote Sensing techniques for the analysis and conservation of plant diversity across multiple scales, identifying the specific needs of the plant conservation community and addressing them through the development of novel applications. Specific objectives are to:

1. Analyse current practices and predominant applications of Remote Sensing across the plant conservation community, identifying gaps, limitations and challenges to the use of these data and techniques for the conservation of plant diversity.
2. Map the specific needs (in terms of data, tools and techniques) of the plant conservation community, addressing them through a series of case studies

including original research and developing innovative tools and methodologies to address these needs.

3. Identify opportunities for further development of this technology within the plant science and conservation community.

3. Methods

I have a used a series of methods and techniques, some of them specific to each case study, looking to apply the latest and most up to date technologies to the solution of each plant conservation scenario. Cutting edge methodologies such as support vector machine (SVM) based classifications, post-classification change detection analysis, expert knowledge-based accuracy assessment and object based image analysis (OBIA) have been employed. These are fully described in each of the papers that have been produced as part of this thesis and a brief description features at the end of the section (see 3.4. Case studies – page 5). The methods employed for the realisation of the objectives of this research as a whole include:

3.1. Literature review

Current literature related to the use of Remote Sensing techniques and Earth Observation data across the plant conservation community have been reviewed, aiming to gain an overview of current practices and predominant applications of these techniques across the plant conservation community. This review also intended to find exactly what we understand by plant conservation and where it fits within global biodiversity conservation. As part of this process, it was possible to identify current conservation policies, initiatives and frame works with direct implications for the conservation of plant diversity and how these policies are to be implemented (e.g. CBD and AICHI targets, GSPC, Biodiversity indicators, Essential biodiversity variables). Finally, a literature review also helped with identifying the latest technological developments in Remote Sensing that can be utilised to the benefit of the conservation of plant diversity across multiple spatial and temporal scales.

This review can be found in Paper 1 (see B.1 - Paper 1: Remote sensing and plant conservation: current practice and future trends – page 18).

3.2. Institutional survey

The literature review was reinforced by a survey in a plant conservation organisation to identify the specific limitations and challenges that plant conservation scientists and practitioners come across when applying these technologies to their projects and research. Royal Botanic Gardens, Kew is placed in a unique position to be the target population. Kew is a world leader organisation in plant science and conservation, being one of the most important global resources for plant and fungal knowledge. It has one of the largest and most diverse collections of plant and fungal specimens (living and preserved) in the world, as well as the largest ex situ plant conservation programme in the world (The Millennium Seed Bank Partnership).

The objective of this organisational survey was to gather information regarding the use of Remote Sensing technologies and Earth Observation data for plant science and conservation across Kew's science directorate. It aimed to investigate the level of awareness within the organisation of the advances in Remote Sensing technologies and the increased availability of Earth Observation data as well as the current uses and applications of Earth Observation for plant sciences and conservation. It also aimed to gain knowledge on the limitations of the use of Earth Observation across the organisation, the specific needs for Earth Observation derived data products, the challenges when using Earth Observation data and Remote Sensing techniques for plant sciences and conservation and opportunities for further development. The institutional survey was carried out by email. The questions on the survey (which were mainly closed-ended) were piloted within the Spatial Analysis department and a refined and finalised version was emailed to all science staff (not in support or technical roles) within the Science Directory. The survey questions (Appendix I) were divided into different sections: Background, awareness, uses, limitations, needs and future opportunities. From the 241 science staff approached 68 replied, achieving a 28% response rate, which is average for studies collecting data from organisations (Baruch and Holtom, 2008). It is acknowledged that research positionality may have played a role in this institutional

survey, mainly influencing participation in the survey. Staff participating in the survey were colleagues who may have felt obliged to respond, but it is not clear that researcher positionality created bias in the survey results.

Results from the survey constituted the backbone of the research on "Remotely sensed solutions for plant science and conservation" and the findings are presented in Paper 1 (see B.1 - Paper 1: Remote sensing and plant conservation: current practice and future trends – page 18).

3.3. Semi-structured interviews

The survey was followed up with a series of semi-structured interviews with a smaller group of conservation scientists and practitioners from within Kew Gardens. This sample was chosen (non-randomly) amongst the most experienced Remote Sensing users in order to gain a deeper understanding on the specific uses, limitations and challenges associated with the use of these technologies by the plant conservation community as well as to identify opportunities for the further development of these technologies in the plant conservation field. They also helped in selecting a series of case studies from a wide range of plant conservation scenarios covering a variety of spatial and temporal scales and aiming to provide state of the art Remote Sensing solutions for plant conservation applications.

These semi-structured interviews were key to the identification of opportunities for further development of these technologies for the conservation of plant diversity. They were also crucial for the selection of case studies to further explore Remote Sensing applications to plant conservation. Questions guiding the personal interviews are included in Appendix I.

3.4. Case studies

Biodiversity is strongly determined by the spatial and temporal variability of the environment and therefore conservation practices and policies are inevitably focused on particular criteria or spatial and temporal scale (Cardinale et al., 2012). It is evident that different scales of observations are required to capture both biodiversity patterns

and the impact of conservation practices. Following this approach and covering a range of spatial scales, different case studies have been used to address specific observation needs of the plant conservation community making use of the most contemporary technological developments in the field of Remote Sensing. The temporal component has also been taken into account by either looking into the past, using historical data to gain knowledge of past trends, or looking into the future by either considering monitoring systems or predicting future distributions.

At the local scale, the possibilities of Unmanned Aerial Vehicles (UAV) to satisfy the needs of the plant conservation community in terms of being able to capture very high spatial resolution data affordably throughout different ecosystems around the world has been explored (see B.2 - Paper 2: UAVs in pursuit of plant conservation. Real world experiences page 19). Capturing data at this spatial scale requires a set of analyses suitable for very high resolution data (Strahler et al., 1986). In this thesis state-of-the-art techniques to process this very high resolution data were applied to a scenario in northern Peru in order to map and identify the keystone tree species of a highly threatened coastal dry forest system and its health across the landscape (see B.3 - Paper 3: Mapping and identifying species from the air: The very high resolution challenge for plant conservation - page 20).

At national scale, this thesis demonstrates the potential value of multi-temporal data for plant conservation through the analysis of image data archives, identifying trends in vegetation cover to determine the conservation status of a highly sensitive dry deciduous vegetation type in Zambia (see B.4 – Paper 4: Earth observation archives for plant conservation: 50 years monitoring of Itigi-Sumbu thicket - page 21). The use of the ever-extending multi-temporal remote sensing datasets is particularly pertinent given that the time-series has reached a milestone in length that is of crucial importance for conservation (Rodriguez et al., 2015).

At a regional scale, this research unravels the full potential of the Landsat continuity mission in combination with spatial distribution models and future climate projections to map and predict the distribution of wild coffee forests in Ethiopia (see B.5 – Paper 5: Resilience potential of the Ethiopian coffee sector under climate change – page 22). At

a global scale, this thesis discusses the potential of Remote Sensing for tracking and reporting on global plant conservation policies (see B.1 - Paper 1: Remote sensing and plant conservation: current practice and future trends – page 18).

A brief description of each of the case studies used for this research along with a brief description of the methods used and the specific needs addressed (Table 1) is provided below:

3.4.1. UAVs in pursuit of plant conservation. Real world experiences

Findings from over seven field work campaigns flying over 4500 Km were draw on to provide information on real-world experiences of using an off-the-shelf fixed wing UAV in plant conservation projects in remote areas across the world. Paper 2 addresses the need of affordable and flexible very high resolution Remote Sensing data through images acquired by Unmanned Aerial Vehicles (UAVs). It covers the acquisition and application of these data across various ecosystems, from Peru's hyper-arid vegetation to the dry forests of the Caribbean and to the humid woodlands of South Africa.

The paper can be found in section B.2 - Paper 2

3.4.2. Mapping and identifying species from the air: The very high resolution challenge for plant conservation

Paper 3 focuses on forest reserves for local communities in the dry forest of northern Peru, using different Remote Sensing techniques applied to very high resolution UAV images in order to identify and map the keystone tree species and their health across the landscape. It addresses the need for specific tools to process very high resolution data for plant conservation purposes, applying object based image analysis techniques to UAV data to identify individual plant species.

This paper seeks to provide solutions at local level whilst taking into account a temporal component with the view that this could form the foundation of a monitoring system.

The paper can be found in section B.3 - Paper 3

3.4.3. Earth observation archives for plant conservation: 50 years monitoring of Itigi-Sumbu thicket

Paper 4 focuses on identifying trends in Itigi thicket cover in Zambia to assess its conservation status. It uses historic aerial photography along with satellite images from data archives to analyse trends in a highly sensitive deciduous vegetation type to determine whether it is a threatened habitat. It addresses the need of customised land cover change products to support conservation assessments, applying change detection techniques to a comprehensive set of historical data available from a combination of aerial photography and Landsat archive images.

Spatially it is set on a national level as it analysis the distribution of the ecosystem in a country and takes into account a temporal component by making use of all available historical knowledge and records.

The published paper can be found in section B.4 - Paper 4

3.4.4. Resilience potential of the Ethiopian coffee sector under climate change

Paper 5 focuses on building a climate resilient coffee economy for Ethiopia. It Makes use of data from sensors on board of new satellites and state of the art modelling techniques to both identify the country's coffee resources and to analyse the potential distribution of coffee bearing forest under climate change. It addresses the need of the plant conservation community of accurate and up to date information on the current distribution of vegetation and plant resources to be able to project future ones. To do so, it makes use of the latest satellite technology (Landsat 8) and a combination of mapping and modelling techniques.

This paper sits in a regional spatial context as coffee bearing forest spreads through numerous geographical and political boundaries in this African region

and it has a strong temporal components since the final goal of this research is to predict future distribution under climate change.

The published paper can be found in section B.5 – Paper 5. Appendix II presents a more in-depth description of the Remote Sensing methods used in the published paper

3.4.5. Remote Sensing and plant conservation: current practice and future trends

Paper 1 seeks to highlight the full potential of RS for tracking and reporting on global plant conservation policies, more specifically the Global Strategy for Plant Conservation (GSPC), an international framework for a coordinated approach to plant conservation. This paper analysis the role of the most contemporary technological developments in the field of Remote Sensing to monitor and report on the GSPC targets. Spatially, it is set on a global level and it takes into account a temporal component by providing the tools for a global monitoring system.

The results can be found in section B.1 - Paper 1

A combination of these case studies was used to produce a poster presented at different Remote Sensing and Conservation conferences (Appendix III).

This thesis is structured by way of a series of scientific papers; each one presenting methods and findings of specific aspects of this research. Background information, a literature review along with results from the organisational survey and personal interviews are presented in Paper 1. Papers 2 to 5 cover the case studies addressing plant conservation needs across spatial and temporal scales (Figure 1 and 2 and Table 2). Table 3 provides a summary of publication status of each of the papers (at the time of thesis submission)

Case study	Title	Plant conservation need addressed	Spatial component	Temporal component	Ecosystem / Sps affected	EO data	RS technique
Paper 2	UAVs in pursuit of plant conservation. Real world experiences	Affordable and flexible very high resolution EO data	Local (Very high resolution)	Present status	* Hyper-arid vegetation * Dry forests * Humid woodlands	UAV images	Visual interpretation
Paper 3	Mapping and identifying species from the air: The very high resolution challenge for plant conservation	Tools to process very high resolution data for plant conservation	Local (Very high resolution)	Present status / Future conditions (monitoring)	Drylands / *Prosopis pallida*	Available UAV images	Object Based Image analysis
Paper 4	Earth observation archives for plant conservation: 50 years monitoring of Itigi-Sumbu thicket	Customised change detection product to support conservation assessments	National (Medium resolution)	Past trends	Dry forest / Itigi thicket	Aerial photography / Landsat archive	Change detection (support vector machine)
Paper 5	Resilience potential of the Ethiopian coffee sector under climate change	Current vegetation distribution data to project future ones	Regional (Medium resolution)	Future trends	Tropical forest / *coffee arabica*	Landsat 8	Vegetation mapping/Modelling/Climate change
Paper 1	Remote Sensing and plant conservation: current practice and future trends	Tools for tracking and reporting on plant conservation policies	Global	Present status / Future trends (monitoring)	Terrestrial ecosystems	Globally available EO data	Mapping and monitoring

Table 1: Summary of case studies. Shows each one of the papers within the spatial and temporal context as well as summarising the EO data and RS techniques used to address the plant conservation needs.

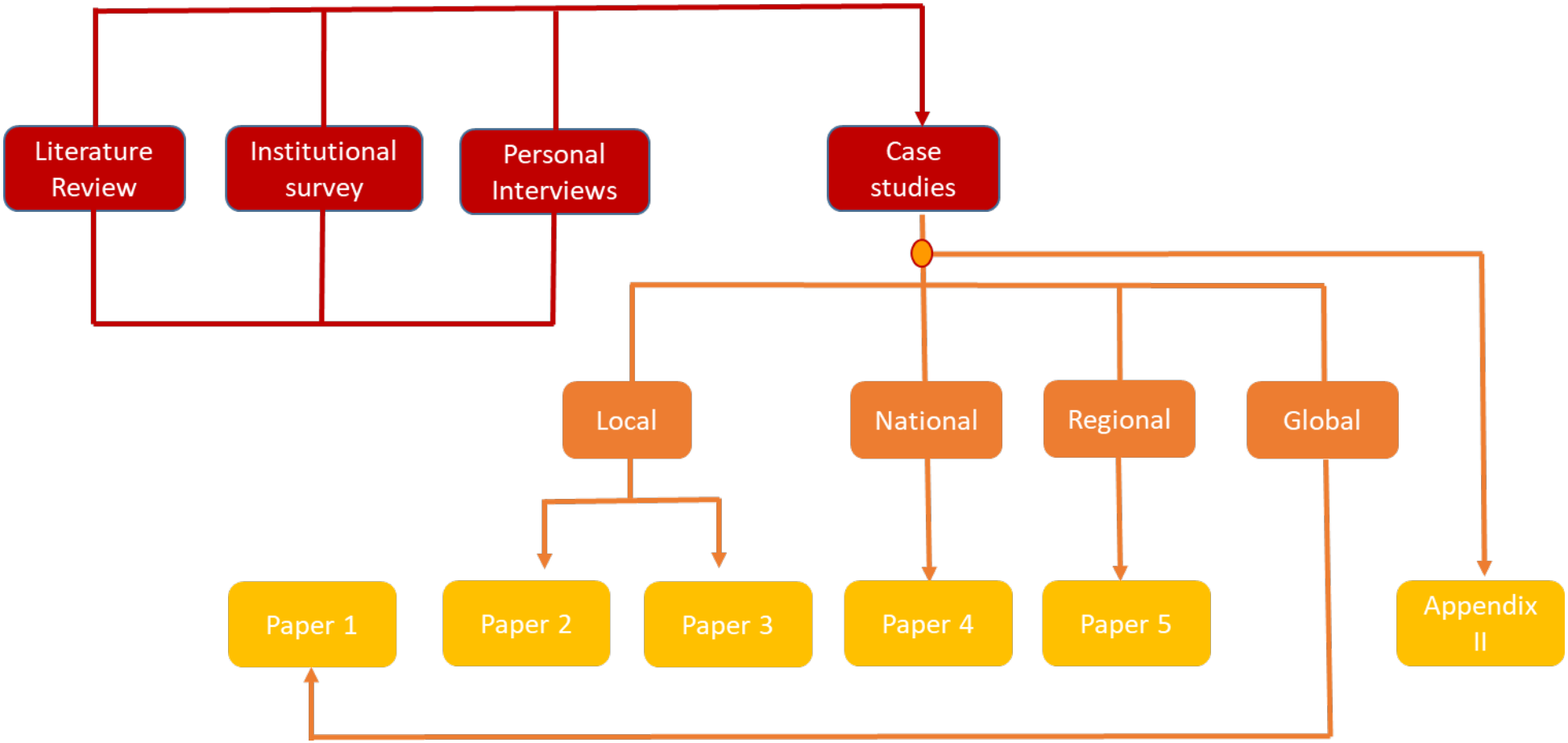


Figure 1: Structure of the thesis. How each of the individual papers feed to the entire research

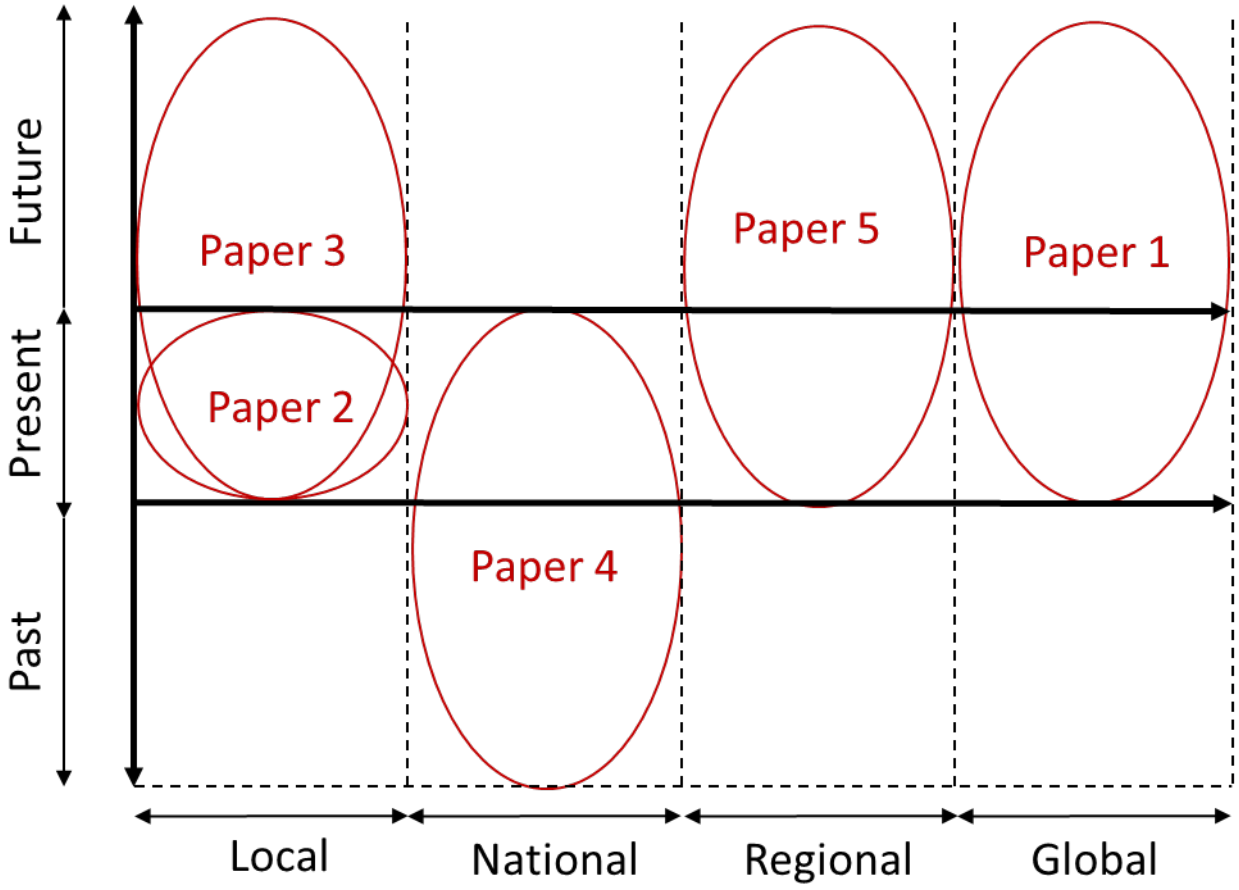


Figure 2: Spatial and temporal context of each paper

Papers	Title	Contents
Paper 1	Remote Sensing and plant conservation: current practices and future trends	Introduction (Background information & literature review)
		Results of organisational survey
		Feedback from personal interviews
		Conclusions and future opportunities
		Case Study (Global scale)
Paper 2	UAVs in pursuit of plant conservation. Real world experiences	Case Study (Local scale).
Paper 3	Mapping and identifying species from the air	Case Study (Local scale).
Paper 4	Earth observation archives for plant conservation	Case Study (National scale).
Paper 5	Resilience potential of the Ethiopian coffee sector under climate change	Case Study (Regional scale).

Table 2: Structure of the thesis. Specific aspects of the research and its inclusion in each of the individual papers.

Papers	Title	Publication status
Paper 1	Remote Sensing and plant conservation: current practices and future trends	In preparation for publication in "Biodiversity and Conservation"
Paper 2	UAVs in pursuit of plant conservation. Real world experiences	Published 15th November 2017 in "Ecological Informatics"
Paper 3	Mapping and identifying species from the air:	Published 27th November 2017 in "PLOS ONE"
Paper 4	Earth observation archives for plant conservation	Published 23rd May 2016 in "Remote Sensing in Ecology and Conservation"
Paper 5	Resilience potential of the Ethiopian coffee sector under climate change	Published 19th June 2017 in "Nature Plants"

Table 3: Publication status of each of the papers.

4. Original contribution to knowledge, relevance and impact

Global change at an unprecedented speed is on our doorstep (Trumbore et al., 2015) and the impact that change is having on the loss of plant biodiversity is huge. But the same forces causing those rapid change is also bringing extraordinary technological developments to every scientific field. Earth Observation by Remote Sensing is doing just that for plant diversity conservation. Making use of the latest technologies to the benefit of plant diversity biodiversity monitoring and helping to palliate the effects of global environmental change on the loss of plant diversity are of the highest importance.

4.1. Paper 1: Remote sensing and plant conservation: current practice and future trends

Plants are essential to life on Earth and yet plant communities around the world are under increasing threat. This has been recognised by some of the major conservation frameworks specifically the Convention on Biological Diversity (CBD) and the Global Strategy for Plant Conservation (GSPC). Still, plant conservation initiatives lag behind and receive considerably less attention than animal conservation (Balding and Williams, 2016). This is indeed the case in the growing field of Remote Sensing and its applications to biodiversity conservation very dominated by the animal kingdom and the particular observation needs of this community (Havens et al., 2014). Certainly, Remote Sensing of vegetation has a long research history within the field, where plants are considered as the elements conforming the basis of the ecosystems rather than the focus of the conservation efforts. It is therefore essential for the plant conservation community to find its niche within the global biodiversity conservation.

This paper analyses the observation needs of the plant conservation community within the context of the current plant conservation policies and framework which is essential in order to find the niche of the plant conservation community and of Botanical Gardens as leading institutions in the field.

My contribution: The full authorship contribution is listed on the title page in Section B1 (page 18). I am the leading author in this paper and conceived the research. I designed

the experiments with the contribution of co-authors. I collected the data and performed the analysis and interpretation. I wrote the paper with the contribution of co-authors.

4.2. Paper 2: UAVs in pursuit of plant conservation. Real world experiences

This paper responds to the need of affordable very high resolution data, something that the plant conservation community has been urging for quite some time. There are currently a wealth of reviews of UAVs for conservation (Anderson and Gaston, 2013; Koh and Wich, 2012; Marris, 2013) the majority of them with a clear animal focus. This paper presents the experiences of using UAVs in real plant conservation projects around world showing how this technology can be used in different plant conservation applications. This adds a wealth of practical knowledge on the use of UAVs which is especially relevant to the plant conservation community.

My contribution: The full authorship contribution is listed on the title page in Section B2 (page 19). I am the leading author in the paper. I conceived and designed the research with the contribution of co-authors. I collected the data, performed the analysis and wrote the paper with the contribution of co-authors.

4.3. Paper 3: Mapping and identifying species from the air: The very high resolution challenge for plant conservation

UAVs with their capacity to acquire very high resolution images naturally generate a great amount of data which in many cases, due to the lack of appropriate algorithms or tools for their processing are visually interpreted. The need of methodologies and algorithms to process that amount of data is evident. Furthermore, for the plant conservation community to be able to identify individual species throughout the landscape is imperative. To be able to do this represents an exciting development for the fields of Remote Sensing, ecology and conservation (Pettorelli et al., 2014a).

This paper address this need by developing a methodology based on state of the art algorithms to automatically extract 3D information from UAV images and applies novel image analysis techniques to automatically identify individual tree species throughout

the landscape. Furthermore, it takes the methodology one step forward, taking into account the health of the ecosystem, identifying mortality rates and providing the opportunity to monitor the effects of diseases adding to the relevance and potential impact of the paper.

The paper focuses on a unique ecosystem of seasonal dry tropical forest of South America and provides relevant information related to species composition and health of one of the most threatened yet understudied and poorly surveyed tropical forests in the world. But even if the paper focuses on this unique ecosystem, the possibility of using the same methodology on other ecosystems is also discussed adding to the relevance of the paper.

My contribution: The full authorship contribution is listed on the title page in Section B3 (page 20). I am the leading author in the paper. I conceived and designed the research with the contribution of co-authors. I collected the data, performed the analysis and interpretation and wrote the paper with the contribution of co-authors.

4.4. Paper 4: Earth observation archives for plant conservation: 50 years monitoring of Itigi-Sumbu thicket

The need for customised change detection studies to support conservation assessments has been recognised by the plant conservation community for quite some time, but only recently with the opening of Earth Observation data archives, the possibility of performing these types of studies has become a reality. Furthermore, in areas where historical data is available the archive can be extended back to an ideal period of 50 years as specified by the Red List of Ecosystems. This is highly relevant for the plant conservation community as it opens the possibility of using this information to support conservation assessment of ecosystems.

This paper takes the opportunity provided by the opening of Earth Observation data archives, applies the latest and most appropriate algorithms for mapping priority habitats over time and uses a novel approach to expert knowledge to assess the accuracy of the final change detection product. This is highly relevant as it addresses the problem and provides a solution to the lack of validation data for historical records.

The paper focuses on a unique and very spatially restricted ecosystem believed to be highly threatened and provides crucial information to support a full ecosystem conservation assessment.

My contribution: The full authorship contribution is listed on the title page in Section B4 (page 21). I am the leading author in the paper. I conceived and designed the research with the contribution of co-authors. I collected the data, performed the analysis and wrote the paper with the contribution of co-authors.

4.5. Paper 5: Resilience potential of the Ethiopian coffee sector under climate change

Arabica coffee provides Ethiopia with its most important agricultural commodity, generating a quarter of the country's export earnings. Coffee is produced within specific agro-ecological zones, with most of the coffee production coming from forest habitats. With a scenario of increasing temperatures and decreasing rainfall, there is an urgent need to understand the influence of climate change on coffee bearing forests.

This paper uses data from the latest satellite technology, the Landsat Continuity Mission (Landsat 8) in combination with a modelling approach supported by rigorous ground-trothing to map the current extent of coffee bearing forest and to analyse its potential distribution under different climate change scenarios.

My contribution: The full authorship contribution is listed on the title page in Section B5 (page 22). This paper is the result of long and complex research project carried out by different researchers both in the UK and Ethiopia. I had a leading role in the Remote Sensing side of the research, conceiving and designing that Remote Sensing methodology. I collected the Earth Observation data and performed the analysis with the contribution of Tim Wilkinson (also co-author in the paper).

B. Results –Published and un-published papers

1. Paper 1: Remote sensing and plant conservation: current practice and future trends

Status:

First draft prepared. Awaiting feedback from co-authors before submission to the journal Biodiversity and Conservation.

Authorship statement:

Authors: **Susana Baena**, Doreen S. Boyd, Steve P. Bachmanı and Justin Moat.

SB is lead author. SB conceived the research. SB, DSB and JM designed the experiments. SB collected the data. SB performed the data analysis and interpretation. SB draft the article. SB, DB, SPB and JM wrote the article.

REMOTE SENSING AND PLANT CONSERVATION: CURRENT PRACTICE AND FUTURE TRENDS

Susana Baena[1, 2], Doreen S. Boyd[2], Steve P. Bachman[1, 2] and Justin Moat[1, 2]

[1] Royal Botanic Gardens, Kew, Richmond, Surrey, TW9 3AB, UK. Email: s.baena@kew.org

[2] School of Geography, University of Nottingham, Nottingham, NG7 2RD, UK; orcid.org/0000-0003-3040-552X

ABSTRACT

The latest reports on the state of the world's plants indicate that they face intensifying threats and biodiversity loss on a global scale. More than ever, a plant conservation focused strategy like the Global Strategy for Plant Conservation (GSPC) is needed. Underpinning the Strategy are 16 targets which require action and their impact should be tracked and reported. We argue that using Remote Sensing (RS) for Earth Observation (EO) provides a firm basis for tracking and reporting, but also acknowledge that Botanical Gardens should play a leading role in the implementation of the GSPC targets. With a view to facilitating successful delivery of the Strategy towards the 2020 targets, we review the current and potential role of RS in the conservation of plant diversity within this framework, identifying the latest RS technological developments with the greatest potential use in this regard. Further we highlight how Botanical Gardens are currently using remote sensing through a survey undertaken at the Royal Botanic Gardens, Kew, a world leading organisation in plant science and conservation. It is concluded that there is much untapped potential in using remotely sensed data by the plant conservation community, including Botanic Gardens. We hope this paper serves as a catalyst for realising this potential and offers a roadmap for doing so.

Key Words: Remote Sensing, Earth Observation, Plant conservation, GSPC, Botanical Gardens

Correspondence:

Susana Baena,
Royal Botanic Gardens, Kew, Richmond, Surrey, TW9 3AB, UK. Email: s.baena@kew.org
Tel: +44 (0)2083325276

1. INTRODUCTION:

All life on Earth depends on plants. They are the basis of ecosystems in which all animals, including humans, live, grow and survive (Wood and Habgood, 2010). Yet the latest reports on the global status of biodiversity (Willis, 2017) present a worrying future for the state of the world's plants; they face intensifying threats and biodiversity loss on a global scale (Pereira et al., 2010). This situation has been recognised by the Convention on Biological Diversity (CBD) who launched the Global Strategy for Plant Conservation aiming to halt the continuing decline of plant diversity. Simultaneously, we are experiencing a dramatic increase in the availability and quality of Earth Observation (EO) data from Remote Sensing (RS). A sophisticated network of satellites, along with newly developed aerial platforms are capturing data and adding it to a timeline, providing a consistent record of the Earth (Pettorelli et al., 2016a). This record has already been successfully used for biodiversity conservation and its relevance for conservation efforts have been recognised (Kerr et al., 2003; Turner et al., 2003).

Indeed remote sensing has played a crucial role in obtaining long-term global coverage of the Earth's surface, on a wide range of spatial scales, and in a consistent and repeatable manner (Turner et al., 2014). However, it is still the case that these technologies are greatly underused by the conservation community (Turner et al., 2015), who seemingly are not taking advantage of the full potential of the EO data from remote sensing (Buchanan et al., 2015). This is particularly the case within the plant conservation community. Efforts have been made to use RS to track progress towards the global biodiversity conservation Aichi targets (Skidmore et al., 2015), but no such effort has been made towards the specific needs of the plant conservation community and in particular the GSPC conservation targets.

The reasons for this "underuse" might include technical constrains such as data suitability, costs related to data collection or the capacity needed to process this data (Turner et al., 2015). However, it may be also due to a lack of awareness of these technological developments and how they can directly contribute to the conservation of plants across different scales. For the full potential of RS to be realised, the exact reasons for its limited use need to be identified and also its potential contributions noted. In this paper we review the current and potential role of RS in the conservation of plant diversity within the plant conservation framework of the GSPC targets, identifying the latest RS technological developments with the greatest potential use in this regard. This paper recognises that GSPC targets often have a national and regional focus and highlights how these targets can benefit from RS. In particular, this paper reports how Botanical Gardens, which have been suggested should play a leading role in the implementation of the GSPC targets (Williams et al., 2012), could be utilising the potential of RS. We do this through the lens of one such Garden, the Royal Botanic Gardens, Kew (Kew Gardens), a world leading organisation in plant science and conservation, being one of the most important global resources for plant and fungal knowledge. Kew Gardens has one of the largest and most diverse collections of plant and fungal specimens (living and preserved) in the world, as well as the largest ex situ plant conservation programme in the world (The Millennium Seed Bank Partnership). We analyse the RS capacity within this Botanical Garden by way of: (1) identifying challenges and limitations on the use of RS for the conservation of plant diversity; (2) mapping their specific needs in terms of RS data and techniques, and (3) exploring opportunities for further development of this technology for the conservation of plant diversity. This type of analysis

is essential if Botanical Gardens are to fulfil their potential in taking a leading role in the implementation and reporting of GSPC targets (Mounce et al., 2017).

2. CONSERVING THE WORLD'S PLANTS

The extinction crisis faced by plants worldwide has been recognised for quite some time (Groombridge, 1992) and although it is acknowledged that their conservation is fundamental to the future survival of humanity, it is only relatively recently plant conservation has received the attention that is required (Wyse Jackson and Kennedy, 2009). In a CBD Conference of the Parties, held in October 2010 in Nagoya, Japan, a revised and updated Strategic Plan for Biodiversity, including the Aichi Biodiversity Targets, for the 2011-2020 period was adopted. This plan extends to 2020 an international commitment to halt biodiversity loss, with Target 11 having the aim of achieving the formal protection of at least 17 % of all terrestrial areas. Conserving habitats is unarguably the best way to preserve plant species (Kramer and Havens, 2009) and it is widely accepted today that the primary strategy for nature conservation is the establishment and maintenance of a system or network of protected areas (Heywood and Iriondo, 2003). But it can be argued that plant species should be afforded protection in whatever landscape they find themselves and moreover it is the case that regions with the most plant species have only slightly more land protected than those with fewer (Joppa et al., 2013). With this in mind, Target 12 covers a more species-based approach, seeking to prevent the extinction of known threatened species. Currently, most species of vertebrates have already been globally assessed for their conservation status, whereas only approximately 3.2 % of plant species are currently listed by IUCN Red List and only two small groups of plants (conifers and cycads) have been assessed (Schatz, 2009). Even though there is no current global assessment of how threatened plants are (Brummitt et al., 2015), estimates of the potential number of threatened plant species have been made at approximate 50% (Pitman and Jørgensen, 2002). Given these figures it seems clear that plants currently have an undeservedly minor role in the conservation-planning process (Wyse Jackson and Kennedy, 2009).

In an attempt to overcome these challenges, the CBD agreed to adopt the Global Strategy for Plant Conservation (GSPC), providing an international framework for a coordinated approach to plant conservation (Williams et al., 2012) and offering an important opportunity to halt the potential extinction of tens of thousands of threatened species (Wyse Jackson and Kennedy, 2009). The GSPC contains 5 objectives (Table 1) with 16 specific targets, and the overall aim of halting the continuous decline of plant diversity. It also provides a framework for the definition of plant conservation, understood as a broad group of activities which aim to prevent plants from becoming extinct. It includes the documentation of plant diversity (on-line flora and conservation assessments of all known plant species), an ecosystem approach to plant conservation both through ecological regions and important areas for plant diversity, as well as a species approach through *in situ* and *ex situ* conservation of threatened plant species. Biological invasions, genetic diversity of crops, indigenous and local knowledge of plants, as well as regulation of international trade of wild flora. These targets are in turn reinforced by education, training and public awareness (targets 14 to 16). Botanic gardens have great and longstanding strengths in all of these fields, giving rise to the suggestion that Botanical Gardens should be leaders in the implementation of the GSPC (Williams et al., 2012).

The question of how the GSPC targets will be monitored remains uncertain however. For a global approach towards the CBD's Aichi targets, a specialist group first established by the CBD and then coordinated by the UN Environment Programme World Conservation Monitoring Centre (Biodiversity Indicators Partnership) has developed a series of Biodiversity Indicators to assess progress at the global level and to effectively communicate trends in biodiversity. A set of 55 biodiversity indicators were used as mid-term assessment of progress toward these global targets for 2020 (Tittensor et al., 2014). A different but complementary framework for assessment is the Essential Biodiversity Variables (EBV) (Pereira et al., 2013) proposed by the Earth Observations Biodiversity Observation Network (GEO BON). A total of 22 individual EBVs have been proposed, arranged around six classes covering a range of scales from ecosystems to species to genes. No such indicators currently exist for the GSPC.

3. THE ROLE OF REMOTE SENSING IN THE CONSERVATION OF PLANT DIVERSITY

Several high impact research papers have contributed to the field of Remote Sensing for Conservation (Gillespie et al., 2008; Kerr et al., 2003; Nagendra et al., 2013; Pettorelli et al., 2014b; Roughgarden et al., 1991; Scholes et al., 2012; Turner et al., 2003) although it is only recently that the conservation field and its specific RS needs, have been considered separately from the fields of ecology and biodiversity (Rose et al., 2015). Most of these papers often discuss the issues from the stand point of the ecologists, conservationists and biodiversity experts and a few from the Remote Sensing specialists (Wang et al., 2010). But common to most of these reviews is the general call for better and stronger communication channels between conservationists and the RS community. Efforts towards building this bridge were made by NASA (e.g. Ecological Forecasting Program), CEOS (Committee on Earth Observation Satellites), GEO-BON (Group on Earth Observations – Biodiversity Observation Network), CCI (Cambridge Conservation Initiative) and JRC (Joint Research Centre) facilitating meetings and workshops to bring together members of the conservation and the RS community. Encouraging outputs such us the 10 conservation questions that can be addressed using RS (Rose et al., 2015) which was the result of these collaborative meetings. These series of dialogues culminated in a call to use EO products to track progress towards global conservation targets (Skidmore et al., 2015) and to agree on a set of biodiversity variables under the umbrella of the "essential biodiversity variables" (Pereira et al., 2013) that can be monitored remotely. Ten so called Remote Sensing Essential Biodiversity Variables (RS-EBVs) have been proposed, but a definitive list is still being discussed (Pettorelli et al., 2016b). To date, different studies have reviewed how RS can support global conservation initiatives under different frameworks such as biodiversity indicators (Stritthol, J., Miles, L., Horning, N. Fosnight, 2007) and EBV (O'Connor et al., 2015).

Remote sensing in the context of the GSPC targets

The potential of Remote Sensing for Earth Observation for assessing progress towards the Aichi Biodiversity targets have already been highlighted (O'Connor et al., 2015); our goal here is to analyse the suitability of Remote Sensing to fulfil the monitoring requirements for the GSPC targets and to identify how these technologies can be best used to help conserve plant diversity. Our approach was to identify which indicators within the existing GSCP framework (10th meeting CBD, 2010) could potentially be measured using EO data products. Following the O'Connor *et al.* (2015) approach, each GSPC target, with an indicator that was potentially measurable through RS, was analysed and

assigned a rating using a qualitative scale ranging from not observable (red rating), partially observable (amber rating) and totally observable (green rating) (Table 1).

Nine of the sixteen GSPC targets (2, 4, 5, 6, 7, 8, 10, 11 and 12) were identified as potentially benefiting from the use of RS. GSPC targets 4 and 5 can be directly measured using RS data with the suggested indicators as they have a clear spatial component whereas the other 7 targets could benefit from the use of RS but would need additional ancillary data for full measurement. Objective I has some requirement from RS within the important role in the assessment of the conservation status of plant species using the Red List Index (RLI) or the Sampled Red List Index (SRLI) for a global approach as indicators. RS contributes directly to Red List Assessments measuring declines over time through habitat loss and deforestation. Of special interest here are deforestation and land cover change products, which depending on the scale of the species distribution, global datasets may be available (Hansen et al., 2013) or specific custom change detection studies may have to be produced (Baena et al., 2016; Buchanan et al., 2008). Furthermore, RS can provide information about threats affecting the species being assessed (Joppa et al., 2016). There is a wealth of studies supporting the monitoring of threats to biodiversity (Peres et al., 2006; Pettorelli et al., 2014a) including land degradations and fragmentation (Bai et al., 2008; Nagendra et al., 2010; Prince et al., 2009) and urban expansion (Ji et al., 2001; Taubenböck et al., 2012). Both RLI and SRLI are somewhat made possible through data on species abundances and distributions. The direct detection of plant individuals using RS is very much related to the resolution of the RS system being used. Successful examples can be found using both high spatial resolution system (Pu and Landry, 2012) as well as fine spectral resolution ones (Dalponte et al., 2013) and in combination with 3 dimensional data (Dalponte et al., 2012). The direct monitoring of species remotely is a field with great potential and represents an exciting and challenging development for both ecologists and remote sensing specialists (Pettorelli et al., 2014a). Species distribution modelling is another approach to gain information on the distribution of plant species and where RS shows great potential through the indirect detection of environmental parameters (He et al., 2015; Turner et al., 2003).

Objective II has the greatest potential to benefit from RS, with all targets fully or partially measured by RS except for target 9, which relates to genetic diversity with no current use of RS data although experimental work has shown that aspen genotypes (different clones) can be discriminated using hyperspectral images (Madritch et al., 2014). Similarly, landscape genetics has emerged as a new research area integrating population genetics and landscape ecology (Manel and Holderegger, 2013) where RS is able to provide information on the latter (Storfer et al., 2007).

Target 4 relates to ecological regions being secured through effective management and/or restoration. RS plays a major role in mapping the extent of different ecosystems with many different examples from global land cover products (Bartholomé and Belward, 2005; Friedl et al., 2002) to forest cover (Hansen et al., 2013) or more specific habitats such as mangroves (Giri et al., 2011) or dry forest (Sugden, 2017). Once the extent of the ecosystem has been assessed it can be easily mapped against the network of protected areas (Nagendra et al., 2013). However, for an ecological region to be considered secured not just by its inclusion in a network of protected areas but also through effective management (understood as the set of practices aimed to ensure the persistence of the vegetation) and/or restoration in degraded ecosystems to enhance their conservation status and improve delivery of ecosystem services (10th meeting CBD, 2010). Both effective management and restoration work can be measured through time to assess the effectiveness of the interventions, setting up monitoring systems (Duro et al., 2007) aiming to assess change over time both in habitat extent (Achard et al., 2002) and quality through a three dimensional approach to vegetation structure (Asner et al., 2012; Lucas et al., 2012). The delivery of ecosystem services can be inferred

through plant functional traits such as leaf traits, strongly influenced by land use and with follow on effects on several ecosystem properties (Homolová et al., 2013; Lavorel et al., 2011; Pettorelli et al., 2017). Vegetation structure is also a reliable quantifier of natural capital assets and ecosystem services such as carbon flow (Asner et al., 2011; Patenaude et al., 2004). Effective management plans should also include options for adaptation to climate change. RS has a long record of providing evidence of climate change and its effects on natural systems (Lucht, 2002; Parmesan et al., 2003) and it has proved to be an invaluable tool for assessing the consequences of climate change on wild plant species providing adaptation strategies (Moat et al., 2017) Furthermore, exploring variations in seasonality over time through time series analysis of RS data can be used to gain knowledge on plant resilience and vegetation responses to climate change (De Keersmaecker et al., 2014; Verbesselt et al., 2016; Zhou, 2001).

Target 5 refers to important areas for plant diversity or IPAs (Important Plant Areas). For each ecological region these can be identified according to a set of criteria including: endemism, species richness, genetic variability patterns and/or uniqueness of habitats. There has been significant progress in modelling species richness using RS to provide land-cover information and landscape metrics (habitat mapping), measures of productivity, and measures of heterogeneity (Gillespie et al., 2008). Many studies have related species richness to land-cover information (Bremer and Farley, 2010; Thuiller et al., 2004) and to impacts associated with changes in the habitat mosaic, such as fragmentation based on landscape metrics (Griffiths and Lee, 2000; Luoto et al., 2002). An increasing number of studies and reviews have found significant associations between primary productivity and species richness (Levin et al., 2007; Rocchini, 2007) although the nature of the relationship is contentious (Turner et al., 2003) and there is no consensus as to which scale results in the greatest accuracy (Gillespie et al., 2008). Species richness is commonly predicted using RS data to provide information on environmental heterogeneity since it is expected to be related to the spectral heterogeneity in RS data and therefore it can be used as powerful proxy of species diversity (Rocchini et al., 2016). Both targets 4 and 5 can be fully measured by RS and represent the greatest use of RS.

Target 6 can be partially measured using RS and relates to the sustainable management of production lands, including forestry. Several spatial features can be measured and monitored through time to ensure a sustainable approach to forest management (Franklin, 2001). Of special interest is the three dimensional measures of habitat structure, providing information on stand and landscape level features such as canopy heights, stand volume, basal area, and above-ground biomass that can be measured using RS (Lefsky et al., 2002; Lim et al., 2003; Lu et al., 2016). But also sub-canopy vegetation height can be monitored using the appropriate RS technique which is a function of species composition, climate, and site quality (Dubayah and Drake, 2000). Finally, affective management plans should take into account the ecosystem health directly related to natural and anthropogenic stress and disturbance (Lausch et al., 2016).

Both targets 7 and 8 refer to the conservation of threatened plant species and can be monitored through the change in status of threatened plant species which would in turn benefit from RS through tracking the conservation status of plant species. In situ conservation needs to consider not just the genetic diversity of the species but also the potential impact of climate change and other pressures (10th meeting CBD, 2010). RS can help here by providing information about threats but also about plant resilience to climate change, as specified above.

Target 10 relates to biological invasions. The detection and mapping of non-native invasive species has long been carried out using RS based on the spectral separability of native and invasive species

(Asner et al., 2008; Ustin et al., 2002) but also in a combination with a modelling approach to predict the presence of invasive species through spatially explicit predictor variables (Bradley and Mustard, 2006).

It is more challenging to find a RS role for Objective III, although indirect input on the change in status of threatened species acts as an indicator for target 11 related to international trade of wild flora and an indirect approach thorough measures of habitat structure and productivity could act as a proxy for target 12 related to plant-based products sourced sustainably.

RS has a limited role for Objectives IV and V related to capacity building and public engagement, however the visual power of EO data for creating awareness of plant diversity values (visual displays such as images and videos) should be considered.

Objective	GSPC target	RS	Proposed indicator	RS approach
I. Plant diversity is well understood, documented and recognized	1. An online flora of all known plants	🔴		
	2. An assessment of the **conservation status** of all known plant species (Priority at national and regional level)	🟡	% of known plant on **RLI** or **SRLI**	(i) Species abundance and distribution (ii) Land cover change (iii) Monitoring threats (iv) Indirect detection of environmental parameters
	3. Information and research to implement the Strategy	🔴		
II. Plant diversity is urgently and effectively conserved	4. At least 15 % of each **ecological region or vegetation type** secured through **effective management**[1] and/or **restoration**[2] **(**Priority at national and regional level)	🟢	% of ecological regions within **protected areas**	(i) Ecosystem mapping (ii) Monitoring change in extent and quality (iii) Plant functional traits (iv) Vegetation structure (v) Resilience
	5. At least 75 % of the **most important areas for plant diversity**[3] (IPA) of each ecological region protected with **effective management**[1] in place	🟢	Coverage of Important Areas for Plant Diversity in Protected Areas	(i) Ecosystem mapping (ii) RS measures of productivity (iii) Habitat heterogeneity (iv) Monitoring change in extent and quality (vi) Resilience
	6. At least 75 % of **production lands** in each sector **managed sustainably**.	🟡		(i) Vegetation structure (ii) Plant Health
	7. At least 75 per cent of known **threatened plant species conserved**[4] in situ.	🟡	(i) Change in status of threatened sps (ii) Trends in abundance and distribution of sps	(i) Species abundance and distribution (ii) Land cover change (iii) Monitoring threats (iv) Resilience
	8. At least 75 % **of threatened plant species** in ex situ collections and at least 20 per cent available for recovery and restoration programmes.	🟡	(i) Change in status of threatened species	(i) Species abundance and distribution (ii) Land cover change (iii) Monitoring threats
	9. 70 % of the **genetic diversity** of crops conserved	🔴		
	10. Effective **management**[1] plans in place to prevent new **biological invasions**[5] and to manage important areas for plant diversity that are invaded.	🟡	Trends in biological invasions in IPA	(i) Population abundance and distribution (ii) Indirect detection of environmental parameters (iii) Monitoring change in extent and quality (iv) Resilience
III. Plant diversity is used in a sustainable and equitable manner	11. No species of wild flora endangered by international trade.	🟡	Change in status of threatened species	(i) Population abundance and distribution (ii) Land cover change (iii) Providing information about threats
	12. All wild harvested plant-based products sourced **sustainably**.	🟡		(i) Indirectly through habitat structure (ii) EO measures of productivity
	13. Indigenous and local knowledge maintained or increased	🔴		
IV. Education and awareness about plant diversity promoted	14. The importance of plant diversity incorporated into **education and public awareness** programmes.	🔴		
V. The capacities and public engagement developed	15. Sufficient people **trained**	🔴		
	16. Institutions, networks and partnerships established	🔴		

[1] "**Effective management**" understood as the area is managed to ensure the persistence of the vegetation, and associated biotic and abiotic components. Management plans should include options for **adaptation to climate change.**

[2] "**Restoration**": in degraded ecosystems to enhance their conservation status and improve delivery of **ecosystem services** whilst securing plant diversity

[3] The most important areas for plant diversity can be identified according to a set of criteria including endemism, species richness, genetic variability patterns and/or uniqueness of habitats, including relict ecosystems, also taking into account the provision of ecosystem services.

[4] "**Effective conservation**" implies the need to consider (i) the genetic diversity of the species; and (ii) potential impact of **climate change** and other pressures, for example by determining whether the **protected area network includes corridors**…

[5] Invasions as a phenomenon and not just the species: Therefore combines (i) invasion of the alien species and (ii) Reactions of ecosystems or habitats into which they are introduced

Table 1: Summary of GSPC objectives and targets and their suitability to be measurable through RS. Rating shows red (hot observable), amber (partially observable) and green (totally observable)

REMOTE SENSING: NEW ERA OF TECHNOLOGICAL DEVELOPMENTS

There are a wealth of Remote Sensing reviews directed to the conservation community providing overviews of Remote Sensing sensors and products and their utility for different applications in biodiversity science and conservation (Kuenzer et al., 2014; Wang et al., 2010). However the pace at which this technology evolves makes it essential to keep a constant review. Here we focus on the most contemporary RS technological advances with relevance to the plant conservation community which we believe will have an impact in the field.

In the last decade there has been an exponential increase in the number of satellites being launched, adding to the increasing longevity of sensors and making the temporal revisit of any point on the Earth surface higher than ever before. Spatial resolutions are down to centimetres for both optical and radar sensors and the spectral capability of sensors is such that it will change our ability to observe the Earth (Belward and Skøien, 2015). In April 2014 Europe launched the first satellite of one of the most ambitious Earth-observation programmes. Once its Sentinel satellites are fully operational, Copernicus will probably be the world's most comprehensive programme (Butler, 2014a). Sentinel-1A and 1B are two identical radar systems designed to operate in tandem, cutting down revisiting time and enabling quick-succession imaging. This will allow the continuous imaging of cloudy areas such as tropical forest. Sentinel 2 (also in tandem) carries a high resolution multispectral imaging devices with spatial resolution down to 10 meters and revisit times of just 2-3 days, it holds great potential for monitoring biodiversity and for plant conservation. The final relevant satellite of Copernicus, the Sentinel-3, was launched in 2016 and with its Ocean and Land Colour Instrument carrying 21 spectral bands with a swath width of 1270 km and, this extends the temporal coverage and spectral range of Sentinel-2's multispectral imager. The two missions will therefore be complementary for land applications, such as biodiversity monitoring. These are just 3 of the 6 missions planned, comprising radar and optical sensors, radiometers and spectrometers designed for different applications and with long term continuity (Berger et al., 2012).

Continuity is also maintained with the launch of NASA's Landsat Data Continuity mission also known as Landsat 8 (2013), extending the longest temporal record of space-based surface observations with enhanced capabilities (Roy et al., 2014). This long-term Landsat record is being enhanced by new satellite systems (such as Copernicus) and multiple sensors in a global network or virtual constellation (Wulder et al., 2015). Scientists from the Sentinel-2 and Landsat-8 programmes have been working together to make their data compatible and to develop joint archives (Butler, 2014a). Data continuity ensures consistently processed, global, long-term terrestrial data records which are essential to understand trends and develop robust predictions on future impacts on biological diversity (Turner et al., 2015). But data continuity also refers to the maintenance of a global image archive with policies that ensure access to these data. In that respect, the opening of the Landsat archive in 2008 (Wulder et al., 2012) had a tremendous impact allowing free access to more than 5 million images dating back to 1972 and it has been described as the beginning of a new era of open-access satellite data (Wulder and Coops, 2014). Data accessibility in this context also refers to the ability of the user to discover, retrieve and manipulate data to extract meaningful information (Turner et al., 2015). The emergence of Digital Earth technologies or Virtual Globes (VGs), symbolised by Google Earth, have had a profound impact on the use of Earth Observation data

expanding access to vast amounts of current and historical imagery beyond the contents of individual institutions (Olea, P. and Mateo-Tomás, 2016). But also, through cloud computing, VGs have the capacity to augment the processing capabilities without the need of supercomputers. For instance, global forest cover change map derived from Landsat data was made using Google Earth Engine (Hansen et al., 2013; Tracewski et al., 2016).

In addition to this, with the planned EnMAP, HyspIRI, PRISMA and ESA's candidate FLEX imaging spectrometer missions there will be large hyperspectral data streams for land monitoring, which will soon become available to the conservation community (Verrelst et al., 2015). Commercial cube satellites have also been identified as potential space borne earth imaging platforms (Belward and Skøien, 2015). CubeSats (measuring 10 by 10 by 10 cm and weighing just over 1 kg) by US' Planet Labs and Skybox are commercial project aiming to fly multiplatform constellations of Earth imagers (Butler, 2014b). Furthermore, the forthcoming space borne LiDAR sensor, The NASA Global Ecosystem Dynamics Investigation (GEDI), will provide the first global, high-resolution observations of forest vertical structure and will provide data that will drastically alter LiDAR cost estimates (Pettorelli et al., 2016a).

Nonetheless, airborne data collection has also experienced a dramatic increase in availability, mainly in the form of Unmanned Aerial Vehicles (UAVs) which provide accurate and affordable high resolution data. Low altitude flights allow for sub-meter spatial resolution and different sensors can deliver multispectral information from the visible, to the near infrared (NIR) through to the thermal and microwave parts of the spectrum (Colomina and Molina, 2014). Moreover, three dimensional information can be derived from UAV data using newly developed algorithms, such as structure from motion (Baofeng et al., 2016), adding valuable information on the structure of vegetation.

Supplementing all this remotely sensed data is the necessary calibration and validation data to ensure quality of measurement. These ground data take enormous effort and expense to collect, however of late there has been a rise in the number of citizens scientists willing to volunteer data that could be used for this purpose (Foody and Boyd, 2013; Kosmala et al., 2016; Pratihast et al., 2014) but also the preparedness of scientists to share formally collected data (e.g., ForestPlots.NET and EU-BON (Hoffmann et al., 2014)). Both these recent developments expand the coverage of ground data over space and time affording a comprehensive monitoring remote sensing system to be developed (Foster et al., 2017). However, these developments are not without their constraints (Grainger, 2017) and Botanical Gardens could play a pivotal role in shaping these developments for the benefit of biodiversity studies. Table 2 summarises the EO technological developments presented here highlighting the key contribution to plant conservation

EO technological development	Satellite/specifics	Key contribution to plant conservation
New satellites being launched	Sentinel 1	Global plant status at high resolution.
	Sentinel 2	Vegetation status and trends especially in tropical forest.
	Sentinel 3	Global plant status medium to low resolution and adaptations to climate change.
	Landsat 8	Global plant status at high resolution.
Data continuity	Consistent future data records	Robust predictions on future impacts on plant diversity.
	Global image archives	Past trends in plant status. Land cover change.
Data accessibility	Virtual Globes	Easy visualisation of species abundance and distributions.
Hyperspectral data	EnMAP	Biochemical and biophysical plant traits at high resolution.
	HyspIRI,	Assessments of vegetation canopy condition, invasive species and plant health.
	PRISMA	Biochemical and biophysical plant traits at high resolution.
	FLEX	Overall vegetation photosynthetic performance with implications for carbon sequestration.
Commercial cube satellites	CubeSats	Global plant status at high resolution.
Space borne LiDAR	GEDI	Vegetation three-dimensional structure.
UAVs	Different cameras/sensors	Global plant status and vegetation structure at very high resolution.
Citizen science	ForestPlots.NET	Measure, monitor and analyse tropical forest.
	EU-BON	Measure, monitor and analyse vegetation.

Table 2: Summary of upcoming EO technological development with potential to support the conservation of plant diversity.

4. RBG KEW AS A CASE STUDY – PRACTICAL IMPLEMENTATION (RS WITHIN A PLANT CONSERVATION ORGANISATION)

There has been a dramatic increase in the availability and quality of Earth Observation data along with a growing awareness of the relevance of Remote Sensing in the conservation of plant diversity. Botanical Gardens have a crucial role to play in plant conservation and the monitoring and implementation of GSPC targets and for this it is essential to assess the current RS capacity within the organisations in order to understand the challenges and to recognise the opportunities for further development. To this end we conducted a survey of Royal Botanic Gardens, Kew's science directorate with the overall aim of identifying challenges and limitations on the use of Earth Observation data and Remote Sensing techniques across the organisation and to explore the opportunities for RS technologies for the conservation and analysis of plant diversity.

The survey inquired about the level of RS expertise across the organisation and asked the participants to identify current applications, challenges and their specific needs for RS derived products and tools. Answers to questions that asked about participants' specific RS expertise were based on self-assessment. The general trend is that plant conservation practitioners self-rated their knowledge of Earth Observation products and Remote Sensing techniques as medium to low. When asked about specific RS products and tools, Google Earth was rated as the most useful application. Most participants were aware of Google Earth data repertoire and browsing capabilities and they felt confident using it. Global Deforestation and land use / land cover change were the RS products more widely known. There was less awareness of other value-added data products such as vegetation indices, fire products, global elevation datasets and climate datasets and their usefulness for ecological modelling (i.e. species distribution models) but participants were unsure as where to find them or their specific use (i.e. how to choose the best environmental layers). When asked about raw RS products such as new satellites and sensors or the opening of data archives there was a general lack of knowledge. Generally there is awareness that RS products and tools are available (Figure 1) and of great use but it is unclear for most participants what products and tools are available and where they can be found.

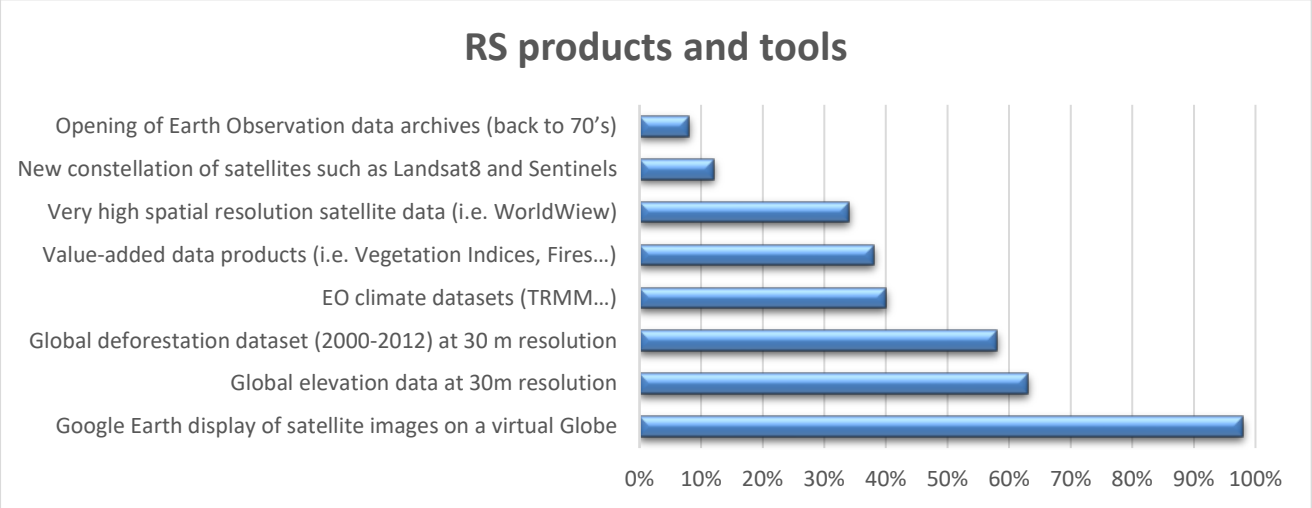


Figure 1: Distribution of RS data products and tools according to awareness of survey participants

The survey also aimed to gain an insight into the specific applications participants use RS techniques and EO products for. The most widely used application is for Plant conservation assessments, ecosystem mapping and land cover change. Most people also used RS for more practical applications such as baseline data for general mapping and support for fieldwork planning and sampling design. Indirect detection of environmental parameters for species distribution was also a widely used application of RS and slightly less were protected areas, spread of invasive species and ecosystem services. The overall use for applications such as Plant health and Vegetation resilience was minimal (Figure 2)

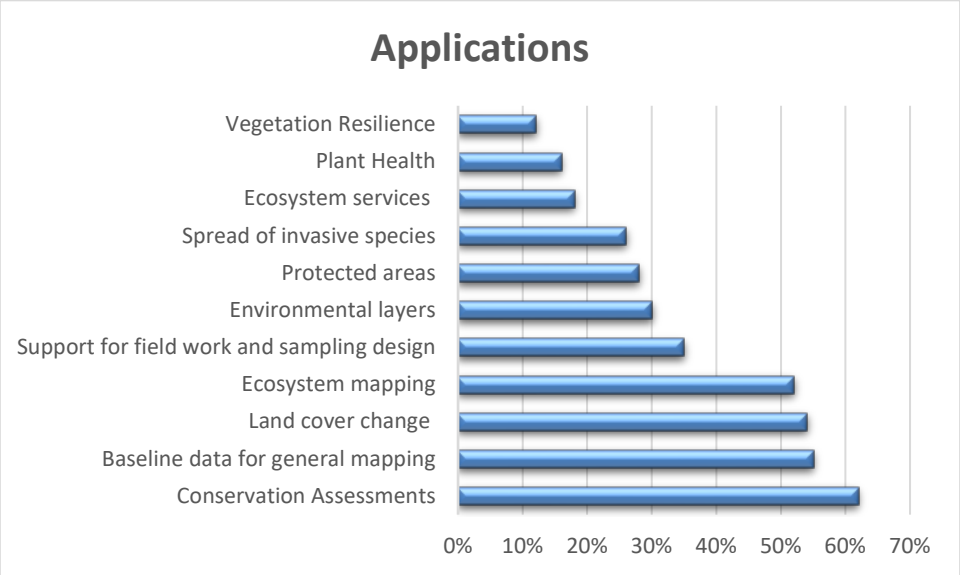


Figure 1: Distribution of RS data products and tools according to awareness of survey participants

The majority of participants making use of EO data for plant diversity conservation use freely available products, very few use data from commercial providers (mainly those involved in consultancy work related to projects with higher economical resources) as conservation related activities, on a regular basis cannot readily afford commercial prices.

Participants were also asked about specific challenges when using RS as well as issues that may limit their use of RS for plant conservation related applications. Survey results showed that for the plant conservation practitioners surveyed, the main challenge is the nature and availability of data. The number of different resources can be overwhelming and the lack of understanding the type of data and their usefulness for a specific application is reported as a constant barrier. Moreover the lack of awareness that new products exist limits the take up of this technology for plant conservation as much as the uncertainty of where to find specific products (too many data portals). Issues such as cost of data and insufficient spatial resolution were also reported as limitations. Also the lack of specific, easy to use methodologies and tools to process RS data to derive plant conservation related information directly from satellite images was reported as a limitation as much as lack of computer power to work through large multi-year global datasets or very high resolution images for large areas.

Besides limitations and challenges, the survey also enquired about specific needs of RS amongst participants. We can summaries these answers into 6 grounds of requirements: (1) Affordable very high resolution data for identification of individual plant species in order to gain information about

species abundance and distribution patterns. (2) Specific tools to process and extract quantitative information from high resolution data, (3) Tools and applications to create custom deforestation/land use/land cover change products specific to the plant conservation needs, such as custom time periods (for specific dates and epochs) and land cover classes / vegetation types. (4) Tools ideally implemented in user friendly environments such as Google Earth. (5) Specific training focused on the needs of the plant conservation community. (6) A single global biodiversity repertoire where users can browse and access available data that has undergone standard quality filter and has sufficient metadata to guide on their appropriate use.

5. FUTURE OPORTUNITIES

Gaining insight into the requirements of the GSPC targets for plant conservation and how RS can be used towards fulfilling and reporting on these targets, as well as learning from plant conservation experts about their needs and expectations, was key to identifying future opportunities for the use of Remote Sensing in the conservation of plant diversity. We have identified two areas within plant science and conservation with the highest potential to be further developed and greatly improved by the use of RS: (1) plant health and (2) plant resilience to environmental changes.

Very high resolution remotely sensed images can give insight into changes in plant traits that are related to plant health. Very fine spatial resolution images can be used along with three dimensional models of the vegetation to gain knowledge about changes in plant structure (such as defoliation or death of branches) caused by plagues and diseases. In that sense UAVs are a promising tool for the acquisition of both very fine resolution images and three dimensional models of the vegetation in a relatively inexpensive and frequent manner. Very high spectral resolution data are also a source of information on plant's chemical composition that can be related to the plant's health (Asner et al., 2012). On a larger scale, levels of infestation in the vegetation across the landscape can be identified and used to target interventions, conservation and restoration initiatives.

Time series analysis of EO data can be used to explore changes in plant seasonality that can be related to the changing environment. Phenology information such as early or late onset of greenness or senescence as well as the length of the growing season, can be directly retrieved from time series of vegetation index and presents valuable information on the ecosystem condition and health. Recent studies present promising results for monitoring resilience of tropical forest, by looking at temporal autocorrelation of time series of RS images and its relation to the ecosystem recovery rate after extreme climatic events (De Keersmaecker et al., 2014). Both fields, plant health and plant resilience to environmental changes, are very much interrelated. The resilience to disturbances is much higher in healthy ecosystems and the greater the ecosystem resilience the greater its capability of withstanding the negative impacts from external influences such as pests and diseases (Lausch et al., 2016).

In addition, there are other fields within plant conservation sciences where the use of RS is relatively common and will continue to benefit from future RS technological advances. This is the case of (1) plant conservation assessments, in particular the IUCN Red List of species, where high resolution mapping of individuals will allow species to be more readily assessed using Criterion D – size of populations. Plant Red List assessments have previously been relatively restricted to Criterion B assessments that relate to geographic range size. EO data and RS technologies have great potential for applying criterion A – the reduction in population size as this can be based on habitat loss.

It is also the case of (2) Climate Change impact on plants. The temporal scale of RS allows monitoring of these changes from climate, to vegetation, to species, capturing both the intra- and inter-annual variations that are essential to understand species adaptation to a changing environment. Furthermore, tracking variations in climate with RS, is fundamental to understanding the influence of climate on plants, allowing both the prediction of species distributions in the past and into the future using species distribution modelling (Franklin, 2010).

Furthermore there are other fields where the application of this technology is only incipient or relatively new, such as seed banking where RS could have great potential. Moat and Smith, 2003 highlight three major areas of development in seed banking where RS could have major contributions: targeting species and habitats for seed collecting, assistance in seed collection campaigns and further reintroduction of species. This is largely based on the capacity of RS to indirectly detect environmental variables which are input to species distribution models. Species niche can then be used to targeting collection as well as select most suitable areas for reintroduction. Very high resolution data, such as that derived from UAVs, can be used to identify species in remote areas and help targeting seed collection campaigns. Finally, the temporal nature of RS can be used for phenology studies to show where plants are likely to be in seed or flower to allow collection at the right time of the year.

6. DISCUSSION

We have shown that RS techniques and EO data have a great potential to support the conservation of plant diversity in fields such as plant health and plant resilience to environmental changes where the use of this technology even though it is only incipient, could be a major contribution. We also show that the use of current and emerging RS technology can fulfil some of the monitoring requirements for more than half of the GSPC targets and could play a significant role in assisting botanical gardens take a lead in the implementation of this strategy. Still there are key challenges to utilising RS techniques and EO data products for plant conservation.

There is a generalised lack of awareness of what Remote Sensing can offer to plant conservation scientists and practitioners. The increasing amount of EO data with potential use for biodiversity conservation is scattered in many different institutional “data portals” which are in many cases difficult to track and in constant flux. When looking at available data sets with potential use for plant conservation assessments we found useful data spread across multiple institutions and via numerous data portals with varying levels of accessibility. The same applies to satellite images, accessible at different processing levels from different institutions through a variety of user interfaces, online searches and ordering tools. Platforms such as USGS Landsat archive and Google Earth act as nodes for satellite data access and provide examples of how RS can be made available globally, but still, there are many other useful satellite data sets are not centralised.

Furthermore, the increase of new satellite missions gives great potential and value for plant conservation, but they need to be translated into biodiversity useful information. The need of prepossessed and value-added data that would enable greater use of satellite imagery by conservationists it is a requirement that has already been highlighted by global biodiversity conservationists (Turner et al., 2015). Regularly updated global land cover products (Gong et al., 2013), vegetation maps and deforestation datasets (Hansen et al., 2013) are of great value for plant

conservation practitioners but also other useful data sets largely derived from satellite data would need to be created and regularly updated. Still, the initial processing step in between raw satellite Remote Sensing data and finalised data products is needed and beyond the skills of most conservation practitioners. Higher level products such as orthorectified data sets are essential to reach a wider audience amongst the plant conservation users. Specifically, atmospherically corrected data products, such as those available for Landsat data (Landsat surface reflectance data products) are essential for many applications especially for time series analysis of Remote Sensing data. Moreover, when looking at time series, which are especially useful for the trend analysis of plant diversity, being able to use data from different sensors in a fully comparable way is still an unresolved problem. Issues such as cross-calibration and validation need to be resolved if we want to take advantage of continuous data records. Examples such as the comparability of the Landsat continuity mission (Landsat 8) and Copernicus Sentinel 2 should be followed to take full advantage of the combined high spectral and temporal resolution (O'Connor et al., 2015)

The idea of a common platform for Ecologists, Remote Sensing specialists and data providers is not new (Pettorelli et al., 2016b). A centralised platform acting as Global Biodiversity Repository where users could choose the most appropriate dataset according to their needs is something that the conservation community has long called for. Such a platform could also promote the use of novel technologies and serve as a focal point for regular updates. Several institutions have been suggested for hosting such incentive including GEO BON and the Group on Remote Sensing for Biodiversity and Conservation (CEOS biodiversity) (Pettorelli et al., 2016b; Turner et al., 2015).

Capacity-building and specific training would help overcome many of this issues not only by improving the technical abilities to deal with remote sensing data but also making conservationist more aware of the potential of these technologies, allowing the necessary conservation input in the definition of future RS-based products (Palumbo et al., 2017; Wegmann, 2017). The need of specific tools to extract biodiversity information from Remote Sensing data in a user friendly and intuitive manner has also been highlighted. Extracting quantitative information, such as number of individual plant species, from high resolution datasets in an automated way or the development of customised change detection products for specific areas, resolutions and time periods are examples of applications required. Such tools could be implemented in user friendly environments such as Google Earth (Google Engine) using cloud computing and will benefit from the ever expanding repertoire of open source software code. Finally, data affordability, in particular of high resolution data sets, remains an issue. Google Earth provides a valuable source of high resolution data which is useful for visualisation purposes but not to use programmatically or for scientific purposes (proprietary issues). In this respect the use of Unmanned Aerial Vehicles (UAVs) as a source for very high resolution data is growing as an affordable solution.

It is clear that Earth Observation provides substantial information and it has the potential to play a central role in plant conservation, however, field data acquired by in situ methods such as plant surveys, are indispensable for the vast majority of studies and it remains the most reliable way of obtaining training and validation data for Remote Sensing methods (Pettorelli et al., 2014). There are also intrinsic limitations and uncertainties derived from the use of Earth Observation data such as clouds and cloud shadows in optical imagery, sensor calibrations and geocorrections/orthocorrection (especially from airborne sensors such as UAVs) as well as

atmospheric corrections and illumination variations which should be considered when using Earth Observation data for plant conservation applications.

7. CONCLUSION

Remote Sensing technology shows a significant potential for plant conservation and provides a valuable tool for tracking and reporting on the GSPC targets. Still the full potential of these technologies to prevent future plant diversity loss is yet to be achieved. The amount, quality and accessibility of EO data is steadily increasing (Belward and Skøien, 2015), recent events such as the opening of EO data archives as well as upcoming developments such as the space-borne LiDAR have a major role to play in the conservation of plant diversity. Moreover, botanical gardens are the recipients of a wealth of plant information and knowledge which is essential to extract much more of the information available in Earth Observation data (Bush et al., 2017). Plant conservation scientists and practitioners should be prepared to embrace these challenges.

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2. Paper 2: UAVs in pursuit of plant conservation. Real world experiences

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UAVs in pursuit of plant conservation - Real world experiences

Susana Baena[a,b,*], Doreen S. Boyd[b], Justin Moat[a,b]

[a] Royal Botanic Gardens, Kew, Richmond, Surrey, TW9 3AB, UK
[b] School of Geography, University of Nottingham, Nottingham NG7 2RD, UK

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ABSTRACT

Small Unmanned Aerial Systems (UASs) (more commonly called Unmanned Aerial Vehicles, UAVs or drones), have the potential to enhance current understanding and management of a range of environmental applications. There has been much coverage on the use of UAVs for conservation applications in the recent years, yet little on specific applications in plant conservation. Here we present our experience of using an off-the-shelf fixed wing UAV for plant conservation projects ranging from Peru's hyper-arid vegetation to the dry forests of the Caribbean and finally to the humid forest of South Africa and the Brazilian Amazon. We present our findings from over ten successful (but also our unsuccessful) field work campaigns flying over 4500 km. We show how the technology is being used for mapping, quantifying and monitoring plant species, but also review the real-world issues of using UAVs, particularly in remote areas.

1. Introduction

In the past decade, the use of Unmanned Aerial Vehicles (UAV) in ecology and conservation has experienced an exponential growth (Sandbrook, 2015), with an increasing amount of literature being published supporting their use. Between 2013 and 2016 there was a doubling in the number of papers related to the use of UAVs for conservation[1]. The majority of papers suggest that the main use of UAVs in conservation is focused on the counting and monitoring of animals (Marris, 2013; Schiffman, 2014) and law enforcement in relation to illegal hunting (Schiffman, 2014). It is recognised that UAVs provide a flexible, accurate, yet affordable solution to the spatial information needs of many conservation applications (Koh and Wich, 2012). In this paper, we highlight that little attention has been given to the specific issues associated with plant conservation. Here we are treating plant conservation in the broadest sense: i.e. all actions aiming to address the potential loss of plant diversity worldwide (Wyse Jackson and Kennedy, 2009). Applications of UAVs in plant conservation related fields have been extensively documented and reviewed, specifically in ecology (Anderson and Gaston, 2013) conservation (Koh and Wich, 2012) forestry (Torresan et al., 2016) and precision agriculture (Zhang and Kovacs, 2012), as well as in other applications of interests for plant conservation such as mapping vegetated areas (Salamí et al., 2014), photogrammetry and remote sensing (Colomina and Molina, 2014). These applications suggest that UAVs have enormous potential for plant conservation, but bring with them a number of associated issues. These include ease of use, obstacles to moving the system between countries, deployment under different environments and in socially sensitive circumstances. Issues such as the complexity of choosing and setting up a UAV (Torresan et al., 2016) or the social implications of its uses in conservation (Sandbrook, 2015) have previously been discussed. In this paper, we present our experience of using an off-the-shelf fixed wing UAV in plant conservation projects ranging from Peru's hyper-arid vegetation to the dry forests of the Caribbean or the humid forests of South Africa and the Brazilian Amazon. We present findings from successful (and unsuccessful) fieldwork, comprising UAV flights of over 4500 km. We illustrate how the technology is being used for mapping, measuring and monitoring of plant conservation activities, but also review the real-world issues of using a UAV in remote areas.

2. UAV applications in plant conservation

The main uses of UAVs in plant conservation applications can be broadly classified into one of three categories: Mapping, Measuring and Monitoring.

2.1. Mapping

2.1.1. Base maps

The use of baseline geo-referenced images as an alternative to more traditional paper maps. This can be exceptionally useful for locating individual plants in the images to avoid later location errors associated

* Corresponding author at: Royal Botanic Gardens, Kew, Richmond, Surrey TW9 3AB, UK.
E-mail address: s.baena@kew.org (S. Baena).

[1] Source: Google Scholar Citations (accessed 10/02/2017 using search terms "conservation UAV") – Figures between 2013–2016 = 4360, between 2010–2013 = 2530.

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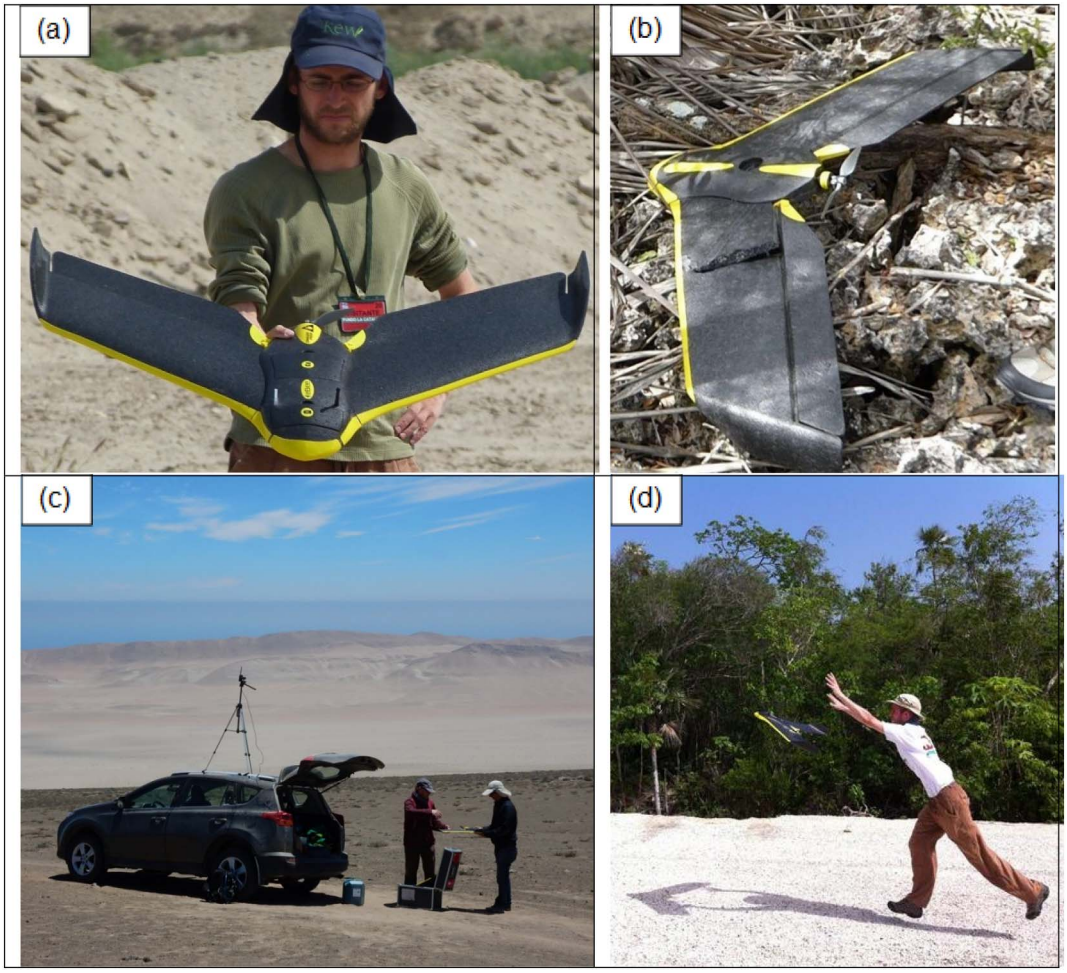


Fig. 1. (a) Fixed-wing UAV (senseFly eBee). (b) After a difficult landing in the Cayman Islands, luckily the wings are easily replaced. (c) Ground Control Station in Peru. (d) UAV takeoff in the Cayman Islands.

with using GPS in the field, as well as providing baseline images for electronic navigation devices (Jóźków and Toth, 2014).

2.1.2. Visualisation

In many cases visual interpretation of high resolution UAV images provides sufficient information for the user, without the need for further image processing (Husson et al., 2016). In fact, manual interpretation has been the primary means of extracting ecological population data from UAV derived images (Anderson and Gaston, 2013).

2.1.3. Identification

Individual plant species can be identified by taking advantage of the high spatial resolution of UAV (Getzin et al., 2012). In many cases, the quality of the images allows experts to visually identify species, but the process can be time consuming over large areas. Image analysis techniques can be used to automate the process and have proved successful in different environments (Gini et al., 2012; Hung et al., 2012; Michez et al., 2016). The combination of multispectral UAV images and 3D point clouds in an object-oriented image analysis environment are also showing promising results (Díaz-Varela et al., 2015).

2.1.4. Discovery

The hyper-spatial resolution of UAV images can be employed to attempt to locate rare or obscured (on the ground) plants taxa in remote environments or to locate likely candidate sites for field work. This has been used extensively in animal conservation where great advances have been made in automated location of individuals (Martin et al., 2012; van Gemert et al., 2015).

2.2. Measuring

- Determining the abundance and spatial distribution of individual plants is an essential part of many surveys and plant conservation projects, providing the baseline knowledge to implement conservation actions. However, if there are numerous individuals, manual interpretation can be time consuming. Automated efforts towards quantification of plant individuals (mainly tree species) are often related to image segmentation techniques for tree crown delineation (Mansur and State, 2014). These are very much enhanced by using three-dimensional information (Díaz-Varela et al., 2015; Wallace et al., 2014a) and examples of this can be found in animal conservation (Pierce et al., 2006; Sardà-Palomera et al., 2012).
- Identifying the extent of specific habitats or vegetation types is particularly important for habitats of restricted distribution or which are highly threatened (Gonçalves et al., 2016), where accurately mapping their distribution and changes over time, can be used to evaluate their conservation status (Baena et al., 2016). This can also be used for determining the specific habitat niche of rare or endangered species (Bartel and Sexton, 2009).
- Assessing the condition of individuals or the wider vegetation and the extent of the damage caused by specific diseases, is of considerable interest for plant conservation. Modified cameras recording in the near infrared part of the spectrum are particularly useful and have been successfully employed for plant health studies

Table 1
UAV related issues by country. please note that regulations and permission are changing rapidly across the world.

Country	Permits	Customs	Regulations	Obstacles
UK (Wakehurst palace)	Land owner and within regulations	n/a	Within 500 m, below 120 m and within sight only	–
UK (RGB, Kew)	Within Heathrow flight path. UAV flight not practical	n/a	Not allowed	–
Peru	None needed, but Land owners permission given	20% of value and permission to import ($2000 deposit and 4 days to get paperwork)	None for flight, permission for used of radio equipment need	Birds of prey, Magnetite
Cayman Islands	CAA, permission given, land owners permission given	Letters from partners	Within sight	Landing limited, weather conditions, Bird of prey
Burkina Faso	Insurance cover refused	–	–	–
TCI	CAA, permission given, land owners permission given	Declaration needed	Within sight	Landing limited, weather conditions
South Africa	CAA refused	–	–	–
Brazil (acre)	UAV registration needed	Before arrive online declaration needed	Within sight and below 120 m	Overheating electronics at mid-day.

in fields such as forestry (Lehmann et al., 2015; Näsi et al., 2015) and precision agriculture (Candiago et al., 2015; Garcia-Ruiz et al., 2013).

- Modeling and measuring vegetation structure plays a major role in plant conservation. The rapidly developing “structure from motion” algorithms (Dandois and Ellis, 2010) can be used to derive three-dimensional information (in the form of point clouds) from UAV images. This can be used to generate models of canopy structure and therefore to assess floristic biodiversity (Getzin et al., 2012), but also to define ecosystem services such as carbon storage (Paneque-Gálvez et al., 2014) and derive the economic values of forests and woodland ecosystems bearing plants species of high conservation value for local communities (Wallace et al., 2014b).

2.3. Monitoring

This is possibly one the most promising applications of UAVs for plant conservation. By detecting and measuring change, UAVs allow for responsive and timely conservation interventions as well offering a flexibility and temporal resolution suited for many plant conservation applications (Anderson and Gaston, 2013; Zhang et al., 2016). An area can be revisited repeatedly before, during or after critical events. This provides an extremely efficient means to monitor both human induced changes (with negative environmental consequences as well as interventions for protection and restoration), as well as those related to natural events (e.g. seasonality and climate change) (Pimm et al., 2015).

3. UAV: the system and the imaging process

The UAV used in this study was an off the shelf fixed-wing UAV (senseFly eBee) (Figure 1). It has a delta wing shape and has efficient aerodynamics that allows for flight times of a maximum of 45 min. Up to 10 km^2 can be surveyed during this flight duration. This contrasts with manual field surveys where in a relatively simple, open, flat and dry forest in Peru it can take over 4 h to fully survey manually a 0.01 km^2 plot. Moreover, the system can be deployed and work some distance from the ground station (as much as 10 km, dependent on local rules and regulations), making it potentially invaluable in many remote environments.

The UAV can be equipped with an automatic consumer-grade digital camera which can be easily changed on the ground to the most appropriate camera, for the needs of the area and survey. We have successfully used a Canon S110 to acquire image data in the visible part of the spectrum (three bands in the blue, green and red), but also modified cameras such as S110 NIR and S110 RE to collect images in the Near Infra-Red (NIR) and Red Edge parts of the spectrum (Fig. 4a). The modification of consumer cameras to allow NIR and Red Edge detection consists of removing the original internal NIR filter and adding specific band-pass filters (Lebourgeois et al., 2008) therefore these extra spectral bands, replace either the red or the blue bands.

There is much associated technology beyond the aircraft themselves, which is needed to consider allowing successfully deploy and utilization of UAVs. The ground control station (Fig. 1c), comprises transportable hardware/software devices to monitor and command the UAV (Colomina and Molina, 2014) is set up on a ruggedised portable computer using Emotions (Emotions 2.1 Sensefly) for the flight management and planning. Even though the UAV can fly autonomously (flight path is preloaded before take-off) the software allows for changes in the flight path of the UAV to deal with payload sensor errors or emergencies that may occur during the flight. Other equipment often used for ground control (either at the time of the flight or post/pre-flight) are digital data collection devices, Android phones or tablets with ODK (ODK Collect, OpenDataKit) and Locus pro (Locus Pro™) software in our case, and a Bluetooth GPS (Garmin Glo) to record the accurate locations of features which will can be used to geolocate the resulting images. In cases where there is lack of clearly identifiable features we put out recognisable objects on the ground (such as Cornish flags).

The gain in flexibility offered by UAVs has been highlighted in previous studies (Anderson and Gaston, 2013; Koh and Wich, 2012). Within reason (subject to rain, winds, etc.) the system can be deployed on demand to respond to specific requirements (i.e. after rains, planting or restoration, or seasonally or during different times of the day). Moreover, the flight heights and therefore the spatial resolution can be adjusted providing potential ground resolutions from 2 to 32 cm depending on country regulations. UAVs can be extremely flexible and cost effective in capturing high resolution earth observation data. The cost of commercial UAV are in the range of $13k, but DIY kits and open source software can reduce this cost to a few thousand dollars (and possibly $100s). Comparing this to the costs of high resolution satellite imagery, which is in the region of $33 per km^2 or the much more expensive aerial surveys, costs can be quickly recuperated. A summary of specific UAV operational issues the authors have encountered in

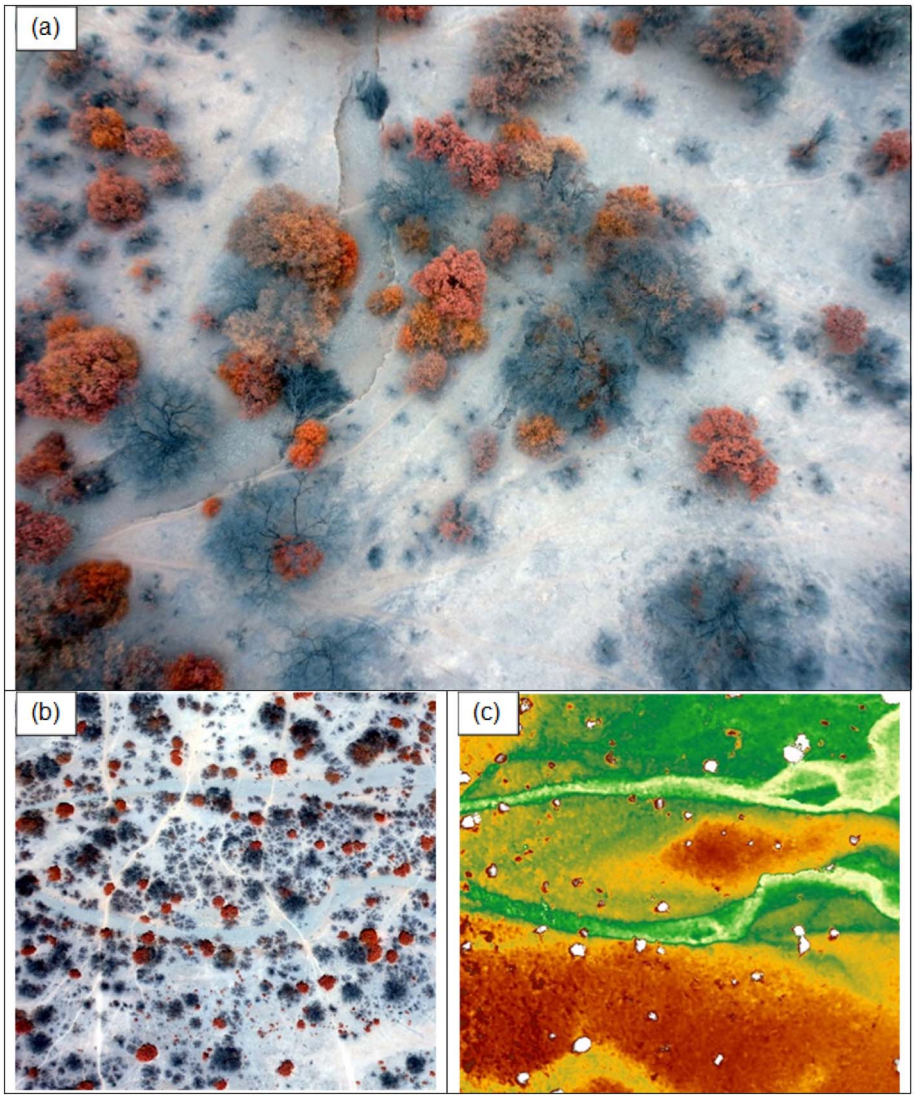


Fig. 2. Forests reserves for the local community (Northern Peru). Identification, measuring the abundance and distribution of plant species throughout the landscape as well as the temporal monitoring of forest condition and the restoration efforts are the main applications of UAVs in this area. Vegetation structure (3-D models of the vegetation) also plays a major role in the identification of individual species. (a) Red edge image. (b) Red Edge image alongside 3-D model (c) DSM (Digital Surface Model). (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

different countries is presented in Table 1.

4. The use of UAVS in plant conservation projects – real world experiences

Throughout the world, The Royal Botanic Gardens, Kew (and partners) have implemented a broad range of plant conservation projects. Many of these have greatly benefited from the use of UAVs to derive valuable plant conservation information:

1. Forests reserves for the local community (Northern Peru): Focusing on *Prosopis pallida* (Algarrobo) and in the context of a highly-threatened ecosystem, this project aimed to preserve and restore the native Algarrobo forest for local communities. Novel information on species composition and population dynamics have been used to develop sustainable livestock management strategies and assess their socio-economic impacts. High spatial resolution UAV images, multispectral information (including the Red Edge band), and three dimensional models of the vegetation were used to identify and measure the abundance of different species throughout the landscape (Fig. 2). This information proved crucial to targeting restoration and reforestation efforts and to monitor outcomes.
2. Relict forest and biodiversity networks (Southern Peru): The dry forest and ecosystems of southern Peru have undergone a prolonged process of deforestation and only small forest relicts remain. These ancient trees still provide most of the genetic resources and biodiversity necessary to restore forest and associated habitats. The aim of the project was to conserve these sites under a protected area network (PAN). UAV images were used to provide detailed mapping and delimitation of relict forest sites and to identify and quantify enduring ancient trees and their health (Fig. 3). This information was essential for the development of the PAN and to co-ordinate restoration and monitoring activities.
3. Caicos pine recovery project (Turks and Caicos Islands). The endemic and vulnerable Caicos pines (*Pinus caribaea*) have been devastated by the attack of the non-native invasive tortoise scale insect (*Toumeyella parvicornis*). This project aimed to halt the extinction of the Caicos pine forest, delivering a strategy to restore pine habitat. The full multispectral potential of the UAV system was used, flying the pine areas repeatedly using all available cameras to provide a complete picture of the damaged caused by the scale insect in the endemic population of Caicos pines (Fig. 4). Results show that less than 10% of Caicos pines have survived. A monitoring system has been put in place to ensure the conservation of remaining population as well as to facilitate restoration activities.
4. In pursuit of the 'lost' Mistletoe (Cayman Islands). The aim of this research was to try and locate a potentially extinct plant species (*Dendropemon caymanensis*) which was last seen in 1991, known to be located only in Little Cayman. This Mistletoe is a parasite on the Headache Bush (*Capparis cynophallophora*) and the Black

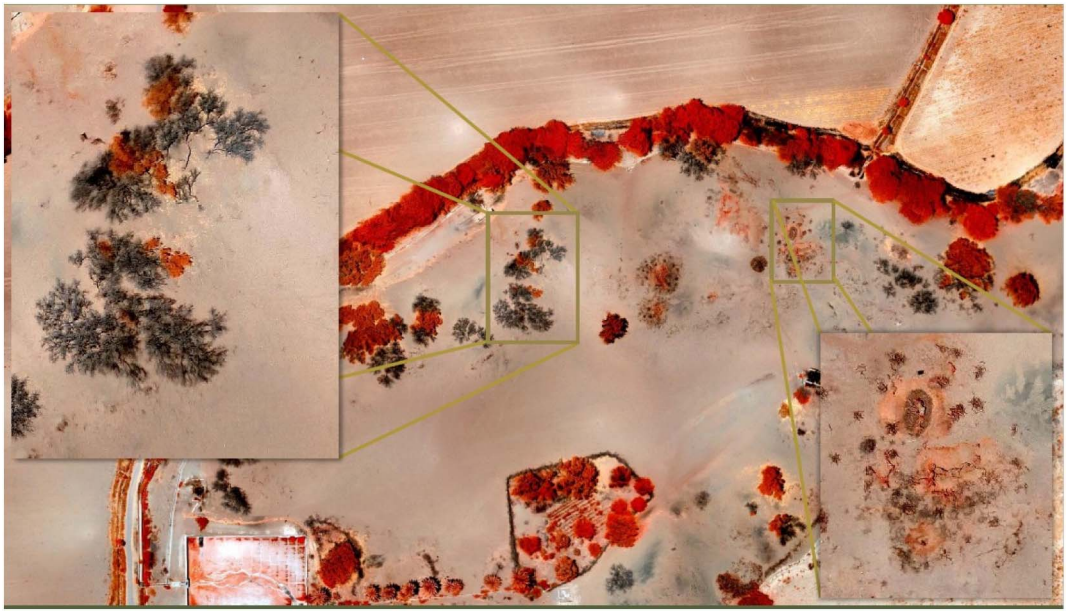


Fig. 3. Relict forest and biodiversity networks (Southern Peru). UAV data was used as baseline images for mapping and measuring the extent of a specific habitat (relict forest). Thorough visual interpretation ancient trees were identified, the level of health quantified.

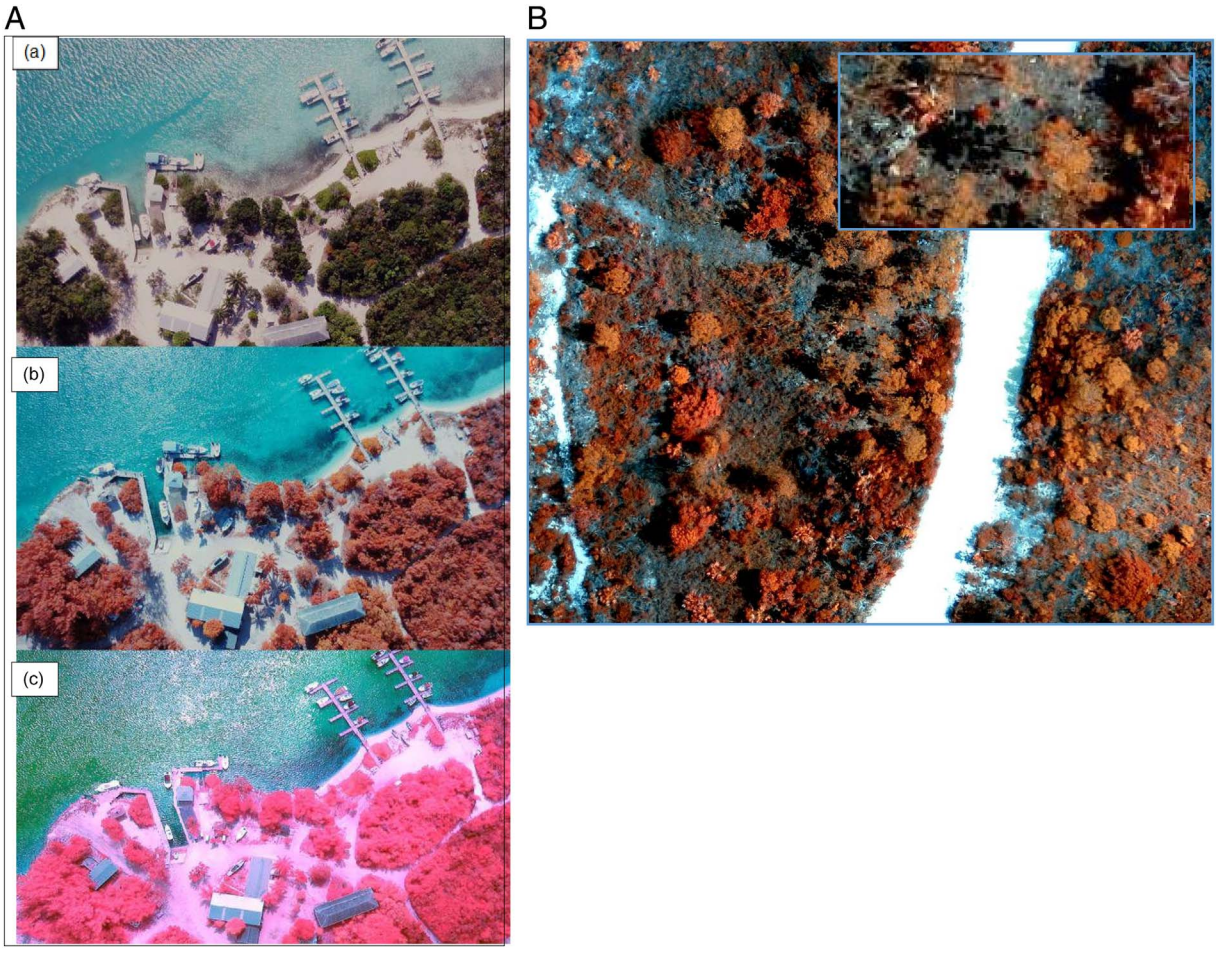


Fig. 4. A: Caicos pine recovery project (Turks and Caicos Islands). 3 different sensors (a) visible: red, green and blue. (b) Red edge camera: green, blue and red edge. (c) NIR camera: green, red and near infra-red.
B: Caicos pine recovery project (Turks and Caicos Islands). Red edge imagery of infected pine forest. Health pine trees show up as light orange (with a feathered texture). Insert shows close up of pine trees, where the shadow has a distinctive pine outline. A first assessment of the forest condition and plant health was carried out using UAV derived images, measuring the current extent of the scale damage. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

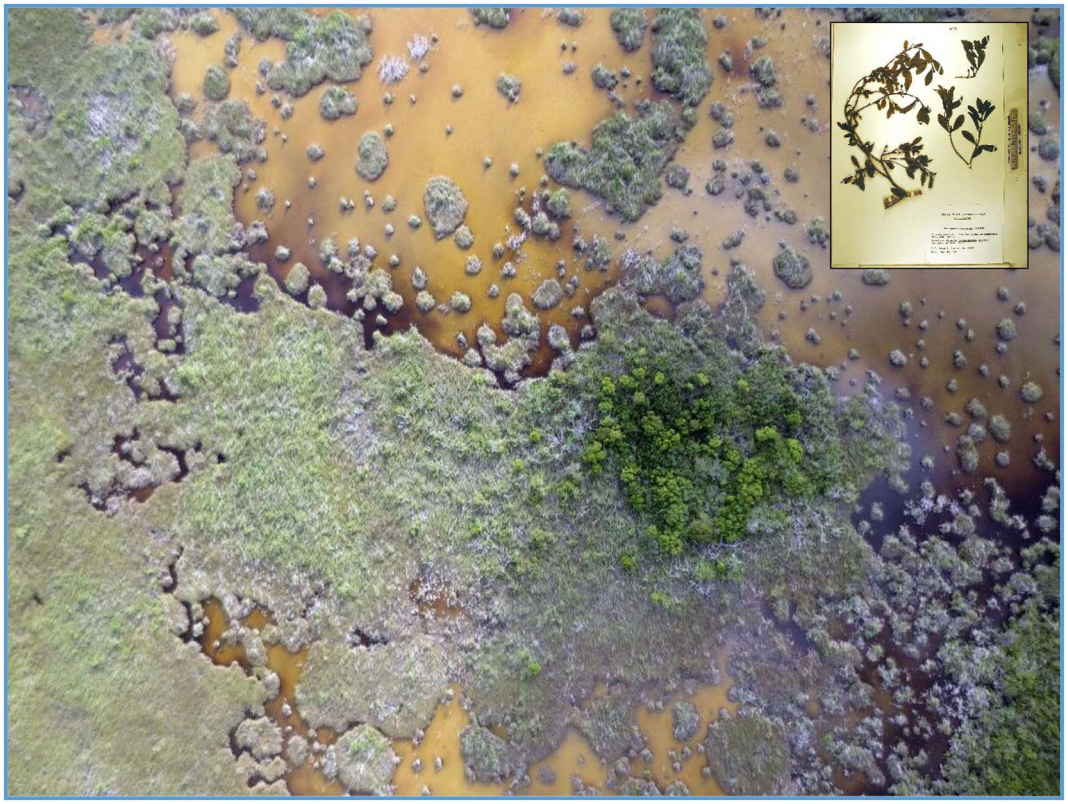


Fig. 5. In pursuit of the "lost" Mistletoe (Cayman Islands). UAV images used for discovery; areas of Headache Bush and Black Candlewood are visually identified as candidate sites for finding the "lost" Mistletoe.

Candlewood (*Erithalis fruticosa*) which grow in remote areas with very difficult access. This area represents one of the most challenging sites visited, where field work can be impracticable. UAV's are used to locate candidate sites where *D. caymanensis* may be found to direct plant discovery expeditions (Fig. 5).

5. Kew and Wakehurst Place: test sites for conservation work (UK). The grounds at Kew's country estate at Wakehurst Place were used as test sites to develop novel technical developments using different sensors and data analysis techniques for UAV derived images. These will be integrated into future plant conservation applications. Images of the whole gardens were successfully collected (Fig. 6) at very high resolution (4 cm) allowing three dimensional models to support infrastructure planning, landscape design and interpretation for the public
6. Integrating UAV's remote sensing and ground-based spectral analysis to investigate biodiversity of archaeological sites in Amazonia (Brazil). The aim of this project was to use UAVs to investigate historic anthropic impacts on biodiversity in the Brazilian Amazonian rainforest. Here data from UAV surveys (multispectral images and derived three-dimensional data), was integrated with ground LiDAR, ground spectral analysis and traditional plot surveys. The analysis of these data will enable to assess the impact of past human activity on biodiversity, with the aim of extending these finding to the investigation of the human footprint within the wider landscape.

Other areas of potential use for UAVs but where local conditions were not favorable:

1. Strydom's yam Conservation Initiative (South Africa): *Dioscorea strydomiana* is a critically endangered and recently discovered yam from South Africa, with only two populations recorded in the wild (of about 200 individuals). The project aims to enhance the limited conservation measures already in place, by using innovative technology to produce highly accurate maps of known populations and potentially discover other populations in the wild. Unfortunately, due to South African ban on the use of UAVs, the area has not yet been surveyed with UAVs.
2. The Great Green Wall for the Sahara and the Sahel Initiative (Burkina Faso): This is a pan- African initiative launched by the African Union aiming to reverse land degradation and desertification in the region. Restoration of agro-sylvo-pastoral landscapes using environmentally well-adapted plant species is one of the priority interventions which will need close monitoring and reporting, for which it was hoped UAVs would be extremely useful. Burkina Faso is one of the first countries to be involved and attempts have been made to take the UAV system in country, but the Burkina Faso UAV work failed a risk assessment process (and was therefore uninsurable) as it was at the time classified as high-risk area by the UK foreign office.

5. Summary of issues

This paper aimed to demonstrate the current and future potential use of UAVs in plant conservation. We believe that developing these applications will further open-up new lines of research focusing on the specific needs of the conservation of plants. This is something the plant conservation community could greatly benefit from. However, we have also shown that UAVs do not offer immediate results and the associated permissions and processing activities should not be underestimated. UAV flying regulations, insurance, bureaucracy and extra costs need to be allowed for in project planning, as well as the need of many dependent accessories and low endurance battery issues.

The radiometric and geometric quality of collected data also needs careful consideration. Accurate ground control points need to be surveyed to ensure the final geometric accuracy of the image products.



Fig. 6. Wakehurst place (Royal Botanic Gardens, Kew): test site for UAV conservation work (UK). Different tools and techniques are tested here before being applied in other countries.

Additionally, radiometric calibration should be considered to allow for variation in angular illumination. This ensures data comparability over time and space (Aasen et al., 2015). Finally, UAV surveys because of their inherent high spatial resolution, produce copious amounts of data which need to be processed, therefore, appropriate data processing capabilities also need to be planned for (Torresan et al., 2016).

6. The future

Regardless of the issues presented in this paper, the underlying technology for UAVs is developing rapidly and legislation on its use is coming into place. The reliability and convergence of technologies (i.e. convergence of ground stations, sensors and aircraft technology) is improving, making UAVs safer and of higher endurance (better batteries, motor, lighter weight and power management). The addition of vertical take-off and landing (VTOL) and collision avoidance system are providing additional functionality, as well as increased automation of the systems. Advances in the accuracy of GPS systems will also increase drone safety, as well as image geometric fidelity (Chiang et al., 2015).

Sensor technology is also moving rapidly, increasingly becoming smaller and more accessible (both in costs and function). Beyond simple cameras, we are gradually seeing UAVs carrying Hyperspectral sensors (Aasen et al., 2015), LiDAR systems (Guo et al., 2017) and more elaborate sensor systems such as radio waves (Chen and Ho, 2016), Radar (Gromek et al., 2016) and even electronic noses which can ‘sniff’ the air for chemicals signals (e.g. particulates and pheromones.) (Pobkrut et al., 2016). In addition, we have more environmental sensors which allow light, radiation, sound, temperatures and humidity to be measured. Gravity and magnetic fields can also be logged giving an insight into the soil and geology of the environment (Anderson and Pita, 2005).

Finally, with the addition of automation, where the UAV is controlled by its on-broad computer (using all of its sensors), UAVs have the potential for moving from sensing the environment to interacting with the environment. Recent examples have been proposed for tree and seed planting, pest detecting and eradication, and the collection of plant specimens from remote or dangerous areas (Bergerman et al., 2016). The next generation of UAVs offer enormous potential for plant conservation, but will require to have adequate and flexible legislation in place.

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3. Paper 3: Mapping and identifying species from the air: The very high resolution challenge for plant conservation

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PLOS ONE

RESEARCH ARTICLE

Identifying species from the air: UAVs and the very high resolution challenge for plant conservation

Susana Baena[1,2]*, Justin Moat[1,2], Oliver Whaley[1], Doreen S. Boyd[2]

1 Royal Botanic Gardens, Kew, Richmond, Surrey, United Kingdom, **2** School of Geography, University of Nottingham, Nottingham, United Kingdom

* s.baena@kew.org

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Abstract

The Pacific Equatorial dry forest of Northern Peru is recognised for its unique endemic biodiversity. Although highly threatened the forest provides livelihoods and ecosystem services to local communities. As agro-industrial expansion and climatic variation transform the region, close ecosystem monitoring is essential for viable adaptation strategies. UAVs offer an affordable alternative to satellites in obtaining both colour and near infrared imagery to meet the specific requirements of spatial and temporal resolution of a monitoring system. Combining this with their capacity to produce three dimensional models of the environment provides an invaluable tool for species level monitoring. Here we demonstrate that object-based image analysis of very high resolution UAV images can identify and quantify keystone tree species and their health across wide heterogeneous landscapes. The analysis exposes the state of the vegetation and serves as a baseline for monitoring and adaptive implementation of community based conservation and restoration in the area.

1. Introduction

The Pacific Equatorial dry forest of Northern Peru (and South Western Ecuador) is recognised as a unique dry forest ecosystem, rich in endemic flora and biodiversity [1]. The region is a vital and unique ecosystem within the Latin American biome of seasonally dry tropical forest and that is one of the most threatened, and yet understudied and very poorly surveyed, tropical forests worldwide with less than 10% of the original extent remaining regionally [2]. The Equatorial dry forest of Peru also provides a wide range of livelihoods and ecosystem services to local communities [3]. However, agro-industrial expansion, over-exploitation of natural resources (for firewood and agriculture land) and climatic extremes (e.g., ENSO events) has left forest relicts and a mosaic of associated arid land vegetation which are now highly threatened and vulnerable [4]. Furthermore, over the last ten years the forest has been experiencing die-back of its keystone species: the Algarrobo (*Prosopis pallida*) upon which communities and livelihoods have historically depended [5]. This is likely due to the combined impact of drought, associated climate change and defoliating plagues, especially *Enallodiplosis discordis* (*Diptera*: *Cecidomyiidae*). The Algarrobo has been the lynch-pin of rural livelihoods as a

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multipurpose tree [6] providing an annual rich harvest of nutritious pods that are used for food and especially for animal forage, as well as a foodstuff for human consumption. Of particular note is that the Algarrobo pods are an essential forage component that allows the ranching of animals on the very poor soils with limited water that prevails in this area. Conversely, other species such as Sapote (*Colicodendron scabridum*) and Overo (*Cordia lutea*) appear to be thriving, possibly due to atmospheric CO_2 enrichment and increasing temperatures [7], especially during summer rains with the free nitrogen released from *Algarrobo* die-back [7].

A highly complex and dynamic ecosystem now exists that requires close monitoring to quantify change and respond effectively with adaptation strategies in order to manage the decline in Algarrobo-dependent biodiversity and sustain community livelihoods. In this context a monitoring system needs to be capable of the following: (i) identifying individual tree species across the landscape; (ii) mapping species association and plant community whilst assessing plant health and (iii) quantifying population dynamics in response to ongoing land management and climate change. Such monitoring is essential from a scientific perspective (e.g.to target and design restoration and reforestation efforts to preserve and restore the native forest relict), but must also be able to communicate to stakeholders the best actions (such as changes in seed banking, reforesting options, irrigation and livestock management) to maintain resilience of ecosystem services. Specifically, the monitoring system must provide spatial data on the principal keystone species, *Algarrobo* (including on their current mortality rates), as well as on *Sapote* other dominant species and do so in a timely fashion.

This detailed ecosystem assessment has traditionally been carried out through field survey, but collection of field data is costly in time, labour and resources [8] and so remote sensing has been much advocated as an approach, as it can characterise an ecosystem in an efficient, systematic, repeatable and spatially exhaustive manner [9]. Remote sensing based ecosystem assessments can be conducted at a range of spatial scales, from global [10–13] to more localised studies [14–19]. However, discriminating between species and quantifying individual plants using remote sensing requires specific acquisition parameters (e.g., data at a sufficient resolution) and processing approaches. Very high spectral resolution (hyperspectral) data have been successful in the identification of canopy tree species [20–23]. Alternatively, very high spatial resolution data is perhaps more accessible and has the potential to be a viable tool for species determination [24–26]. Further, since species identification can be greatly improved by employing the three dimensional information of the vegetation, technologies affording three dimensional measurements (e.g., light detection and ranging (LiDAR) technology) have been widely used [27–30]. However, in all these cases, the costs and availability of the technology would be financially and structurally prohibitive for most conservation efforts [31], yet the potential of remote sensing to support conservation effort has been recognised [32] (Rose et al., 2014). In this paper, we investigate the effectiveness of remote sensing from unmanned aerial vehicles (UAVs) which have the potential to provide accurate and fast analysis and monitoring of ecological features at a cost [33] that can be accessible to most conservation applications and researchers in developing countries [34].

The use of UAVs as a remote sensing approach is now gaining traction. These type of systems are especially well suited to and most commonly used for precision agriculture where the technology is developing fast [35,36] but they have also been employed in different ecological [33], environmental [37] and conservation [34] applications where UAV systems have been identified to have the potential to revolutionize these fields [33]. Low altitude flights can easily provide the sub-meter spatial resolution that allows individual plants to be identified [38]. Also, different sensing payloads can deliver multispectral images, ranging from the visible (RBG) band, to the near infrared (NIR) through to the thermal infrared and microwave [39] although often, because of the low-cost requirements and limited weight capabilities of these

systems, modified consumer digital cameras are used [40], with enhancement to their spectral resolution by using or removing filters to provide RBG and NIR bands [41]. Three dimensional information can be derived from overlapping images taken with uncalibrated consumer-grade cameras using newly developed algorithms [42], in particular structure from motion [43,44], providing extra valuable information on vegetation structure and condition. Moreover, the system can be deployed on demand, providing temporal flexibility to respond to specific needs such as seasonal or climatic circumstances (e.g., an El Niño event) or to monitor interventions (e.g. tree planting or cattle exclusion) [45].

Despite the promise offered by using UAVs, obtaining meaningful ecological information from the captured data remains challenging and so far has predominantly relied on visual interpretation of the imagery acquired, particularly when it comes to quantifying number of individuals [33]. This can be very time consuming and become unfeasible in larger areas with large number of individuals. Further, traditional pixel-based image analysis techniques have limitations when processing such high resolution datasets [46,47] where image targets (such as individual trees) are larger than the pixel size. Combining pixels into groups to form objects could be a way forward to analysing this type of data. Additional spectral information contained in an object (e.g. mean spectral values, variance, mean ratios. . .) can be taken into account along with added spatial and contextual information for the objects (distance, shapes, size, texture, etc.). The inclusion of this extra information is critical when uncalibrated consumer-grade digital cameras are used as these imaging sensors acquire images that have high spatial resolution but lack radiometric quality [48]. Thus object-based image analysis (OBIA) techniques have demonstrated great potential to automatically extract information from very high resolution images [49,50], including those captured by UAVs [51,52].

In this paper we present an efficient and affordable approach to identify and quantify individual trees across the dry forest, as well as mortality rates of its keystone species. We seek to add weight to the growing evidence on the real potential of UAV's for plant conservation, with the view that this could form the foundation of a monitoring system across this particular landscape.

2. Materials and methods

2.1. Study area

The community forest (comunidad campesina) of San Francisco de Asis (CCSFA) in the Lambayeque region in Northern Peru was the focus of investigation (Fig 1). Full permission to carry out UAV flights and botanical collections in the area as part of this study was granted by the president of San Francisco de Asis Community forest. The CCFA is delimited by a low mountain range and it is one of a series of arid slopes and a dry lower watershed basin on the western side of the Andes. Rainfall is very low and rarely exceeds 400 mm (except during some El Niño events), generally falling between December to April. UAV data were captured for an 80 ha area (centred on 79˚ 38'W, 6˚ 20' S, datum WGS84) within the proposed CCSFA community reserve.

The arboreal vegetation associated with the study area is dominated principally by *Prosopis pallida* (Algarrobo) with *Colicodendron scabridum* (Sapote), and *Cordia lutea* (Overo) as a shrub which occurs ubiquitously along the network of ephemeral run-off streams that transverse the bajada (Fig 2). *Vallesia glabra* (Cun cun) occurs as a *Prosopis pallida* sub canopy shrub, and amongst this vegetation, at low density occur *Cynophalla flexuosa* (Sune)—2–5 individuals per ha, *Grabowskia boerhaaviifolia* (Canutillo or Palo negro) occasionally and *Parkinsonia praecox* (Palo verde)—4–10 individuals per ha. At very low density on the lower plain at less than one tree per 5 ha are *Loxopterigium huasango* (Hualtaco) and *Bursera graveolens*

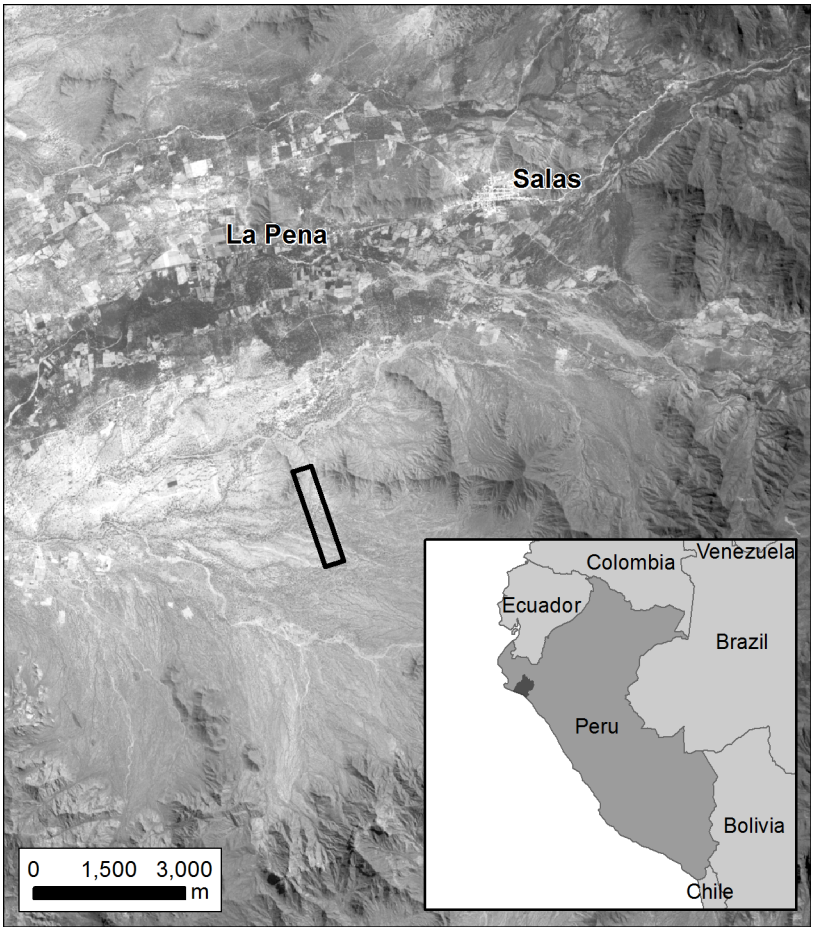


Fig 1. Study site and country map: Country map shows the Peruvian region of Lambeyeque. Main map for context, UAV flight is highlighted in black, overlaid with a Landsat Panchromatic image.

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(Palo santo), and relict large columnar cactus *Armatocereus* aff. *cartwrightianus* and *Neoraimondia arequipensis*).

In this study and for the purpose of identification from UAV images the focus will be on the dominant species. Each of these plant species have a morphology that could help in any identification using remotely sensed data, such as that captured by an UAV. As such, there are several important plant features that can be used for identification of each of the species of interest (Fig 3):

Algarrobo *(Prosopis pallida)*.: This is a non-deciduous tree of up to 15 meters high with a very distinctive star shaped crown when viewed from above. This distinctive shape is modified as a result of the dieback affecting this keystone species.

Overo *(Cordia lutea)* that could get misclassified as *Prosopis pallida* when observed from above but can easily be distinguished as it is deciduous and only up to 2 meter high. It grows along runnels forming a distinctive reticulated pattern

Sapote *(Capparis scrabrida)*: This evergreen tree is very distinctive with compact and round or sub oval shaped crown with large sclerophyllous leaves. It tends to grow partitioned and isolated, this feature is exaggerated in this site through the use of the dense shade for cattle sheltering the extreme midday heats.

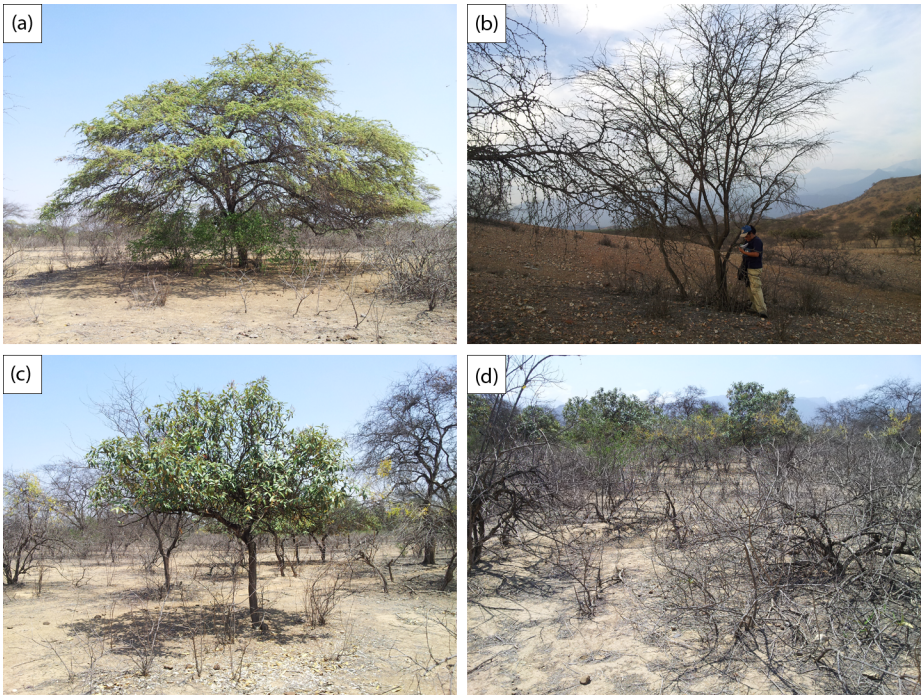


Fig 2. Target species: (a) Alive Algarrobo (b) Dead Algarrobo (c) Sapote (d) Overo.

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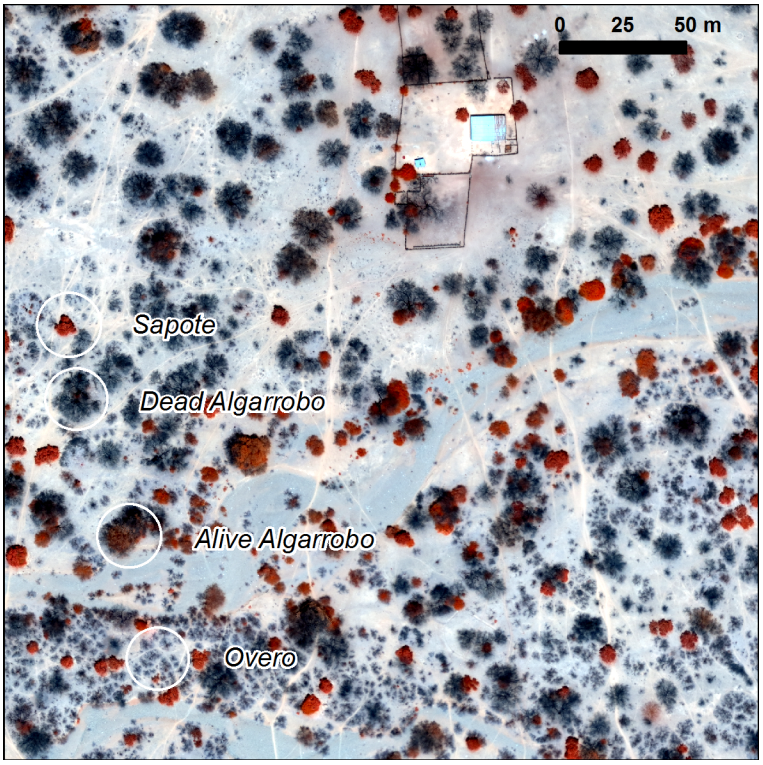


Fig 3. Target species from the UAV image.

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2.2. Datasets: Remote sensing with UAV and supporting ground data

The UAV deployed was the fixed-wing eBee system (https://www.sensefly.com/). This autonomous system is operated by a propeller activated by an internal electric motor. It requires hand launch for take-off and landing is either linear or circular in a relatively clear area (i.e. bare ground or grass). Its efficient aerodynamics allows for long flight durations and high speeds. It can cover up to 12 Km^2 in a single flight and by altering the flying altitude can be used to acquire very high resolution images (i.e. up to 1.5 cm). The imaging sensor used on board was a Canon S110 RE, a customised very light automatic consumer-grade digital camera providing blue, green and red-edge band data. The red-edge band data is obtained by adding an optical red-light-blocking filter in front of the sensor, resulting in red-edge, green and blue images [41]. It has a resolution of 12 MP with a ground resolution at 100m of 3.5 cm/px. The sensor size is 7.44 x 5.58 mm with a pixel pitch of 1.86 um. The UAV was deployed during the dry season (November) to ensure maximum discrimination between deciduous and evergreen vegetation. The flight mission was planned using eMotions software over images imported from Google Earth (Google Earth, 2011) and SRTM DEM [53]. Flight altitude was set up to 260m to provide a ground resolution of approximately 8 cm over the study area and images acquired at 75% forward overlap and 80% side overlap. The ground resolution of 8 cm was chosen to provide ultra-high resolution (both in the resultant point cloud and mosaics), but also to cover a large enough area to include established control plots and demonstrate the benefits of UAV monitoring. The high level of overlap allows 3D reconstruction of point clouds to a higher accuracy, allowing objects in each image to be observed in at least 5 other images and thus affording structure from motion analysis.

Temporally coincident to the UAV flights, four experimental plots were measured. These 1 Ha (100m x 100m) plots were evenly distributed spatially across the study site (Fig 4) recording the presence and species of every mature tree with (> 25 cm girth at 50 cm high) along with the average crown spread. For every *Algarrobo* tree the "degree of health" was also recorded on a 1 to 3 scale (1: healthy tree, 2: infected tree, 3: dead tree). For the shrub layer, presence of *Overo* was recorded where it covered an area of more than 4 square meters (2 x 2 m). In addition, a discontinuous transect throughout the length of the flight (2 Km length by 0.4 Km wide) was surveyed, recording the species of every tree found.

2.3. Pre-processing of remotely sensed data

The raw UAV- derived remotely sensed data were processed using eMotion's Flight Data Manager and Postflight terra (Pix4D) software to produce a geo-referenced orthorectified 3 waveband image mosaic at 8.3 cm spatial resolution (UTM 17S WGS84) and two 3D-derived elevation layers: a digital elevation model (DEM), a representation of the elevation of the ground surface or bare-earth, and digital surface model (DSM) which includes the elevation of both natural and built features. Both layers are delivered as grids with a resolution matching that of the orthorectified mosaic. Both were then used to derive a canopy height model (CHM) of the study area.

2.4. Species mapping from UAV data

Mapping of the target species (Algarrobo, Sapote and Overo), as well as mortality rates of the keystone Algarrobo was undertaken in two steps. The first was to identify individual trees by delineating crowns and the second was to use the individual tree crown as the basic unit for species identification [54]. Object-based image analysis provided the tools to do just this by allowing the isolation of individual homogeneous objects in the image corresponding to one particular tree crown [47]. Unlike most studies in which crowns are delineated in one single

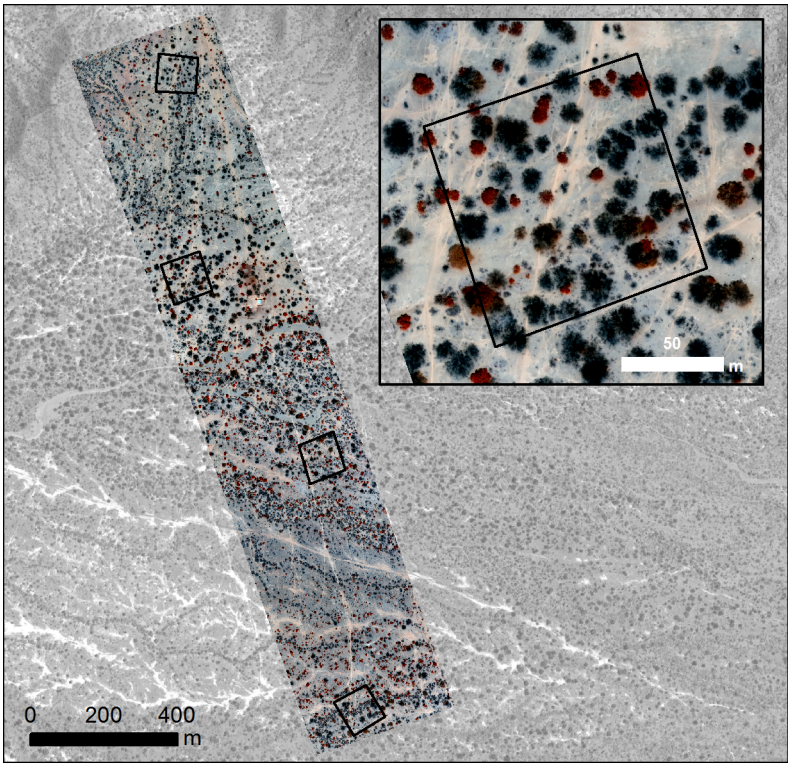


Fig 4. UAV flight (red edge) over the study area and plot distribution (from top to bottom: Plots 1, 3, 4, 2). Background image: panchromatic World View image.

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segmentation process, crown delineation here is achieved by the iteration of segmentation and classification of subsequent segments working at two different levels. A first level aims to isolate individual trees from tree clusters across the landscape using contextual information. At a more detailed second level, individual crowns are identified within these tree clusters using two different approaches according to vegetation types. This allowed for a more efficient methodology focusing processing efforts only where it is most needed, as well as using the best suited methodology for each specific vegetation type. Fig 5 and Table 1 include the methodology workflow and main processing parameters.

Crown delineation. Level 1 (vegetation or contextual level): Firstly a multiresolution segmentation algorithm (using eCognition software) was used to create the basic image objects at a scale that allows for objects to be relatively homogeneous whilst capturing the full scene variability. These "object candidates" [55] will be transformed by further processing into meaningful objects (individual tree crowns). Vegetation is then discriminated from the background by thresholding available band ratios (from Blue, Green and Red Edge bands). Green vegetation is best discriminated using a band ratio, deviation from the normalised vegetation index (1) whiles the non-photosynthetic vegetation (deciduous and dead vegetation) using a combination of the blue and green bands (2).

1. GV (Green Vegetation) = (RE–Green) / (RE + Green)
2. NPV (Non-Photosynthetic vegetation) = (Blue–Green) / (Blue + Green)

Objects classified as vegetation were then combined and reclassified as either isolated trees (individual tree crowns) or tree clusters according to contextual object features (extent and

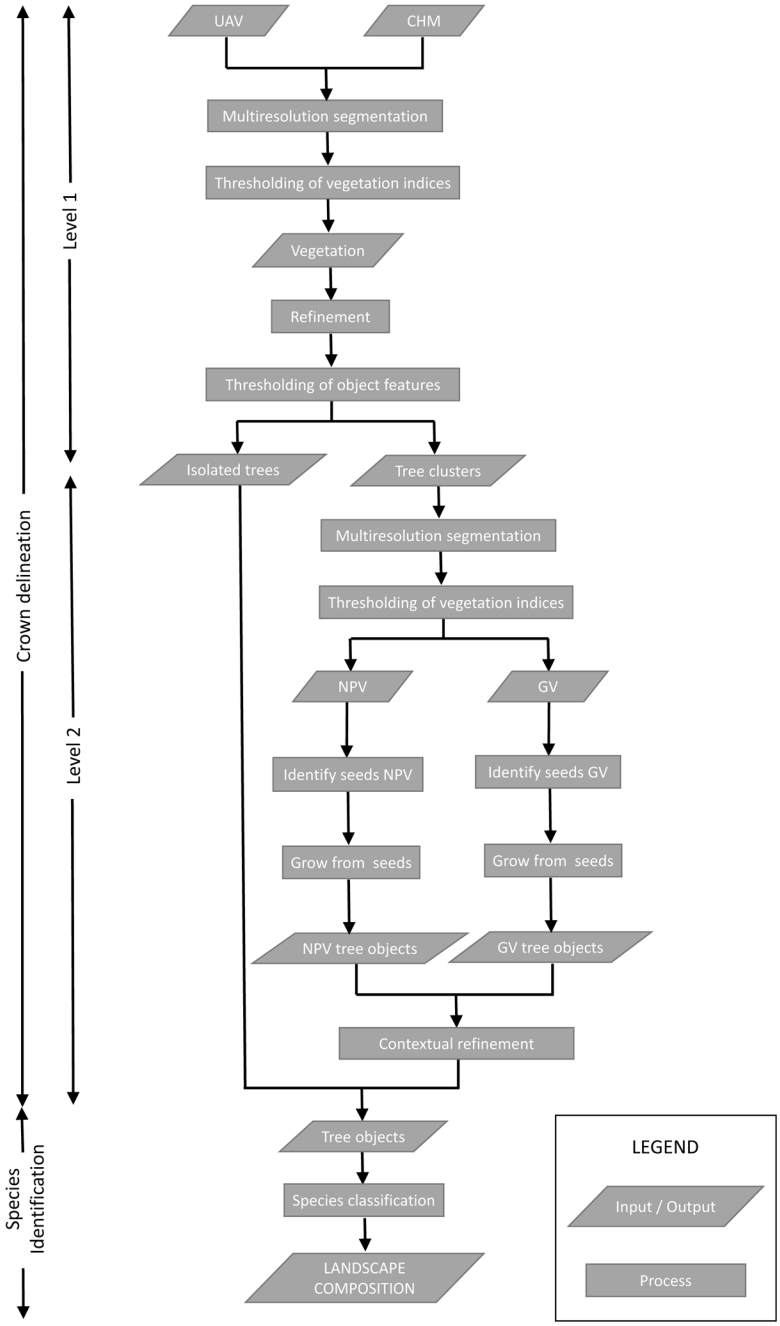


Fig 5. Methodology work flow.

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shape). Vegetation objects smaller than the minimum mapping unit ($4m^2$) are not considered for further analysis. Tree clusters were then need to be further analysed (level 2, see below) to extract individual trees within them.

Level 2 (de-clustering): Most tree crown delineation studies are built around the identification of treetops, assuming that they are at a maxima (most often using CHMs) and that they correspond to the geometric centre of the tree crown [56]. This is normally the case in coniferous trees and can be extended to evergreen vegetation but deciduous tree crowns (and this is

Table 1. Summary of processing parameters.

Level	Operation	Algorithm/Object metrics	Parameters	Value
L 1	Multiresolution segmentation		Layer weights	1 (B) 1 (G) 1 (RE) 1 (CHM)
			Shape	
			scale parameter	
			Compactness	
	Thresholding of vegetation indices		NPV	>0.053
			GDVI	>0.03
	Refinement	Merge Region	Vegetation	
		Remove objects		
		Merge Region		
		Find enclose by class		
		Merge Region		
	Thresholding of Object Features	Roundness	<0.9	
		Area	<30,000 pixels	
L 2	Identify seeds (NPV)	Find local extrema	Search range	20
			Extrema type	Maximum
			Feature	Mean DSM
	Identify seeds (GV)	Find local extrema	Search range	50
			Extrema type	Maximum
			Feature	NPV
	Grow from seeds	Grow region		
	Contextual Refinement	Relative border to		
		Find enclose by class		
		Remove objects		
	Species. Classification (Sapote)	Assign class	GDVI	>_0.08
	Species. Classification (Alive Algarrobo)	Assign class	GDVI	< 0.08
	Species. Classification (Dead Algarrobo)	Assign class	Area	>_10,000 pixels
			NPV	> 0.053
			CHM	>0.4
	Species. Classification (Overo)	Assign class	Area	< 10,000 pixels
			NPV	> 0.053
			CHM	< 0.4

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also the case for defoliated evergreen vegetation) are relatively flat and with multiple branches that can be identified as individual trees [54]. This, added to the challenges presented by drone derived elevation data in deciduous trees prevents the use of CHM local maxima to identify hardwood tree tops. In this case, tree centres are identified using NPV local maxima. Green vegetation was very clearly identified in the elevation model therefore a more traditional CHM local maxima was used to identify tree tops.

Once tree tops have been identified, a region growing algorithm was used to delineate the respective tree crowns [57]. A further step using contextual information was then needed to refine certain tree crowns, such as infested Algarrobo which were in certain cases identified as two different trees (dead branches adjacent to branches with different levels of defoliation). The feature "relative border to" (measuring the relative border length that an object shares with neighbour objects) was particularly useful for this purpose.

Species identification. Once the crowns have been delineated, individual trees have additional spectral information as opposed to single pixels (eg. mean values, maximum and minimum, variance. . .) along with contextual information and specific object features that were to

be used for species discrimination. In our case the most useful features for species discrimination was; mean values of band ratios, mean, maximum and standard deviation of CHM, shape and size, as well as contextual information such as "relative border to". Training information for classification used data collected in a transect along the flight (based on visual interpretation), whilst further plot data was used for validation. The final classification scheme aimed to discriminate amongst four classes: Sapote, Overo, Alive Algarrobo and Dead Algarrobo.

In terms of accuracy assessment of the final species map there were two main objectives. The first was to determine the accuracy in the estimates of number of trees mapped (tree detection) and the second was to determine the level of confidence for the identification of individual species (species classification). The assessment was implemented at a plot level, as a non-site specific measurement, avoiding the need to match individual tree location [58]. Data recorded in the four plots taken at the time of the flight were used as reference. Only trees with an average crown spread greater than $4m^2$ were considered (matching the minimum mapping unit). Algarrobo with "degrees of health" 1 and 2 were considered Alive Algarrobo whereas "degrees of health" of 3 were considered Dead Algarrobo With regard to quantification, only trees were taken into consideration, Overo, as a bush, was identified but not quantified. Error matrix derived measurements along with detection rates were employed to assess the accuracy of the classification and the tree location respectively. Further assessments such as determining the quality of tree crown delineation (i.e. the boundary of the tree crowns) could be implemented but while the actual delimitation of the crown boundaries has a direct influence in the accuracy of both tree detection and species classification it is not a focus of this study.

To examine the species composition in the study area we summarised the numbers of trees per species, numbers of trees, crown cover and mortality rates of Algarrobo, across the study area, using 50 x 50m cell sizes (area of 2500 m^2). This was processed in ArcGIS 10.4 (ESRI 2016), deriving the cells using fishnet and summary statistics using spatial overlay (centroids of the crowns queried against the cells) and zonal statistics.

3. Results

The distribution of species composition across the landscape (Fig 6) reveals the predominance of *Algarrobo* at 69% of delineated tree canopies (i.e., at 21.5 trees per Ha) as opposed to Sapote at 31% of the delineated trees (Overo was mapped but not quantified) (Table 2). At the time of the UAV deployment it is evident that 35% of the mapped *Algarrobo* trees were already dead (Table 2). When reviewing the spatial distribution of species (Fig 7), it is evident that *Overo*, is densest along runnels, whilst Sapote, dominates in the south of our study area. *Algarrobo* shows little trend, but what is evident is the clustering of the dead trees in the north of the area. There could be multiple reasons for this, such as the disease advancing from north to south but also the area to the north is the most disturbed (in terms of cattle and human disturbance) which may help propagate the plague.

The high degree of confidence in this mapping is supported by the accuracy assessment statistics produced. With respect to number of trees delineated, an overall detection rate of 95.3% was obtained (Table 3). When examining detection success per tree species it is evident that there is a general underestimation, except for the alive *Algarrobo* where there is an overestimation. This is most likely caused by distinct alive branches in diseased trees being recorded as a separate tree. Detection rates were used to adjust the final number of trees (by applying percentage of detected trees to the final map figures). With respect to accuracy of species identification of those delineated trees an overall accuracy of 94.10% was obtained (Tables 4 and 5). Optimal classification results are yielded by Sapote with a 100% user's accuracy, although a lower producer's accuracy (88.16%) was obtained, mainly due to alive *Algarrobo* trees being

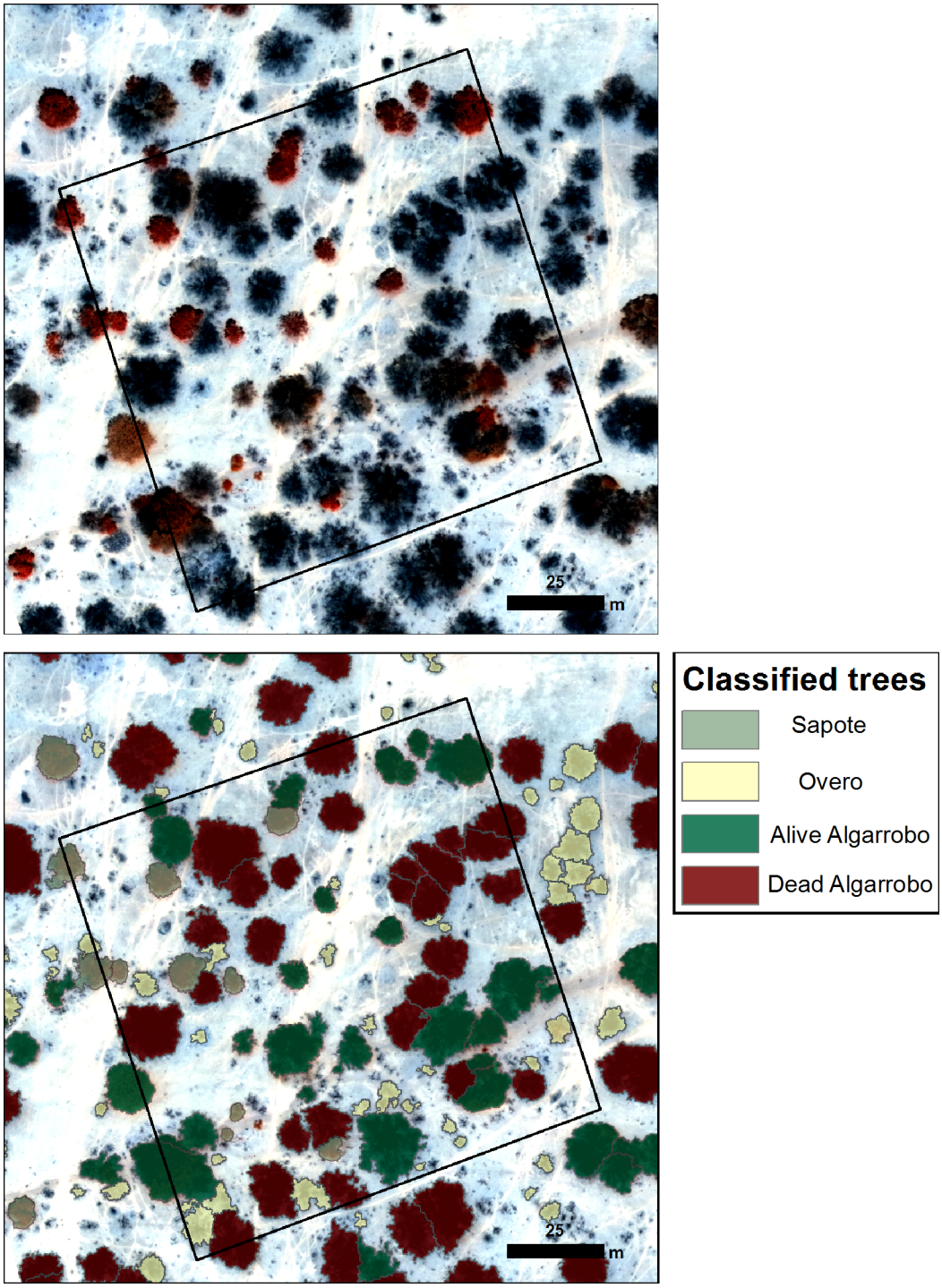


Fig 6. Distribution of species composition in and around Plot 1: A. red edge derive image from UAV mosaic. B Results from crown delineation with species identification.

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classified as Sapote. This is very much related to crown delineation errors; if the crown is delimited in such way that includes non-vegetation pixels (such as background) the average GDVI values of the tree object would be lower and therefore the tree assigned to a different

Table 2. Number and density of trees in the study area.

	Number of trees	Adjusted number of trees	Number of trees per Ha	% Trees	% Dead
Sapote	743	784	9.8	31	
Algarrobo (alive)	1331	1122	14.0		
Algarrobo (dead)	504	601	7.5	69	35
TOTAL	**2578**	**2507**	**31.3**		

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class. The dead *Algarrobo* class presents a similar accuracy statistic behaviour (i.e., a high user's accuracy and lower producer's accuracy) and this is caused mainly by Dead *Algarrobo* trees being classified as *Overo*. This can be explained by inaccuracies in the elevation data; if not enough elevation points are found in the point cloud for the object tree, it will not be recognised as a tree but as a bush and therefore assigned to *Cordea lutea* class (Fig 8). In addition, some of the dead *Algarrobo* were identified as alive *Algarrobo* generally caused by *Vallesia sp*. plants growing under the *Algarrobo* canopy increasing GDVI values and resulting in the tree being classified as alive. This situation causes different accuracy statistics in the two remaining classes, Alive *Algarrobo* and *Overo*, where high producer's accuracy than user's accuracy was obtained. Most of the reference Alive *Algarrobo* were identified correctly whereas trees classified as *Algarrobo* were indeed Sapote.

4. Discussion and conclusions

The high degree of accuracy with which the target species were mapped across this landscape as well as mortality rates of the keystone species *Algarrobo*, demonstrates how useful a monitoring approach using a UAV would be for conservationists working in this area. Although much up front work is need to deploy the UAV, the actual flying time and image acquisition was very fast; covering the area in less than 20 mins.

Of particular note, is that although there are currently many studies reporting advances in the use of UAVs [37,59,60], this study has demonstrated that the simple and cheap consumer grade sensor carried by the system (Canon S110 RE), with its limited spectral resolution, still afforded accurate mapping of the parameters required here. However, when using modified consumer digital cameras as multispectral sensors we need to be aware of certain limitations of these systems to monitor vegetation. Spectral sensitivity and radiometric distortions of the camera optics have an influence in the radiometric and spectral quality of the images acquired [61]. Even if the camera is calibrated, attempting to remove radiometric distortions, theses cameras are sensitive to fairly broad wavelength ranges which also overlap considerably in detriment of traditional multispectral analysis. Furthermore the Red Edge is acquired with the loss of the red band which also limits the range of band indices that can be applied. Still, data derived from this modified cameras provide extremely valuable information for monitoring vegetation if the appropriate image analysis techniques are used. In addition to the ultra-high resolution data, the ability of the system to provide three dimensional information (derived using structure from motion) was useful for vegetation characterization but the contribution was highly dependent on the quality of the point clouds produced. Different studies report on accuracies comparable to those derived by LiDAR systems [62,63]. However, as others have found, there were challenges when generating digital canopy height models of deciduous trees [64]. It was evident that point clouds were dense for evergreen trees with compact canopies but less so for deciduous or defoliated tress where fewer tie points were found in standing branches which could be confused with background points (Fig 8). As a result 3D data was useful when delineating and discriminating evergreen species but not so conclusive for

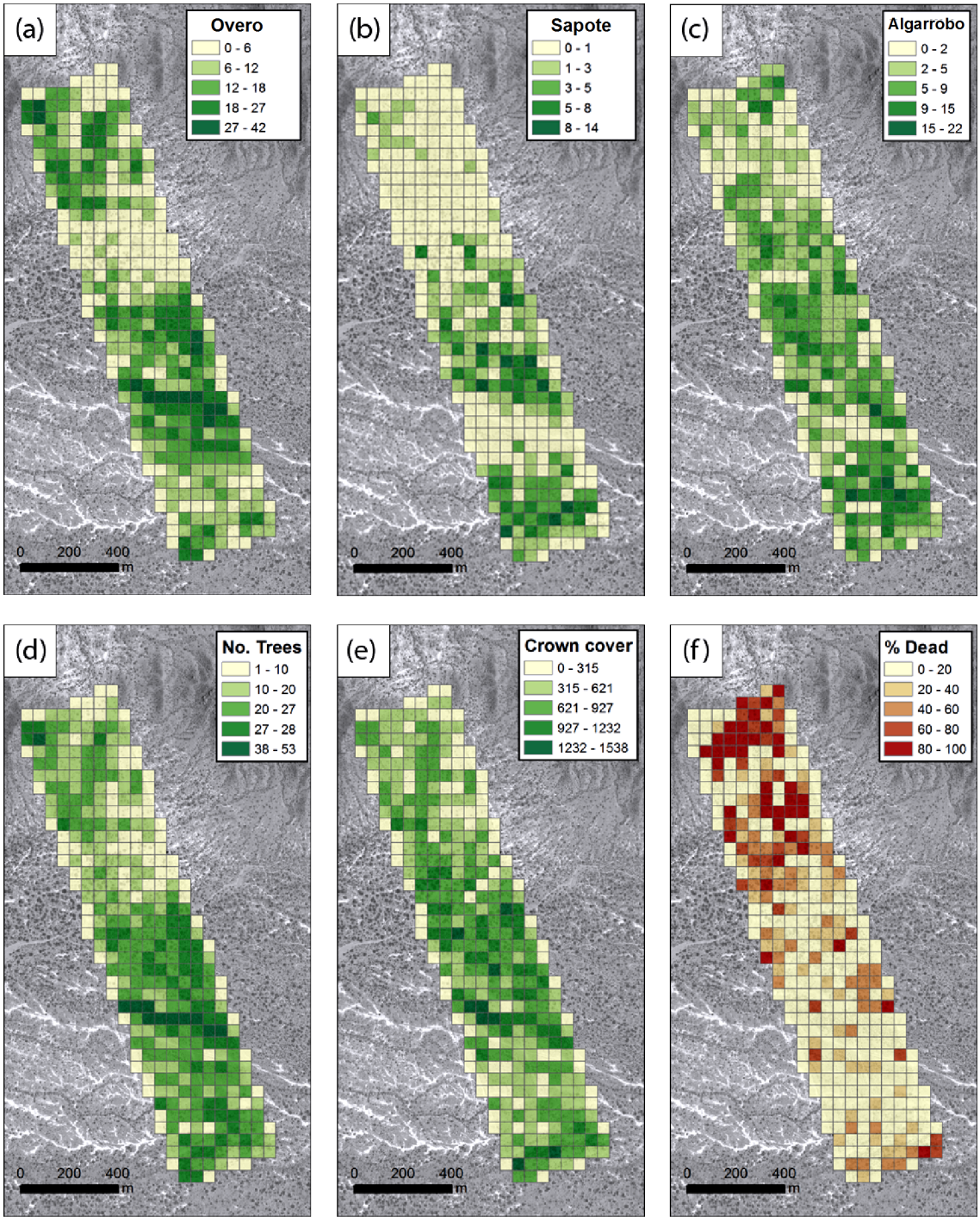


Fig 7. Landscape metrics for targeted species with 50 x 50 m cells (2500 m^2). (a) Number of Overo per cell. (b) Number of Sapote per cell. (c) Number of c per cell. (d) Number of trees per cell. (e) Crown coverage in m^2 per cell. (f) Percentage of dead Algarrobo per cell.

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deciduous trees. However, the methodology approach used in this study allowed for the combined use of 3D and spectral information depending on the nature of the vegetation where spectral information was found more useful in dealing with deciduous trees. Nevertheless the

Table 3. Accuracy assessment: Detection rates.

	Classified	Reference	Difference	%
Sapote	72	76	-4	94.73684
Algarrobo (alive)	59	51	8	115.6863
Algarrobo (dead)	73	87	-14	83.90805
Total	204	214	-10	**95.3271**

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use of 3D information is essential when trying to discriminate Dead *Algarrobo* tress from *Overo* bushes.

Fundamental to this study was the capture of ultra-high spatial resolution data, the ability to derive 3D data, as a result of structure from motion, and extending the spectral resolution of the camera sensor by way of a filter. Although UAVs are relatively easy to deploy, there is the caveat that understanding how they should be deployed with respect to flight planning to capture the optimal data for pre-processing and then subsequently the methods for processing and analysing the data captured for an application are key to successful mapping and monitoring. General pixel based quantitative analysis (relation between pixel values and target radiance, time series analysis, quantification of surface parameters, data comparison across time and scale) is less suitable than object based approaches where spatial and contextual information is also taken into account. The high resolution of the 3 band orthorectified data, such that the features to be mapped are larger than the pixel [65], and derived CHM were well suited to the employment of OBIA for mapping the species of individual trees. Previous studies delineating crowns have used a range of different methodologies, predominantly by applying edge detection [66], watershed segmentation [67] or region growing [68] algorithms, but these have been on remote sensing data captured by other platforms. These include multispectral very high resolution (VHR) satellite imagery [54], airborne LiDAR data [66] or a combination of both [69]. Such studies have normally focused on either temperate forests [54,70] or monospecific tropical environments [71] with relatively simple tree crown structures. Comparatively little research has tried to tackle the complexity of tropical forests with intrinsic interspecific low spectral separability and variable physical parameters [69]. Just a handful focus on these drier environments such as savannah woodlands [67], but so far these methodologies have not yet been applied to dry forests with the added complexity of trees presenting different levels of infestation by a fungal disease. Thus, this study is one of the first studies to demonstrate how OBIA can be successful in analysing data captured by UAVs, particularly the derived 3D models and multispectral imagery from uncalibrated consumer grade digital cameras. This study has also illustrated that the subsequent species classification process post-crown delineation has also benefited from the use of OBIA where information on the trees as objects including contextual information, statistical parameters based on spectral information (such as mean values, standard deviations. . .) provides an advantage over the use of traditional pixel based approaches when identifying individual species [72,73].

Table 4. Accuracy assessment: Error matrix.

		Reference Data				
		Capparis *scabrida*	**Cordia *lutea***	**Prosopis pallida (alive)**	**Prosopis pallida (dead)**	**Row Total**
Classified Data	Capparis *scabrida*	67	0	0	0	67
	Cordia *lutea*	1	225	1	9	236
	Prosopis pallida (alive)	8	1	49	4	62
	Prosopis pallida (dead)	0	1	1	74	76
	Total	76	227	51	87	**441**

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Table 5. Accuracy assessment.

	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Capparis *scabrida*	76	67	67	88.16%	100.00%
Cordia *lutea*	227	236	225	99.12%	95.34%
Prosopis pallida (alive)	51	62	49	96.08%	79.03%
Prosopis pallida (dead)	87	76	74	85.06%	97.37%
Totals	441	441	415		
Overall Classification Accuracy			94.10%		

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The results obtained here are extremely encouraging. They demonstrate that object-based image analysis is an effective image processing technique to analyse very high resolution data allowing for the identification of individual tree species and composition across a heterogeneous landscapes. It is also apparent that from an operational perspective, the relative ease of deploying the SenseFly eBee system across this landscape, in combination with the relative accessibility of using this type of UAV (i.e., costs, training, etc) means that repeat data capture (temporal resolution) should be achievable. Indeed, the need for rapid deployment and repeat data capture is particularly acute across this landscape as Algarrobo has throughout Peru been suffering dieback with the loss of foliage through the combined condition of drought, climate change and defoliating plagues. As a result the *Algarrobo* of our study area, are in a state of rapid decline and mortality, reaching alarming figures of a 35% mortality rate. There is an urgent need of action to reverse this trend putting in place community based conservation activities and restoration initiatives to ensure the survival of Algarrobo forests. Furthermore, extreme events (such as ENSO) are occurring more frequently [74] and their impact on the forest requires monitoring. However, to truly develop a UAV-based monitoring system that is flexible and allows for automation of workflow where possible spectral data derived from the UAV sensors should be calibrated ensuring long term data quality [75] as well as data comparability through time and space [76]. Additionally to fully exploit the multispectral capability of the system using consumer grade digital cameras, post-flight combination of data from

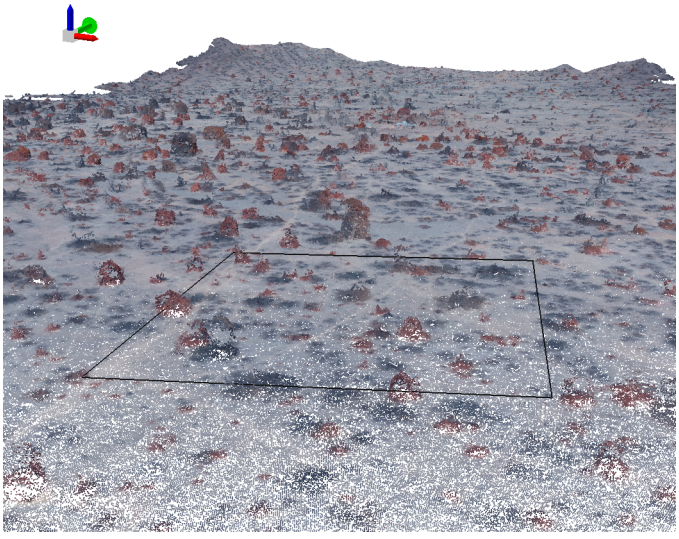


Fig 8. Point cloud showing higher density for evergreen trees as opposed to deciduous or defoliated tress.

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different sensors should be considered allowing for a wider range of multispectral bands enhancing the analytical capability (such as vegetation indices) of the system and therefore being able to capture subtle differences in infestation levels. This would in turn raise the need of accurate ground control points and minimal time delay between flights [33].

The aforementioned improvements in the system are feasible however the present analysis has exposed the state of the vegetation and served as a baseline for future monitoring allowing to further focus on the health (i.e. levels of infestation) of *Algarrobo*. Moreover, once established such a UAV-based monitoring system it could be extended to compute extra individual tree information of great value for many ecological studies [77]. Measures of canopy extent (crown width, crown cover, foliage projected cover. . .) and tree heights values can be easily computed once the right crown delineation algorithm is in place [78], furthermore, tree height and crown width are known to correlate with other tree based metrics such as DBH [69,79]. These tree structural attributes are fundamental for assessing above grown biomass, carbon stocks and for the understanding of ecosystem functions which are essential in support of many conservation activities and the provision of ecosystem services [78]. To be able to do this, as well as identify further species would represent an exciting development for the fields of remote sensing, ecology and conservation [80]. With respect to this landscape in particular, it is clear that what is required of a monitoring system, i.e., provision of spatial data on the principal keystone species, including on their health, in a timely fashion on demand, should indeed be possible. The data generated via this study allows for the isolation of areas needing conservation management and planning, for example targeting areas of healthy trees for seed collecting, and conversely those areas needing assistance in restoration and intervention.

As for the generality of the methodology used, the forest of the study area is at the dry end of the spectrum for tropical dry forest where rainfall is very low resulting in a vegetation type with low number of species. Disturbances in the area have also caused an open structural vegetation formation where tree crowns are in many cases isolated and have developed freely to their mature form but also in tree clusters where crowns from individual trees are interconnected. The methodology used in this study, working at different levels (isolated trees and tree clusters) allows for this approach to be used in different structural vegetation types, either in closer formations such as forests receiving more rainfall where tree canopies are completely interconnected, or in very open formation such as savannahs (e.g. Brazilian cerrado). In more species rich vegetation types such as cerrado, the approach here would still be valid but would benefit from higher spectral resolution, either from an upgrade of UAV sensors or post-flight combination of data in order to fully exploit the multispectral capability for species identification.

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Author Contributions

Conceptualization: Susana Baena, Oliver Whaley, Doreen S. Boyd.

Data curation: Susana Baena.

Formal analysis: Susana Baena, Justin Moat, Doreen S. Boyd.

Funding acquisition: Susana Baena, Justin Moat, Oliver Whaley.

Investigation: Susana Baena, Doreen S. Boyd.

Methodology: Susana Baena, Justin Moat, Doreen S. Boyd.

Project administration: Susana Baena.

Resources: Susana Baena.

Software: Susana Baena, Justin Moat.

Supervision: Susana Baena, Doreen S. Boyd.

Validation: Susana Baena, Justin Moat, Oliver Whaley.

Visualization: Susana Baena, Justin Moat.

Writing – original draft: Susana Baena, Justin Moat, Doreen S. Boyd.

Writing – review & editing: Susana Baena, Justin Moat, Oliver Whaley, Doreen S. Boyd.

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4. Paper 4: Earth observation archives for plant conservation: 50 years monitoring of Itigi-Sumbu thicket

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ORIGINAL RESEARCH

Earth observation archives for plant conservation: 50 years monitoring of Itigi-Sumbu thicket

Susana Baena[1,2], Doreen S. Boyd[2], Paul Smith[3], Justin Moat[1,2] & Giles M. Foody[2]

[1]Royal Botanic Gardens, Kew, Richmond, Surrey TW9 3AB, United Kingdom
[2]School of Geography, University of Nottingham, Nottingham NG7 2RD, United Kingdom
[3]Botanic Gardens Conservation International, Descanso House, 199 Kew Road, Richmond, Surrey TW9 3BW, United Kingdom

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Correspondence
Susana Baena, Royal Botanic Gardens, Kew, Richmond, Surrey TW9 3AB, United Kingdom. Tel: +44 0 208 3325276; Fax: +44 0 208 3325278; E-mail: s.baena@kew.org

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Abstract

Itigi thicket is a spatially restricted ecosystem only present in Zambia and Tanzania. It is thought to be highly threatened and therefore we need to urgently assess the threats to this ecosystem as well as extent and rates of change to derive its true conservation status. In this study we focus on the Itigi-Sumbu thicket surrounding Lake Mweru Wantipa in Zambia, which occurs both inside and outside a National Park (IUCN category II). Earth observation data archives provide the means to assist the conservation assessment process by allowing the monitoring of the ecosystem over time. In particular, the Landsat archive offers over 40 years of imagery at a resolution suited to the distribution of this ecosystem. In this study we exploit this archive and extend it back 50 years using historical aerial photography. The remote-sensing data were classified according to presence of thicket at five dates across a 50-year period and these outputs were combined to produce a deforestation map. Crucially, this map was assessed for accuracy using a novel approach to expert knowledge, which shows that the resultant map is highly accurate (93% overall accuracy). A confusion matrix was used to provide a confidence interval to the deforestation figures. Results indicate that 64% of the Itigi-Sumbu thicket around Lake Mweru Wantipa has been cleared over the last 50 years and that the largest area of remaining thicket is currently situated within the Mweru Wantipa National Park. This deforestation figure provides the means to assess the conservation status of Itigi-Sumbu thicket as part of the Red List of Ecosystem as Endangered (EN).

Introduction

Itigi thicket is a low, dry forest consisting of a closed stand of bushes and climbers between 3 and 7 m tall (White 1983) and is found only in two small areas in Zambia and Tanzania. This dry, primarily deciduous and almost impenetrable vegetation type is unique in its species composition, featuring nearly one hundred woody plant species, many of them endemic (White 1983; WWF 2014).The entire ecosystem is believed to be threatened, with reported clearance of 50% in the Tanzanian portion (Kideghesho 2001) and as much as 71% in Zambia (Almond 2000). These statistics, however, are not verified and thus the conservation status and level of threat of the ecosystem remain unclear (WWF 2014).

In Zambia, this vegetation type (termed Itigi-Sumbu thicket) is highly sensitive to disturbance and this regression appears to be irreversible (Trapnell 1943; Fanshawe 1971); once the thicket has been cleared it does not regenerate and is replaced by a fire climax wooded grassland, Lake Basin chipya (Trapnell 1943; WWF 2014).The main threat to the Itigi-Sumbu thicket comes from rapid population growth resulting in an increasing demand for land and resources. This results in traditional, shifting 'citemene' slash and burn agriculture in which the thicket is cut down, and its branches piled up and burnt to produce ash which fertilizes the crop. Cassava is the main staple grown in the poor, sandy soils of the area and, after only a few years, the soils are quickly exhausted and the farmer moves on (Trapnell 1943). In addition, the

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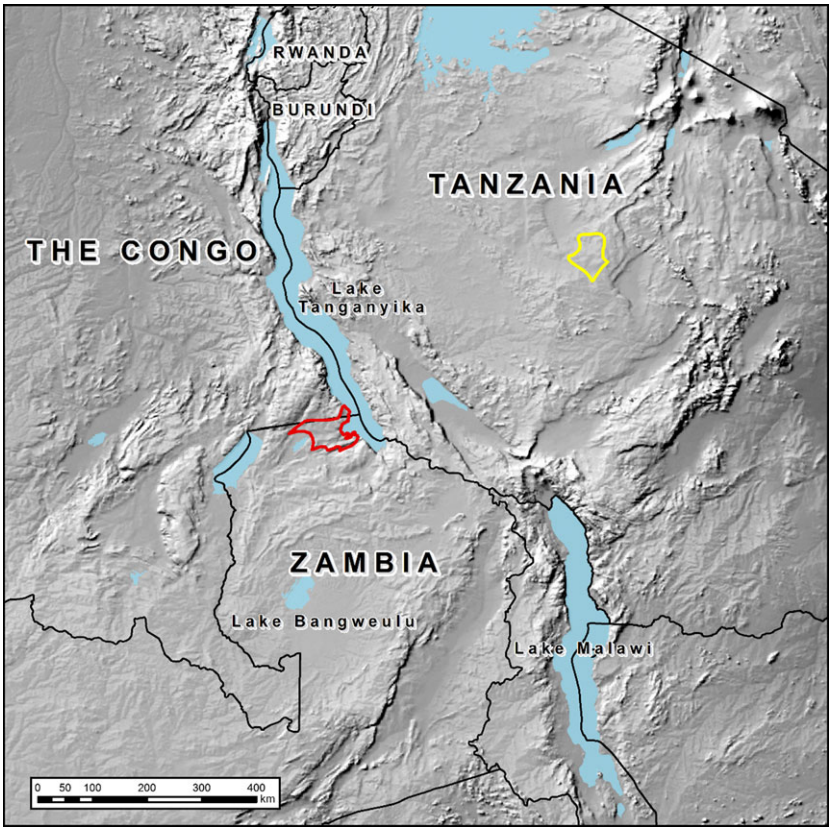


Figure 1. Location map showing areas of known patches of Itigi-Sumbu thicket in Zambia (red) and Tanzania (yellow) based on WWF terrestrial ecoregions (WWF 2014).

close proximity of thicket to Lakes Mweru Wantipa and Tanganyika means that the thicket has come under ever increasing pressure due to immigration associated with the fishing industry on these lakes (NORAD 1989).

The need to conserve the thicket has already been recognized. In 1972 the area along the western shore of Lake Mweru Wantipa, which contained large expanses of thicket, was declared a National Park (IUCN category II). When it was established, the national park had wildlife populations of lion, elephant and the black rhinoceros, all of these species benefiting from the cover provided by the thicket. However, the park's wildlife population has since been much reduced and black rhinoceros have disappeared as a direct consequence of the clearing of the thicket (Almond 2000). It is clear that the need to provide robust data (in terms of quantities and spatial distributions) on the loss of the thicket is pressing. The Red list of Ecosystems provides a scientific tool to document the conservation status of terrestrial ecosystems (http://iucnrle.org/). Five risk assessment criteria have been developed to form the basis of the analysis, one of them being "Decline in Distribution" (Criterion A). This criterion allows for an ecosystem to be assessed (along with other criteria to be fulfilled) based on the reduction in geographic distribution over the past 50 years (Rodriguez et al. 2015).

One approach to deriving data on thicket loss retrospectively is to mine the Earth Observation data (i.e. acquired via remotely sensing) archives. Earth Observation data provide a powerful way to directly observe large-scale ecosystems, consistently across time and space (Boyd 2009), particularly for biodiversity monitoring (Turner et al. 2015). Specifically, these data can contribute to monitoring protected areas and their geographical proximities (Rose et al. 2015). An area can be studied over a period of time using a time series of images with the same coverage acquired at dates of interest (epochs). Here, in this study, the Landsat series of satellites offer the most suitable approach to monitoring Itigi-Sumbu thicket cover over time. They provide repetitive, global coverage, multi-spectral imagery at a spatial scale where natural and human-induced changes can be detected and monitored over time (Markham et al. 2008; Skidmore et al. 2015). The Landsat archive offers over 40 years of imagery (since 1972) freely available to any user (Woodcock et al. 2008) and it will grow in the future given commitments to Landsat-type sensing systems (Committee on Implementation of a Sustained Land Imaging Program 2013). Often a time series of interest can be further extended back in time if complementary remotely sensed data are available. In this study we exploit the fact that

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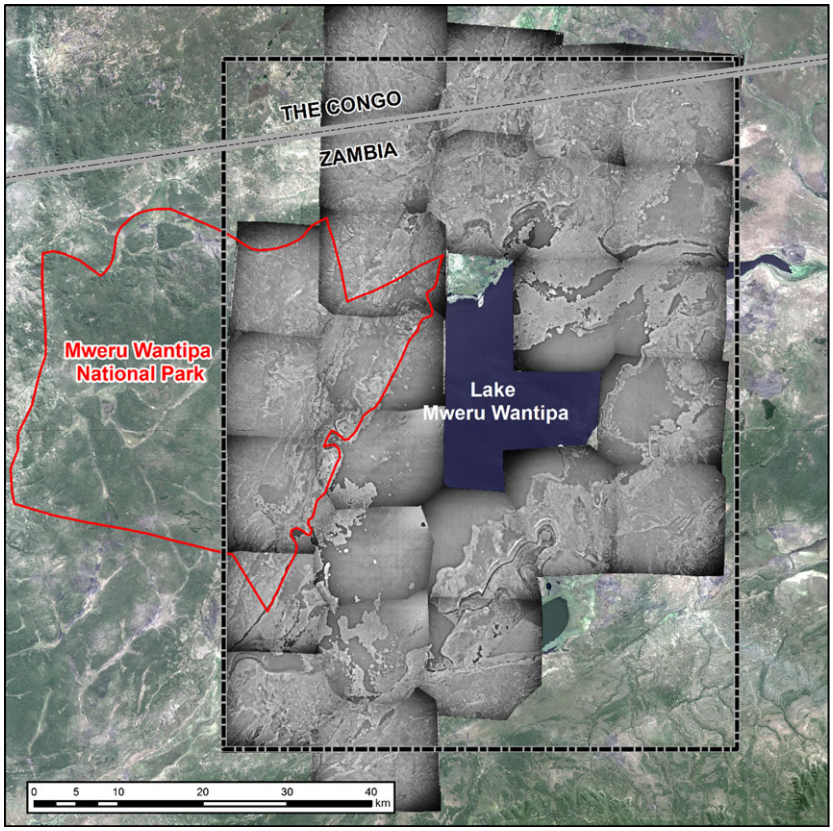


Figure 2. Study area (black box) immediately adjacent the shores of Lake Mweru Wantipa comprising known patches of Itigi-Sumbu thicket in Zambia. The red polygon shows the extent of Mweru Wantipa National Park. Overlapping areas contain the largest block of protected Itigi-Sumbu thicket. Black and White mosaic denotes the extent of aerial photography.

there were aerial photographs captured in this area in 1964 which afforded the extension of the time series of Earth observation data to the ideal of 50 years. Areas where aerial photographs are not available or difficult to obtain could take advantage of the opening up of declassified Corona data (Song et al. 2015) with worldwide spatial coverage and principal focus in Eastern Europe and Asia. This circa 2.5-m spatial resolution dataset would provide a suitable alternative to the aerial photographs used in this study for other areas and ecosystems globally.

It is a key time for the use of remotely sensed data for conservation (Pettorelli et al. 2015), where there is a realization of the intrinsic value of the archive of these data. However, correct practices must be employed in their use and the role of the conservationist is integral to this. The commonly accepted approach to monitoring land cover over time is via a supervised spectral classification which, among other steps, requires an accuracy assessment to be conducted. The remote-sensing science and application communities have developed increasingly reliable, consistent and robust approaches for doing this (Olofsson et al. 2013, 2014) and this ensures integrity in any statistics produced (i.e. for considering the conservation status of an ecosystem) and if used correctly can be extremely informative in ensuring the optimal value of remotely sensed data (Foody 2015). In this study we determine the extent and rates of change in Itigi-Sumbu thicket around Lake Mweru Wantipa, Zambia, over the last 50 years using historical aerial photography in combination with archived Landsat data and expert knowledge.

Materials and Methods

Study site

Itigi-Sumbu thicket occurs in patches that are immediately adjacent the shores of Lake Mweru Wantipa in Northern Zambia, close to the international borders of the Democratic Republic of Congo and Tanzania (Fig. 1). This comprises an area of 5,000 km^2 in total, with a land cover which is a mosaic of Miombo woodland, Chipya, edaphic grasslands and Itigi-Sumbu thicket. Within the study area is the Mweru Wantipa National Park, comprising a 3134 km^2 area to the west of the lake (Fig. 2). The National Park contains the largest known block of protected Itigi-Sumbu thicket around Lake Mweru Wantipa providing a "best-case" scenario in terms of loss compared with the thicket beyond its protective borders. Expert knowledge alongside remotely sensed data (in particular historical aerial photography) was available in this study area. This was not the case for the other portion of

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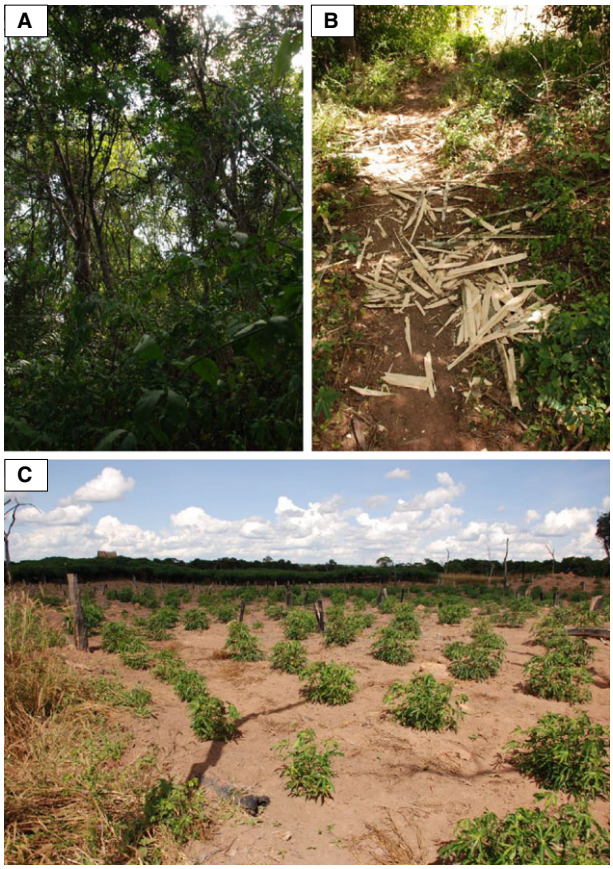


Figure 3. Itigi-Sumbu thicket in various stages of degradation. (A) Intact thicket; (B) degraded thicket with selective logging of larger trees and shrubs and (C) former thicket area cleared for cassava cultivation.

protected thicket in Zambia, within Nsumbu National Park and the unprotected thicket in Tanzania (Fig. 1). Therefore, both of these areas of thicket were outside the scope of this study.

The study area lies typically between 950 and 1200 m above sea level in a relatively flat terrain. The climate for this area can be divided into three distinct seasons: the cool dry season running from May to August, the hot dry season from August to November and the rainy season from November to April. Rainfall is variable in both amount and distribution over time and location, year-to-year variation being as great as 50%. Itigi-Sumbu thicket is linked to soil type. The soils are typically grey-toned pinkish brown and pinkish buff sandy loams, with a higher clayey content in the subsoil and low humic content (Trapnell 1943). Itigi-Sumbu soils often show impeded drainage and, in some cases, a cement-like duricrust may be present (pers. obs Smith; Trapnell 1943; White 1983). As this unique soil structure is broken down by cultivation (p. Smith, unpubl. data), this is the most likely reason why the thicket does not regenerate after clearance, even if it is protected from fire (Fig. 3).

Physiognomically, the thicket is a two-storeyed forest (Fig. 3) with an open overwood of emergent trees, 6–12 m high over a dense thicket underwood (Fanshawe 1971). The understorey is so dense that very little light penetrates to the ground layer, with the result that ground vegetation is sparse, being confined to a few small herbs and grasses (White 1983). Fanshawe (1971) lists 92 woody species in Zambian Itigi, and notes that it shares only a quarter of its floristic composition with the Tanzanian type. The close proximity of the Zambian thicket to the Mbala local centre of plant endemism, and the lack of botanical exploration carried out in this vegetation type, suggests that Itigi-Sumbu thicket contains many undescribed and undocumented species.

Data

The monitoring of Itigi-Sumbu thicket was carried out using a combination of Landsat images and aerial photography to cover the study area on a frequent basis and over a time period of 50 years. Landsat images are provided as part of the GLS (Global Land Survey) dataset, a collection of images optimally selected for land-cover

Table 1. Listing of all data sets, including landsat images and aerial photography used in this study.

Collection	Path/row	Acquisition date	Instrument	Sensor	Spatial resolution*	Spectral resolution*
Royal Air Force	V1/543A/512 V2/543A/512	June 1964	Aerial Photography	PAN camera recorded on film	3 m	PAN
GLS1990	172/66	2nd June 1989	Landsat 5	Thematic mapper	30 m	MS: 6 bands
GLS2000	172/66	13th May 2002	Landsat 7	Enhanced Thematic Mapper(ETM+)	15 m 30 m	PAN MS: 6 bands
GLS2010	172/66	24th May 2009	Landsat 5	Thematic Mapper	30 m	MS: 6 bands
USGS	172/66	10th June 2015	Landsat 8	Operational Land Imager (OLI)	15 m 30 m	PAN MS: 8 bands

*Only those bands used in the analysis.

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change studies (Gutman et al. 2008, 2013). The global GLS dataset has been created using the primary Landsat sensor of the time. The earliest GLS of 1975 acquired by the multispectral scanner did not allow for sufficient discrimination (i.e. to distinguish thicket from non-thicket in the supervised classification process) for this study (due to its limited spectral and spatial resolution). Therefore, only images from GLS1990 to 2010 (individual scene dates may range +/− 3 years) were selected. Specifically for this study we used images collected in 1989, 2002 and 2009. In addition, to bring the monitoring up to date one of the latest Landsat 8 images collected in 2015 was added to the dataset (the latter image was downloaded from the USGS).

Due to technological advances over the past 40 years of Landsat missions, the images used were from different sensors; Thematic Mapper (TM), Enhanced Thematic Mapper (ETM) and the Operational Land Imager (OLI). All images had the same spatial resolution (30 m). The accuracy of GLS 2000 data can be expected to be better than 25 m RMSE for most of its constituent scenes (Rengarajan et al. 2015). The GLS 2000 dataset is the geographic reference for the Landsat Data Continuity Mission (LDCM) and the rest of the GLS data products which have been registered to within one pixel geolocation accuracy (Tucker et al. 2004; Gutman et al. 2008). This geometric accuracy ensures any temporal change observed by the time series is a result of land-cover change rather than image rectification issues.

All Landsat images in the time series were acquired during the dry season (May and June), to minimize cloud cover but also changes due to phenological differences. To take the time series of remotely sensed data 50 years back from the present day (2015), a set of aerial photography was acquired. This was captured by the UK's Royal Air Force in June 1964 (series V1/543A/512 and V2/543A/512) by a panchromatic camera and recorded on film. A set of 26 frames divided into five flight line passes were acquired to cover the area. A summary of the full time series of remotely sensed data used is provided in Table 1.

Field data on the species composition and soils of the Itigi-Sumbu thicket were collected in June 1998 and in May 2012 by one of the authors of this study (Smith). GPS data from herbarium collections and soil sample sites were also used as reference data in this study.

Data processing and mapping of Itigi-Sumbu thicket

Change detection commonly uses a time series of remotely sensed data, applying different techniques depending on the nature of the dataset (Singh 1989; Coppin et al. 2004; Lu et al. 2004). For this study, dataset was uncalibrated (i.e. still at digital numbers) and with different spectral and spatial resolution at each time epoch (Thenkabail 2015). In such cases as this, post-classification comparison is the most practical approach as individual images are processed and classified independently based upon each scene's characteristics. Change is then considered at a later stage as the comparative analysis of the output at each time period (Singh 1989). Thus, the remotely sensed data at each epoch were processed and analysed independently to produce a map of Itigi-Sumbu thicket extent. Individual maps were subsequently combined to quantify the loss of Itigi-Sumbu thicket in the study area over the 50 years of study.

Aerial photography

The first step in using the aerial photography captured in 1964 was to apply a geometric correction so that these data could form the base of the time series. This was challenging, due to variation in pixel size across the set of photographs, the presence of strong geometric distortions introduced by the camera and the lack of photogrammetric information on the camera model. The aerial photographs were therefore registered to the 2002 Landsat 7 panchromatic image (spatial resolution of 15 m) using 16 ground control points selected from temporally stable ground features and adjusted using a third-level polynomial transformation. This was the polynomial function that yielded the lowest RMSE of the many tested using a set of eight check points to assess the accuracy of the geometric registration The RMSE obtained was 30 m which was deemed suitable to be used in a time series with the Landsat multispectral data which has a spatial resolution of 30 m.

The panchromatic aerial photographs (Fig. 3) provide limited spectral information to use in the automated mapping of the thicket. This restriction was further exacerbated by the poor quality of the available frames with obvious vignetting on mosaicking of the data to produce a continuous layer. Therefore, the aerial photography (scanned at 3-m resolution) was visually interpreted and digitized after gaining knowledge of the area from ground surveys of the Itigi-Sumbu thicket in 1998 and 2012. The result of this interpretation and digitizing process was a layer which delimited the extent of the thicket in 1964. This layer was then rasterized and resampled to 30-m resolution (to match Landsat imagery) using a majority filter to produce a map of the extent of Itigi-Sumbu thicket in 1964 that could form the basis of the time series.

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Landsat multispectral images

The most notable characteristic of Itigi-Sumbu thicket is its dense, mixed evergreen and deciduous composition (Wild and Fernandes 1967; White 1983) which contrasts strongly with the other vegetation types in the area (i.e. Lake Basin Chipya and Miombo woodland) which are deciduous and have a less dense canopy. This feature was key when spectrally discriminating Itigi-Sumbu thicket in the Landsat imagery as the evergreen component of the Itigi-Sumbu thicket remains active in the dry season and thus stands out in its spectral response against the rest of the vegetation in the study area. This enabled successful mapping of the thicket when employing a spectral classifier in a supervised classification (i.e. an automated method of mapping thicket extent from each image at each date).

As Itigi-Sumbu thicket is the priority habitat and the other vegetation types were secondary to the study, there was no need to accurately map all vegetation types. Thus, the supervised classification approach adopted here focussed effort principally on the class of interest, Itigi-Sumbu thicket, at all stages in the classification process (i.e. class training, class allocation and accuracy assessment). Support vector machine (SVM)-based classifications have been demonstrated to be especially suitable for mapping priority habitats as the focus of the classification process is on the vegetation type of interest; resulting in a reduction in the number of training sites required (Sanchez-Hernandez et al. 2007a,b; Li et al. 2011; Stenzel et al. 2014).

Each Landsat image in the time series (i.e. 1989, 2001, 2009 and 2015) was classified to produce a map of thicket extent. The first step in any supervised classification is the training process, in which a dataset that spectrally describes each class to be mapped is produced for machine learning (i.e. the SVM). The challenge here was that coincident information on the thicket for each date of mapping was not available. However, as Itigi-Sumbu thicket has a relict ecology in that once cleared it does not regenerate, the training process exploited this as a rule; if the thicket was present in the study area in 2015 it must have been present throughout the time series, and this was confirmed on the base data of the aerial photography. Thus, a set of 150 training pixel locations for the thicket class was generated from high-resolution imagery (via the Google Earth platform) that was temporally coincident with the 2015 Landsat image.

The Google Earth high-resolution imagery has a horizontal positional accuracy that is sufficient for assessing moderate-resolution remote-sensing data such as those from Landsat (Potere 2008) and thus suitable here. Consequently, the 150 locations were applied to the 1989, 2001, 2009 and 2015 images to form unique spectral training sets for each image to be used by the SVM classifier. For non-thicket areas, comprising all remaining vegetation types and land covers, 150 training sites were randomly selected from the beginning of the time series with the assumption that they remained non-thicket throughout. A SVM supervised classification was performed on each image at each date to produce a thematic map with the extent of Itigi-Sumbu thicket.

The final step in a land-cover classification is to provide an accuracy assessment of a thematic map produced. As contemporary testing data (at each epoch) were not available and could not employ the same rule as used in the training step, it was accuracy of the final thicket deforestation map that was assessed (see below).

Post-classification change detection and thicket deforestation map

The resultant maps showing the extent of Itigi-Sumbu thicket at each date were combined to produce a map of deforestation of Itigi-Sumbu thicket throughout the 50 years (Fig. 4). This produced a final map which has five

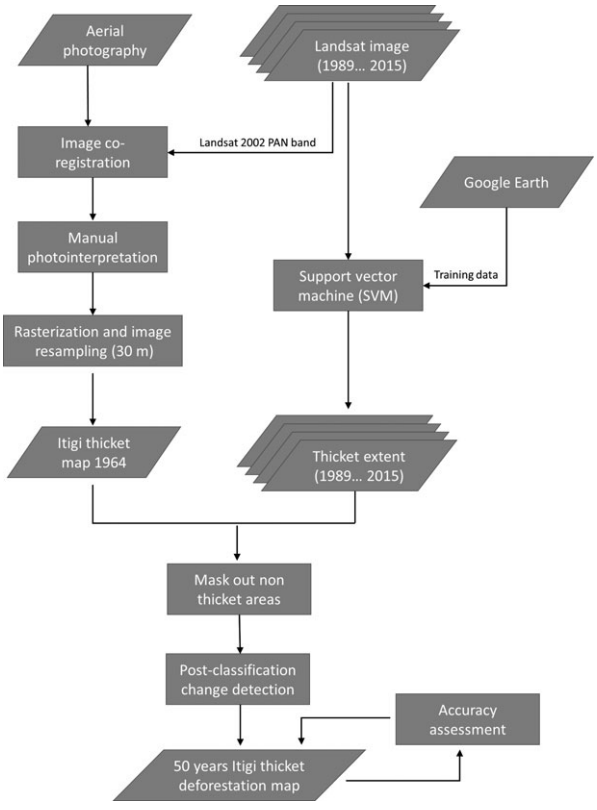


Figure 4. Work flow. Deforestation mapping procedure showing each step of the analysis and the generated final products.

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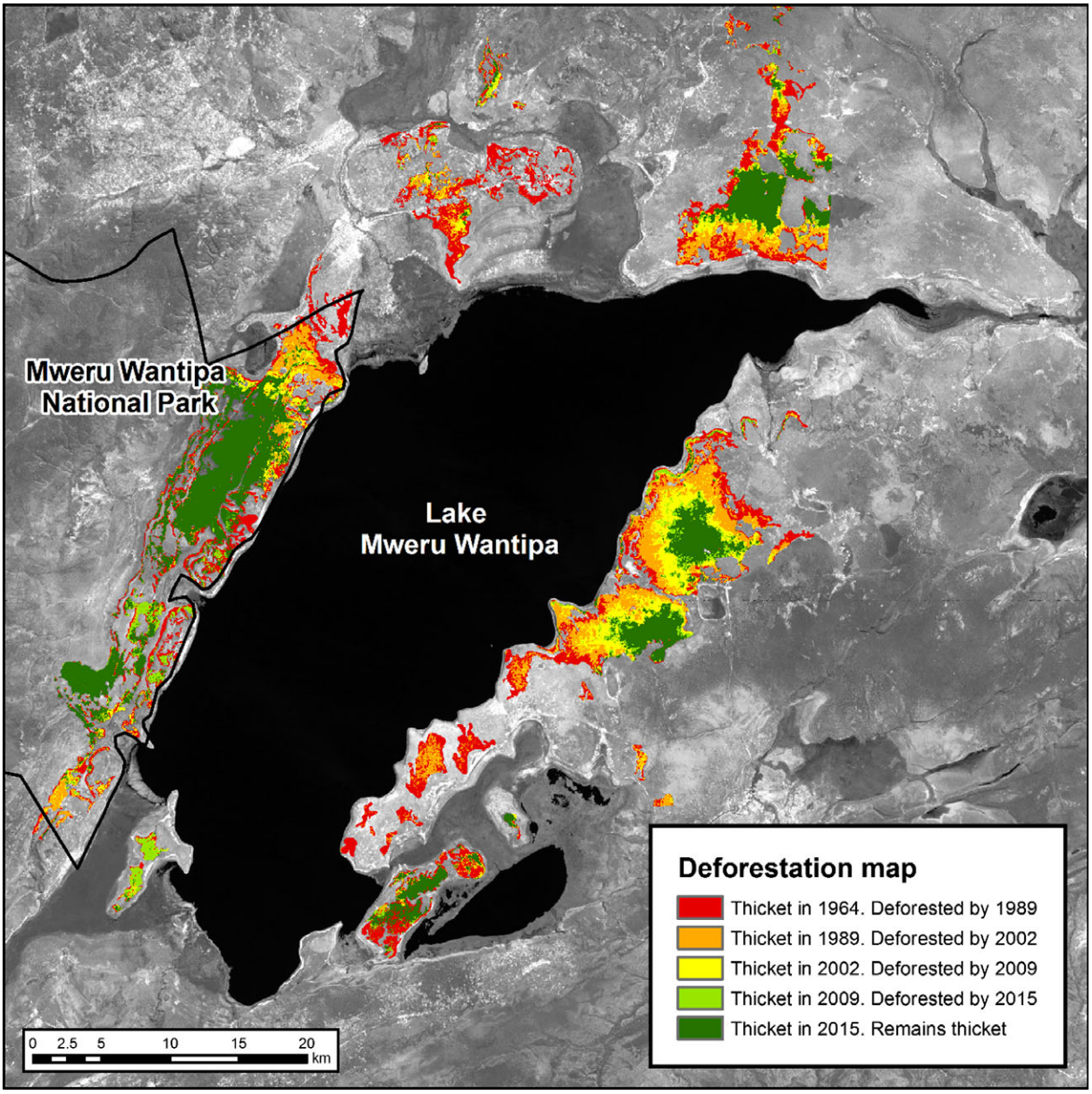


Figure 5. Itigi-Sumbu thicket deforestation map of the study area in and outside of Mweru Wantipa National Park showing the progressive loss of thicket through the 50 years' time span at the five epochs covered in the study (1964, 1989, 2002, 2009 and 2015). Each deforestation class represented in the map provides information on the time span of when the Itigi-Sumbu thicket was lost, e.g. Class 1 shows the extent of the Itigi-Sumbu thicket lost between 1964 and 1989.

classes, each one providing information about where and what period the Itigi-Sumbu thicket was lost. As stated earlier, it was this final map that was assessed for accuracy. A fundamental recommendation of good practice when assessing the accuracy of change maps is that the dataset used for validation is of higher quality change information than that used for training the classification (Olofsson et al. 2014). For change maps going back in time the main issue is the lack of sources for contemporary validation data; Google Earth provides an extremely useful source of high-resolution data suitable for validation (Knorn et al. 2009; Schneider et al. 2010; Giri et al. 2011), but when the time span of the study goes back beyond the era of high-resolution commercial satellites Google Earth is no longer an option. In those cases historical aerial photography is often used for validation (Lunetta et al. 2006), but for this study,

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Table 2. Agreement error matrix – there is full agreement in the labelling procedure by all three experts.

		Reference data					
		Class 1	Class 2	Class 3	Class 4	Class 5	Row total
Classified data	Class 1	86	1	1	0	10	98
	Class 2	1	58	1	0	0	60
	Class 3	0	2	31	0	2	35
	Class 4	0	0	0	19	4	23
	Class 5	0	0	0	2	133	135

	Reference totals	Classified totals	Number correct	Producers accuracy (%)	Users accuracy (%)
Class 1	87	98	86	98.85	87.76
Class 2	61	60	58	95.08	96.67
Class 3	33	35	31	93.94	88.57
Class 4	21	23	19	90.48	82.61
Class 5	149	135	133	89.26	98.52
Totals	351	351	327		
Overall classification accuracy					93.16

the only existing set of aerial photography was used as part of the time series.

High-quality validation data were obtained from three experts directly assessing the final change map rather than the intermediate products (i.e. the maps of Itigi-Sumbu thicket extent at each date). Images were visually enhanced by pan-sharpening methods (where a panchromatic band was available) and/or contrast-stretching techniques to improve visual interpretation. Following best practice (Olofsson et al. 2013, 2014), a probability sample design, here simple random sampling, was used to select 385 validation locations. The sample size selection was informed using sampling theory (Foody 2009; Fleiss et al. 2013). Specifically, for planning purposes it was assumed that the mapping would have an accuracy of 85%, based on a widely used target in remote sensing, and that the half width of the desired 95% confidence interval should be <3% which indicates at least 306 sites be acquired. Each expert was then provided with a project with all enhanced individual images and the 385 validation locations (displayed with black bulls eye symbols with transparent centre for better visibility) and asked to record for each point the date when thicket cover was lost, starting with the 2015 image and working backwards querying out points that had already been assigned. The working scale was set to 1:30,000 to accommodate for differences in image resolution.

Results showed a small amount of uncertainty in the decisions of the three experts (label disagreements in 34 of the 385 locations). Therefore, a confusion matrix was produced using only those points where all three experts agreed on the label, reporting estimates of overall accuracy, user's accuracy (commission error) and producer's accuracy (omission error).

The extent of thicket in each of the epochs was used to calculate the rate of deforestation. This was done temporally, across the 50-year time span, as well as spatially, looking at deforestation rates inside and outside the Mweru Wantipa National Park. The National Park boundaries were downloaded from the World Database on Protected Areas (WDPA) (UNEP-WCMC 2016). Percentage deforestation rates were established by dividing the thicket loss in each epoch (A1−A2) by the original extend (A1), and converted into average annual deforestation rates dividing it by the time difference (t): Average annual deforestation rate (%) = $((A1-A2/A1)\ 1/t) \times 100$.

Results

The final map of Itigi-Sumbu thicket deforestation in the study area throughout the 50 years is shown in Figure 5. The accuracy assessment of this map illustrates that the mapping accuracy is extremely high. Taking the error matrix where there is full agreement between each of the three experts (Table 2), it is evident that the overall accuracy of the deforestation map at 93% far exceeds that of the generally accepted accuracy of 85% for land-cover classifications (Foody 2002). Of the 351 validation points finally employed (using only those where all three experts agreed on the label) only 24 were allocated to the wrong deforestation class and in almost every case it was confused with the neighbouring date. All classes in the final deforestation map had producer's accuracies over 89%. Again this exceeded the mapping target.

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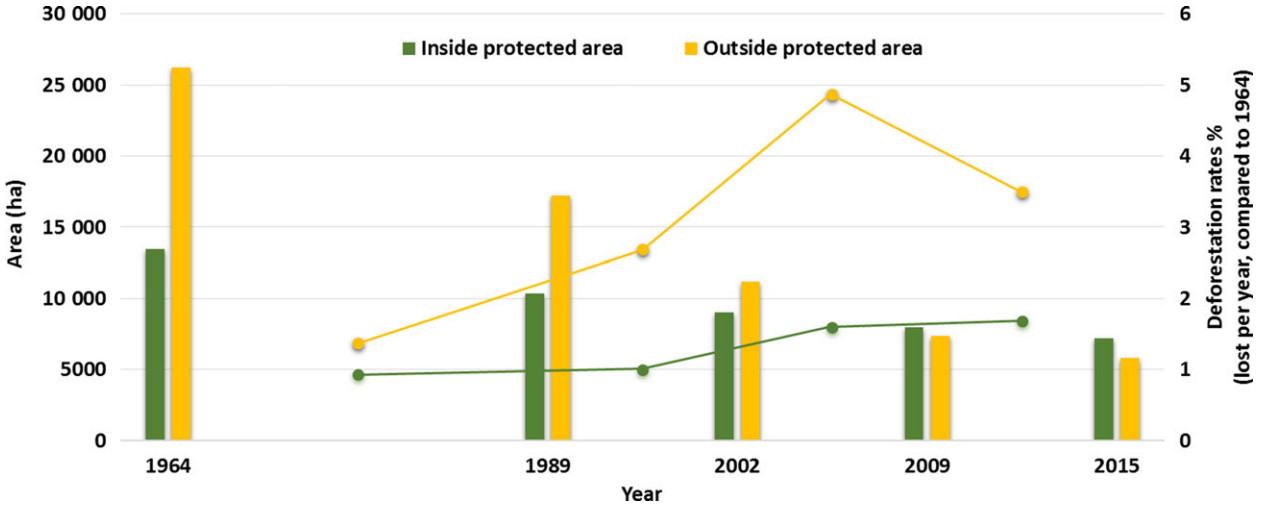


Figure 6. Annual deforestation rates during the 50-year time span of the study.

Employing a rigorous accuracy assessment, as stipulated by Olofsson et al. (2014), allows the adjustment of the amount of thicket mapped at each date. To do so is particularly important here, given the conservation importance of this vegetation. The confusion matrix reports that at the 2015 epoch, of the 351 testing locations 135 had been mapped as remaining thicket by the SVM classifier (i.e. the producer's accuracy). However, 149 of the 351 testing locations were in fact still thicket and therefore in error by ~4%. This error can be applied to the rest of the mapping for that class (thicket remaining in 2015) to adjust the areal estimate of that class and subsequently the deforestation rates. This calculation of required adjustment was applied using the confusion matrix also to the deforestation estimates at each epoch and used to adjust the thicket deforestation rates.

Figure 6 illustrates the extent of remaining thicket at each date along with deforestation rates. The deforestation map (Fig. 5) indicates that 64.8% of the total thicket area has been cleared over the last 50 years. Most of this area (30.6%) was lost before 1989, but the rate of deforestation rapidly increased between 2002 and 2009 reaching annual deforestation rates of 3.4% during this period. When comparing the deforestation patterns inside and outside the reserve, it is evident that Mweru Wantipa National Park experienced the greatest thicket loss during the first period (1964–1989), when 23% of the original thicket extent was lost. By 2015 it is clear that the largest area of the Itigi-Sumbu thicket remaining in the vicinity of Lake Mweru Wantipa lies within the Mweru Wantipa National Park.

These deforestation figures can be used as part of the Red List of Ecosystems framework to provide a conservation assessment for the Itigi-Sumbu thicket. Our results show a 64.8% deforestation rate for the last 50 years in Zambia; this along with the 50% deforestation rate reported on the Tanzanian side (Kideghesho 2001) are within the bounds of 50–80%; this gives Itigi-Sumbu thicket a preliminary ecosystem assessment of Endangered (EN) under criterion A1.

Discussion

The results obtained in this study confirm that the Itigi-Sumbu thicket by Lake Mweru Wantipa in Zambia has been declining over the past 50 years and shows that the thicket is highly threatened in this locality. Given that this area is one of just three areas of this thicket worldwide this is a cause for concern. The thicket deforestation figures agree broadly with the findings of Almond (2000); however, we extended the period of study to afford consideration of this vegetation type by conservation initiatives such as the Red List of Ecosystems. Although our findings indicate lower deforestation rates than those previously reported by Almond (2000), it is evident that removal of thicket has been ongoing for a long time on the shores of Lake Mweru Wantipa and current ecological understanding of this thicket suggests that this decline is irreversible. Lake Mweru Wantipa (as well as Lake Tanganyika) attracts immigrants due to their fishing industries (NORAD 1989) and the thicket in the vicinity of the lake is particularly vulnerable because it occurs on accessible, flat land adjacent the lake shore. Clearing takes two forms: (1) slash and burn 'citemene' agriculture, primarily for the cultivation of cassava (see Fig. 3C) and (2) selective logging of trees and larger shrubs for firewood and charcoal for cooking and smoking fish (Fig. 3B). The peak in deforestation rates recorded between 2002 and

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2009 corresponds with a large influx of refugees in the area from political upheavals in the Democratic Republic of Congo. After the second Congo war finished in 2003, many Congolese became naturalized, settled and started farming in the area (Zytkow C. pers. comm.).

With respect to spatial patterns, it is evident that the clearance of thicket has been occurring within, as well as outside the boundaries of the Mweru Wantipa National Park. Inside the park, substantial deforestation (23%) occurred between 1964 and 1989, much of it probably before the park was established in 1972. This cannot be confirmed though, as early Landsat data (i.e. in the period 1972–1982) were considered unsuitable for use due to their poorer spectral resolution (the MSS sensor). If these data could be used then such information would assist in understanding further the patterns of loss immediately prior to and following the establishment of the National Park. More recently, deforestation rates inside the park are substantially lower than those outside, indicating conservation effort is having an effect. The Zambian National Parks and Wildlife Department conducts patrols regularly with the aim of controlling encroachment and illegal farming within the park (Zytkow C. pers. comm.). A visual inspection of the Landsat images (supported by knowledge of the area) does, however, indicate that inside the park there is substantial degradation of thicket canopy cover, indicating that the selective removal of larger trees is an ongoing problem even if encroachment is under control. This occurrence of degraded thicket could also explain the overestimate in deforestation by the spectral classification approach here (i.e. at ~4%). Notwithstanding this problem, Mweru Wantipa National Park probably represents the best opportunity to conserve the Itigi-Sumbu thicket in the environs of Lake Mweru Wantipa. Remote sensing should be used to continue to monitor the thicket; however, a different approach would be required to ensure that mapping of degraded thicket, in addition to intact thicket, is achieved. This would provide further information with which to target conservation effort.

From this study, the power of the Landsat data archive for conservation efforts is clear. In this case the archive was extended back to an ideal of 50 years (as specified by the Red List of Ecosystems) and the spectral classification approach adopted suited the mapping of Itigi-Sumbu thicket in this landscape. The thicket is spectrally distinctive, which when coupled with its relict ecology (i.e. does not regenerate), allowed the exploitation of the Landsat archive without full reference data (i.e. for training and testing of the land-cover classifications at each time stamp). The achievement of an overall classification accuracy of 93% in the final deforestation map demonstrates just how useful this approach was.

The real benefit here is the combination of expert knowledge with a full understanding of how remotely sensed data can be used; something to be further encouraged (Wang et al. 2010). Of particular note when making proper use of remotely sensed data was the use of the best practice approach to estimating area and assessing accuracy of land change, which often is not conducted (Olofsson et al. 2013, 2014). By employing the implicit information in the confusion matrix an adjustment for error could be applied to the deforestation (thicket cleared) estimates which is particularly important within conservation efforts. The requirement that estimates of land cover (and derived data such as clearance, etc.) should reduce any known uncertainties as much as practicably possible has indeed been noted (e.g. UN-IPCC Good Practice Guidance for Land Use, Land Use Change and Forestry) (Penman et al. 2003); but often this has not been the case (Olofsson et al. 2013).

A number of limitations of this study have been noted. The lack of information on deforestation around the time of establishment of the National Park requires future attention to fully understand the patterns in thicket clearance. Focus here would be on overcoming the lack of spectral detail by improving the spatial resolution of the early Landsat MSS data. Approaches such as super-resolution mapping (SRM) (Muad and Foody 2012) could, for instance, be adopted here. Going forward, however, such limitations occurring as a result of the trade-off between spectral, spatial and temporal resolutions and having in this case to emphasize the temporal detail will start to become less important. This will be of great benefit to conservation efforts. The Landsat archive has already seen improved spectral and radiometric resolution with the launch of Landsat 8 (Irons et al. 2012) and indeed the power of its satellites demonstrated for change detection at a global scale (Hansen et al. 2013) and its application to conservation (Tracewski et al. 2016).

Going forward and looking into future conservation assessments we are on the cusp of the Sentinel era with the recently launched Sentinel 2A awaiting its partner satellite (2B due for launch) and Sentinel 3′s launch imminent. These freely available data via the ESA Copernicus programme are assured for beyond 2030 and available to all via the Scientific Data Hub (European Space Agency 2016). Indeed conservation has been identified as a beneficiary here (Turner et al. 2015). There will still be a need, however, for suitable ground data to support the processing of remotely sensed data, but a growing awareness of the role of remote sensing in conservation should afford targeted ground data efforts. The Web 2.0 era should afford the exchange of such data. We have already seen how the rise of Volunteered Geographic Information (VGI – both formal and informal) (Foody and Boyd

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2013) data exchange platforms such as Google Earth (Google Earth 2016) could benefit conservation.

Overall, this research contributes to the understanding of the conservation status of and level of threat to the Itigi-Sumbu thicket in the vicinity of Lake Mweru Wantipa, Zambia. Our deforestation results support the assessment of this ecosystem as Endangered, but it is recommended that the remaining Itigi thicket (both in Zambia and Tanzania) be fully surveyed. Doing so will also confirm whether the Zambian thicket is a separate vegetation type from the Tanzanian type as it has been reported that they share only a quarter of their floristic composition (Fanshawe 1971). If a full survey confirms that this is a shared ecosystem between both countries, a deforestation study should be conducted on the Tanzanian side. This assessment is based on reported figures of 50% deforestation (Kideghesho 2001) for Itigi thicket in Tanzania, as of 2001, and if in the Tanzanian side deforestation rates resemble that of Zambia, then the rate of deforestation is likely to have rapidly increased after 2002. Deforestation rates >80% would place this ecosystem under the critically endangered category. Remote sensing affords such a survey, if suitable expert knowledge or supporting information is available.

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5. Paper 5: Resilience potential of the Ethiopian coffee sector under climate change

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Resilience potential of the Ethiopian coffee sector under climate change

Justin Moat[1,2]*, Jenny Williams[1], Susana Baena[1,2], Timothy Wilkinson[1], Tadesse W. Gole[3], Zeleke K. Challa[3], Sebsebe Demissew[1,4] and Aaron P. Davis[1]*

Coffee farming provides livelihoods for around 15 million farmers in Ethiopia and generates a quarter of the country's export earnings. Against a backdrop of rapidly increasing temperatures and decreasing rainfall, there is an urgent need to understand the influence of climate change on coffee production. Using a modelling approach in combination with remote sensing, supported by rigorous ground-truthing, we project changes in suitability for coffee farming under various climate change scenarios, specifically by assessing the exposure of coffee farming to future climatic shifts. We show that 39–59% of the current growing area could experience climatic changes that are large enough to render them unsuitable for coffee farming, in the absence of significant interventions or major influencing factors. Conversely, relocation of coffee areas, in combination with forest conservation or re-establishment, could see at least a fourfold (>400%) increase in suitable coffee farming area. We identify key coffee-growing areas that are susceptible to climate change, as well as those that are climatically resilient.

Arabica coffee (*Coffea arabica*) provides Ethiopia with its most important agricultural commodity, contributing around one quarter of its total export earnings[1]. In 2015/16, Ethiopia exported around 180,000 metric tonnes of coffee[2] at a value in excess of 800 million USD, making it Africa's largest coffee producer and the world's fifth largest coffee exporter[2], despite the fact that around half of the coffee produced each year is consumed in-country[3]. Coffee farming provides a livelihood income for around 15 million Ethiopians (16% of the population), based on four million small-holder farms[2,4].

In Ethiopia, coffee is produced within specific agro-ecological zones, over numerous geographical and political boundaries. At least 80% of Ethiopia's coffee comes from forests, forest-like habitats, or farms with shade (canopy) cover, representing land coverage of around 19,000 km^2 (Fig. 1) with around another 4,000 km^2 (c. 20%) grown in small plots in partial shade or full sun. Most of the coffee is grown in areas that are covered, or were previously covered[5], with humid evergreen forest: Moist Afromontane Forest (MAF) and Transitional Rain Forest (TRF)[6]. MAF and TRF are found at 650–2,600 m (450–3,000 m including extremes), although coffee is mostly confined to 1,200–2,200 m. Coffee farming is also undertaken in association with a drier type of vegetation, classified as Dry Afromontane Forest[6], such as that found in the Harar Zone (Fig. 1). The main coffee-growing areas of Ethiopia are found within the south-west and south-east (Oromia Region and Southern Nations, Nationalities and Peoples' Region), with modest and minor production in the north (Amhara Region and Benishangul–Gumuz Region, respectively) (Fig. 1).

Coffee farmers and other coffee sector stakeholders in Ethiopia and East Africa report that coffee production has been negatively influenced by changes in climate. These changes include: an increase in the uncertainty of yearly weather patterns, particularly in precipitation variability and timing of the wet season; an extension of the dry season (shortening of the wet season); a more extreme (drier and hotter) end to the main dry season; more intense (extreme) weather (heavier rain, hotter days); and warmer nights[7,8].

Historical climate data shows that the mean annual temperature of Ethiopia has increased by 1.3 °C between 1960 and 2006, at an average rate of 0.28 °C per decade[9] and by 0.3 °C per decade in the south-west[10] and Amhara in the north[11]. These temperature increases have been most rapid in the main wet season (July to September) at a rate of 0.32 °C per decade[9]. Analyses of extreme temperature changes in various coffee-growing areas indicate positive trends for maximum temperature, warm days, warm nights and warm spell duration; and negative trends for cool days, cool nights, and cold spell duration across different eco/agricultural environments (pastoral, agro-pastoral and highland), although some of the trends are not statistically significant[12]. The strong variability within Ethiopia's annual and decadal rainfall makes it difficult to detect long-term, country-wide trends[13]. Despite these limitations, studies show: that February to May[14] and June to September rains have declined[13,15,16]; a 15–20% reduction in rainfall since the mid-1970s[17] and late 2000s in southern, south-western and south-eastern Ethiopia, particularly in the period of the initial early (February to March) rains in the south-east and east[18,19], with an increase in drought frequency in all parts of Ethiopia during the last 10–15 years[16]; a decrease in June to September precipitation in the Greater Horn of Africa by approximately 1 s.d. during the period 1950–1989, corresponding to decreases of over 30 mm per decade throughout much of the Ethiopian Highlands[20]; and a downward trend in rainfall of 0.4 mm per month per year over the south-western region in the period 1948–2006[10].

The mean annual temperature of Ethiopia is projected to increase by 1.1–3.1 °C by the 2060s, and 1.5–5.1 °C by the 2090s, depending on the emission scenario[9]. Climate model projections under the emission scenarios A2 and B1 show Ethiopia warming in all four seasons across the country[21]. Projections from different General Circulation Models (GCMs) are broadly consistent in

[1]Royal Botanic Gardens, Kew, Richmond, Surrey TW9 3AE, UK. [2]School of Geography, University of Nottingham, Nottingham NG7 2RD, UK. [3]Environment and Coffee Forest Forum (ECFF), PO Box 28513, Addis Ababa, Ethiopia. [4]The National Herbarium, Department of Plant Biology and Biodiversity Management, College of Natural Sciences, Addis Ababa University, PO Box 3434, Addis Ababa, Ethiopia.
*e-mail: j.moat@kew.org; a.davis@kew.org

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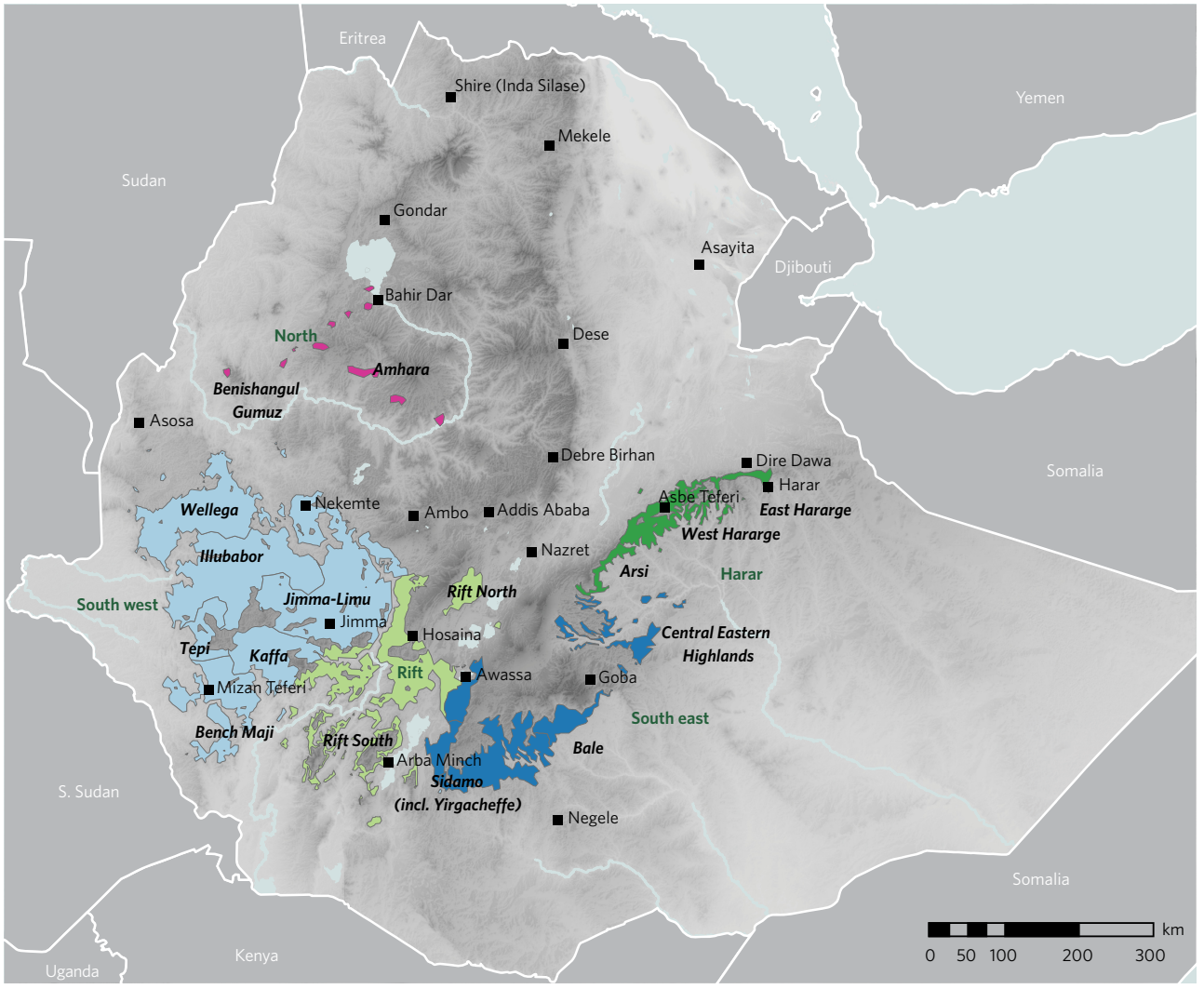


Figure 1 | The main coffee growing zones and areas of Ethiopia. The coffee zones represented by coloured polygons: red/pink, North Zone (coffee areas: Amhara and Benishangul Gumuz); light blue, South West Zone (coffee areas: Wellega, Illubabor, Jimma-Limu, Kaffa, Tepi and Bench Maji); light green, Rift Zone (coffee areas: Rift North and Rift South); dark blue, South East Zone (coffee areas: Sidamo, Yirgacheffe, Bale and Central Eastern Highlands); dark green, Harar Zone (coffee areas: Arsi, West Hararge and East Hararge).

indicating slight increases in annual rainfall in Ethiopia[22,23]. However, it should be made very clear that precipitation projections vary considerably in their agreement; some increases are negligible; the variability for GCM change is extremely high[24]; and for some regions of Ethiopia GCMs do not agree on the direction of change[21].

It is imperative to better understand the influence of climate change on coffee farming in Ethiopia, given the importance of coffee production and consumption for this country. The impacts of observed and projected changes in climate on coffee farming in Ethiopia are largely unknown. The only available climate change study for Ethiopian coffee is for native populations of Arabica coffee, using a single species distribution model (SDM), forest-only data and one GCM[25].

In order to quantify the influence of climate change on coffee farming in Ethiopia, we collated and collected high-quality ground-point data, from across the Ethiopian coffee landscape and beyond, then modelled using an ensemble SDM approach, which was overlaid with Landsat 8 satellite imagery[26] to accurately delimit the main coffee production areas (humid forest). This approach, in conjunction with the use of multiple migration scenarios, fine-level suitability thresholding, multiple GCM appraisal and rigorous ground-truthing (of models and remote sensing outputs), constitutes a significant advancement over previous coffee climate change analyses generally[25,27–33]. Nine environmental variables (from BIOCLIM[34]) were used to understand the current climate conditions for coffee farming, and to project suitable growing areas for the future. Using these data and methods we quantify the potential outcomes of climate change on coffee production across the coffee landscape of Ethiopia until 2099. Our analyses are primarily focused on exposure (based on climate scenario projections from GCMs). The two other aspects of climate change vulnerability, sensitivity and adaptive capacity[35,36], have not been directly addressed, although it should be noted that Arabica coffee is identified as a climate-sensitive species with a low adaptive capacity[25]. The potentially beneficial influence of elevated CO_2, and compounding negative influences (for example, pests, diseases and deforestation) were not included in our analyses, but are discussed.

Results

Model projections overview. We modelled Arabica coffee suitability for Ethiopia using the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3)[37], across four time intervals (1960–1990, 2010–2039, 2040–2069 and 2070–2099; Supplementary Fig. 1), using

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Box 1 | Migration scenarios.

Six migration scenarios used in the modelling (see Supplementary Fig. 5 for further details, and Methods for processing details).

(A) Full Migration. Plants can grow in any suitable niche (can move anywhere).
(B) Plants can only grow within known niche (can only move within presently predicted niche).
(C) Plants can only grow within suitable forest cover, within any suitable niche (can move within suitable forest).
(D) No Migration. Plants can only grow within suitable forest cover and only in suitable known niche (restricted to present-day forest cover and suitable niches).
(E) Plants can only grow within suitable niche but only if niche does not drop outside of suitability during any 30-year time period.
(F) Plants can only grow within suitable forest cover and suitable niche, but only if niche does not drop outside of suitability during any 30-year time period.

Box 2 | Niche classifications.

Environmental niche (coffee suitability) categories (see Supplementary Fig. 2, Methods and Supplementary Information for category threshold visualization and statistics).

(1) Unsuitable. Coffee farming is barely possible to impossible.
(2) Marginal. Coffee farming is possible but often problematic, with poor and very inconsistent yields.
(3) Fair. Coffee farming possible and sometimes good but may require additional inputs (for example, irrigation, good shade and pruning). Yields poor in years with low rainfall.
(4) Good. Coffee farming good, with the potential for consistent, high-quality yields. Yield and quality may be negatively affected in some years (during adverse weather conditions, especially low rainfall and high temperatures).
(5) Excellent. Coffee farming good to excellent, with the potential for consistent, high-quality yields. Yields and quality can be negatively affected by adverse weather conditions, but less likely.

Table 1 | Total suitable niche area change for three selected GCMs.

Scenario (migration – emission)	Area change for low: middle: high outcomes (km^2 with percentage area remaining in parentheses)			
	1960–1990	2010–2039	2040–2069	2070–2099
A – A1B	44,820: 44,820: 44,820 (100: 100: 100)	60,996: 66,158: 74,873 (136: 148: 167)	50,387: 58,036: 72,033 (112: 129: 161)	42,247: 51,280: 61,230 (94: 114: 137)
B – A1B	44,820: 44,820: 44,820 (100: 100: 100)	29,192: 35,270: 41,195 (65: 79: 92)	27,110: 29,838: 35,597 (60: 67: 79)	19,553: 24,379: 26,809 (44: 54: 60)
E – A1B	44,820: 44,820: 44,820 (100: 100: 100)	29,192: 35,270: 41,195 (65: 79: 92)	26,287: 29,079: 34,923 (59: 65: 78)	18,427: 23,389: 26,110 (41: 52: 58)
A – A2	44,820: 44,820: 44,820 (100: 100: 100)	62,774: 74,272: 90,527 (140: 166: 202)	54,722: 57,118: 68,728 (122: 127: 153)	42,004: 50,498: 56,371 (94: 113: 126)
B – A2	44,820: 44,820: 44,820 (100: 100: 100)	31,245: 34,904: 42,046 (70: 78: 94)	28,054: 32,138: 33,438 (63: 72: 75)	19,101: 22,468: 27,647 (43: 50: 62)
E – A2	44,820: 44,820: 44,820 (100: 100: 100)	31,245: 34,904: 42,046 (70: 78: 94)	27,617: 31,717: 33,091 (62: 71: 74)	17,648: 21,415: 26,577 (39: 48: 59)
C – A1B	19,142: 19,142: 19,142 (100: 100: 100)	17,451: 20,575: 23,855 (91: 107: 125)	17,330: 19,588: 22,082 (91: 102: 115)	14,479: 17,139: 20,378 (76: 90: 106)
D – A1B	19,142: 19,142: 19,142 (100: 100: 100)	11,370: 14,319: 17,130 (59: 75: 89)	12,131: 12,897: 14,335 (63: 67: 75)	8,604: 11,256: 12,311 (45: 59: 64)
F – A1B	19,142: 19,142: 19,142 (100: 100: 100)	11,370: 14,319: 17,130 (59: 75: 89)	11,817: 12,556: 14,100 (62: 66: 74)	8,377: 10,464: 12,058 (44: 55: 63)
C – A2	19,142: 19,142: 19,142 (100: 100: 100)	19,111: 21,072: 25,040 (100: 110: 131)	18,092: 20,264: 20,742 (95: 106: 108)	14,189: 17,781: 19,225 (74: 93: 100)
D – A2	19,142: 19,142: 19,142 (100: 100: 100)	13,257: 14,177: 16,319 (69: 74: 85)	11,295: 12,983: 14,964 (59: 68: 78)	8,584: 9,933: 13,013 (45: 52: 68)
F – A2	19,142: 19,142: 19,142 (100: 100: 100)	13,257: 14,177: 16,319 (69: 74: 85)	11,105: 12,789: 14,858 (58: 67: 78)	7,910: 9,502: 12,622 (41: 50: 66)

Percentage and km^2 change (that remaining) in surface area for coffee niche suitability, against 1960–1990, for low, middle and high outcomes (see Methods for explanation) for migration scenarios (A–F) and emission scenarios A1B and A2. GCMs: GFDL-CM2.1, CSIRO-MK3.5 and BCCR-BCM2.0. The table is split: the top section contains niche-only scenarios (A, B, E), while the bottom section consists of forest and niche scenarios (C, D, F).

two emission scenarios (A1B and A2), six migration (coffee area movement) scenarios (Box 1; Supplementary Fig. 5), two biological/climatic coffee groups/areas and 23 GCMs, selecting three GCMs for our final analysis (see Methods). Coffee growing suitability was divided into five categories, based on statistical thresholding: Unsuitable, Marginal, Fair, Good and Excellent (see Methods; Box 2; Supplementary Fig. 2). We restrict our narrative here to two migration scenarios: A and D (Box 1), which we refer to as 'Full Migration (A)' and 'No Migration (D)'. The Full Migration (A) scenario represents the (maximum) potential niche (suitability) for coffee in Ethiopia, invoking an assisted migration scenario, where coffee areas can move to newly available niches, regardless of whether there is forest or not (Fig. 2). This scenario would require considerable intervention, including the provision of canopy cover (tree planting) in many places. The No Migration (D) scenario represents the actual (near-minimum; where scenario F is the minimum) coffee-growing surface area, based on the recent past (1960–1990) (Fig. 3). It assumes non-migration of coffee areas, either natural[25] or assisted (by planting coffee and shade cover) and also that there is zero forest loss or gain, but allows for climate change within the niche. Summary data for other migration scenarios are supplied in Table 1 and

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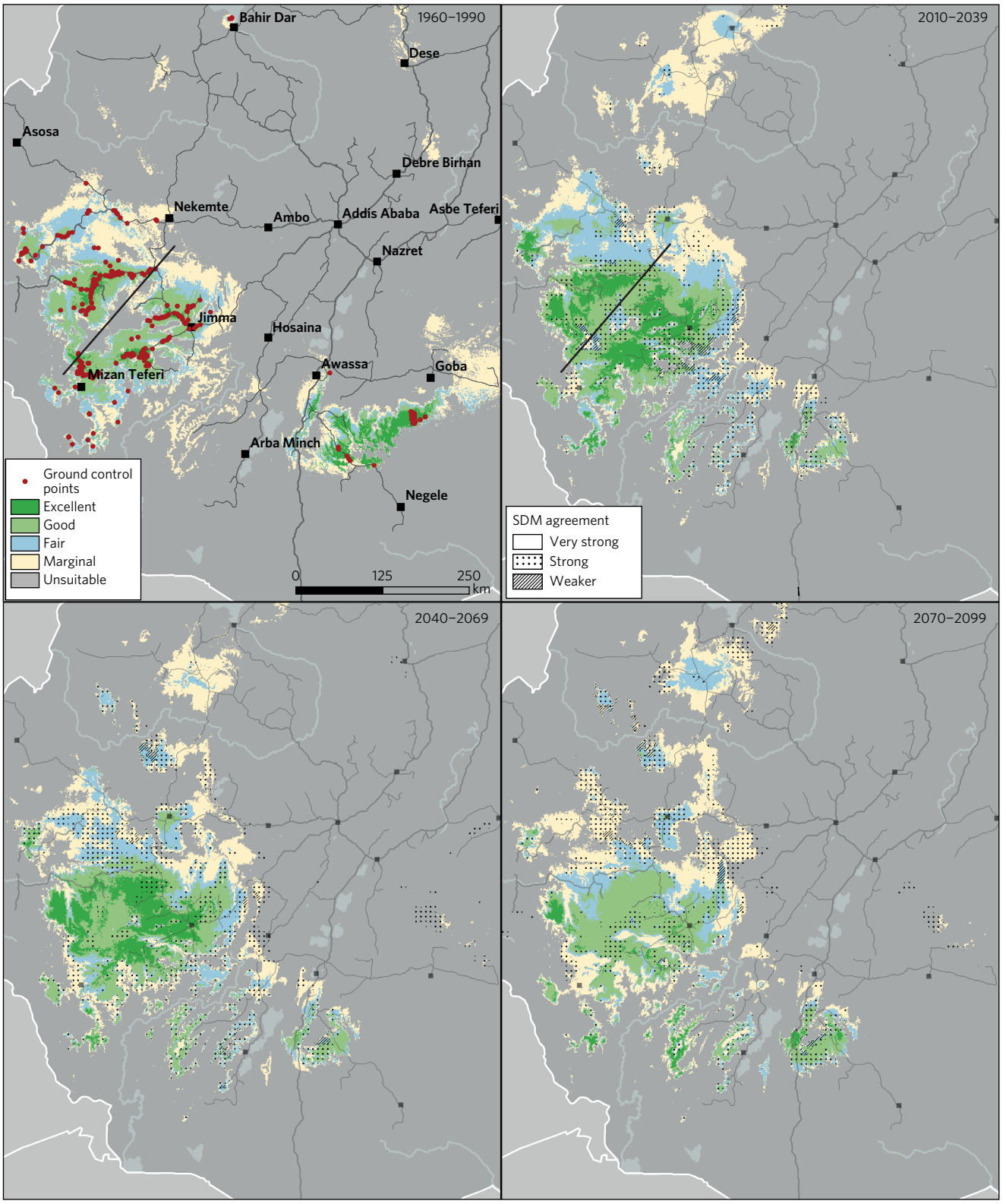


Figure 2 | Future projections for coffee suitability under Full Migration (A) and emission scenario A1B. Median of the three GCMs was used to colour niche suitability. SDM modelling agreement: very strong (average of 86% across study area, for all time periods), solid colour with no overlay; strong (13%), dots overlaid; weaker (1%), diagonal hatching overlaid. The 1960–1990 map shows the ground control data points used in this study and major place names (removed for clarity in subsequent maps). All maps show major roads (as dark lines) for navigation. Diagonal lines on 1960–1990 and 2010–2039 maps show the location of the elevation profile given in Fig. 6.

Supplementary Figs 7 and 8. In our modelling, there were no considerable differences between A1B and A2 (CMIP3 (ref. 37)), and so we restrict our main narrative to scenario A1B, which is the lower emission scenario of the two; results from the A2 analysis and migration scenarios B, C, E and F are supplied (Table 1; Supplementary Figs 7 and 8). We also review the more

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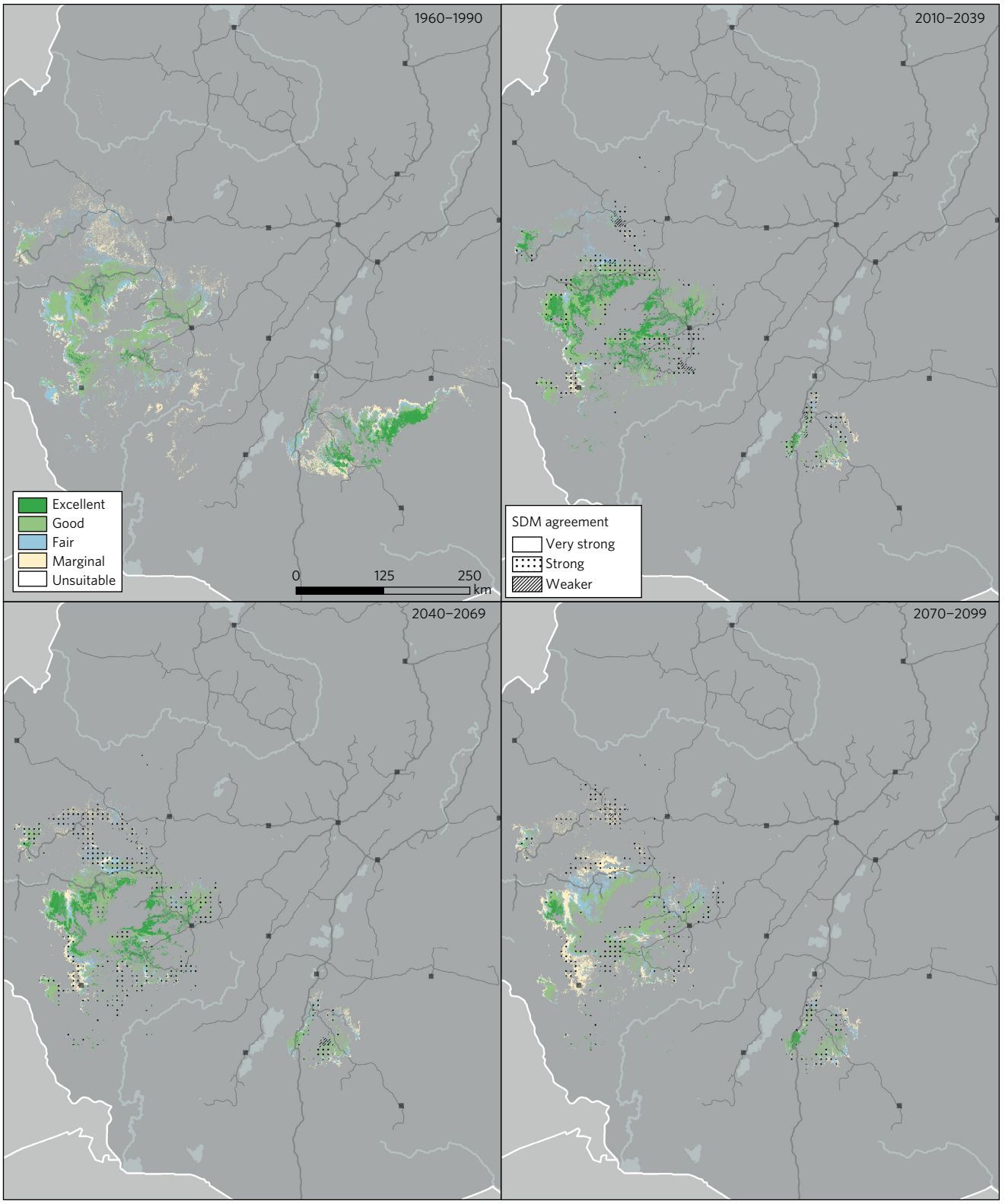


Figure 3 | Future projections for coffee suitability under the No Migration scenario (D) and emission scenario A1B. Median of the three GCMs used. All maps show major roads (as dark lines) for navigation. SDM agreement symbolism as in Fig. 2.

recent Coupled Model Intercomparison Project phase 5 (CMIP5)[38] Representative Concentration Pathway (RCP) Scenario 8.5 (RCP8.5) emission scenarios, following Knutti & Sedláček[39] (see Methods and Discussion). In the following two sections, we provide percentages for the middle range projections and their area (coffee niche suitability in km^2), based on the three selected GCMs (Bjerknes Centre for Climate Research, Bergen Climate Model, Version 2 (BCCR-BCM2.0); Centre for Australian Weather and Climate Research Mark, 3.5 (CSIRO-MK3.5); and Geophysical Fluid Dynamics Laboratory, USA, Coupled Climate Model 2.1 (GFDL-CM2.1)). The range of values for low and high range outcomes, which are also based on the above three GCMs, are given in Table 1.

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Figure 4 | Future projections for coffee suitability under the scenarios of Full Migration (A) and No Migration (D) across emission scenarios A1B and A2. Error bars represent the SDM area (km^2) model variability (low and high model outcome) within the three GCMs (GFDL-CM2.1, CSIRO-MK3.5 and BCCR-BCM2.0). See Methods (section 'Selection of GCMs') and Table 1 for further details. A1B-A is the scenario used in the Results and Discussion.

Projections 1960–1990 to 2010–2039. We see a large increase (Figs 2, 4 and 5) in coffee area suitability under the Full Migration (A) scenario within the present/near future (2010–2039), compared to the recent past (1960–1990). This is due to a dramatic increase in the area available (and suitable) for coffee at higher elevation, as temperatures increase, particularly in the South West Zone and to a lesser extent the North Zone (see Fig. 1 for zone localities). The overall shift for each time period is shown in Fig. 6. If we look at the south-western plateau (South West Zone) there is a vast area (in excess of 15,000 km^2) that comes into suitability in 2010–2039,

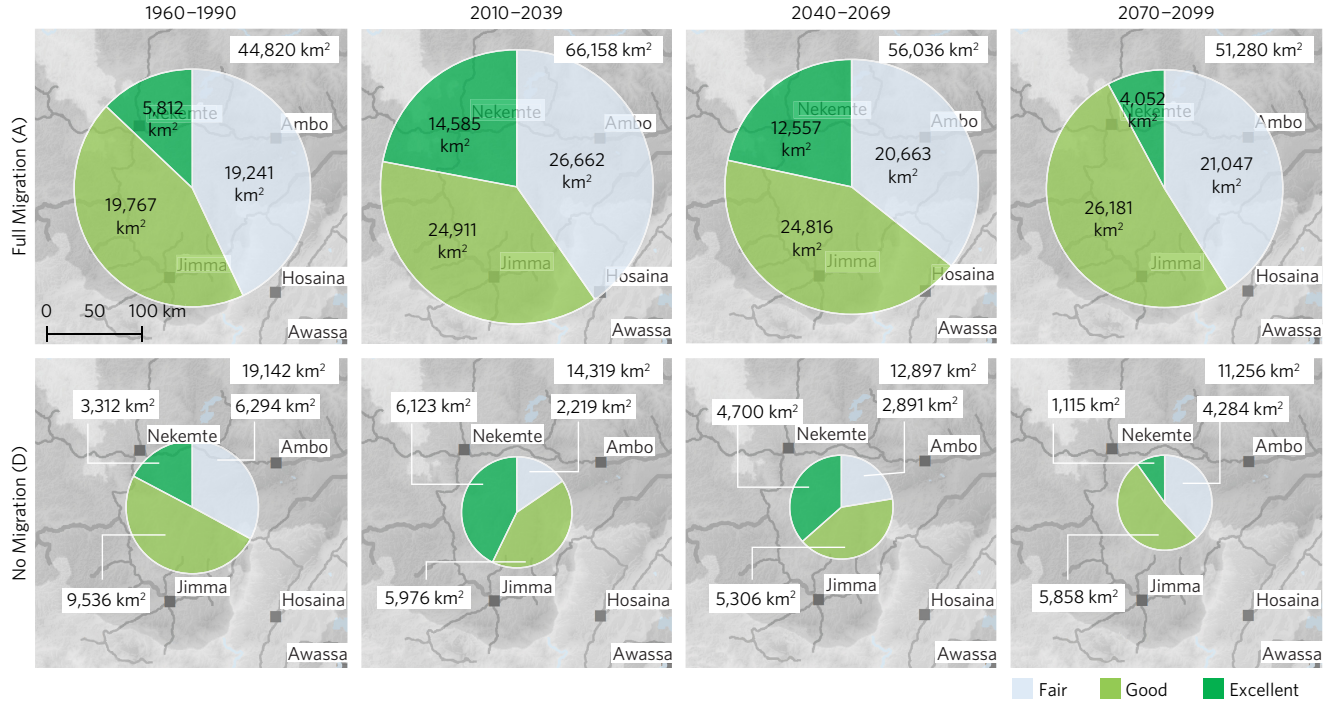


Figure 5 | Availability of suitable coffee niche in km^2 for migration scenarios of Full Migration (A) and No Migration (D). Total suitable area is given in the top right of each pie chart box. See Table 1 and Supplementary Table 1 for all metrics. Scenario A: coffee plants can grow in any suitable niche (can be moved anywhere); scenario D: coffee plants can grow only within suitable forest cover and only in a suitable known niche (restricted to movement within present-day forest cover and suitable niches). See Supplementary Fig. 5 for further details. The background is part of south-eastern Ethiopia, and is given to provide a scale for the ground area.

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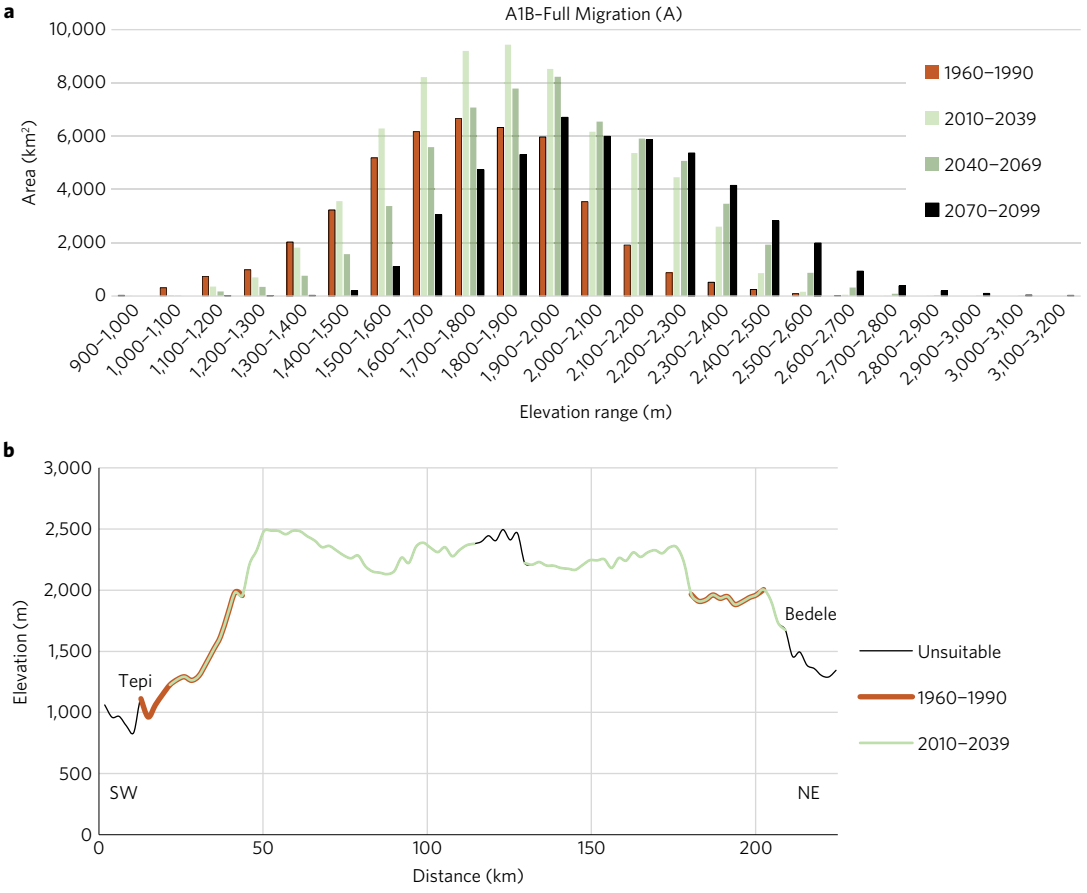


Figure 6 | Histogram and profile for elevation shifts. a, Histogram of elevation range for Full Migration (A) scenario, under emission scenario A1B. The change in ranges shows a potential shift of 32 m in elevation per decade (see Methods). **b**, Elevation profile of the South West Zone with coffee suitability for 1960–1990 and 2010–2039. Location of profile across the south-western plateau, running from south-west corner (SW) to north-east corner (NE), as shown in Fig. 2.

but which declines as the century progresses (Fig. 6). We originally considered the possibility that this expansion in suitability might be due to the 'East African Climate Paradox'[14], where forecasts (from GCMs) show an increase in rainfall for East Africa compared to actual declines in rainfall (from the 1980s to present day)[14,40]. We do not see this in our data or analyses; the increase in suitable area for 2010–2039 is as a result of the interaction between climate change and the topology of Ethiopia (see Discussion).

Under the No Migration (D) scenario (Figs 3–5) and the middle range projection, from 1960–1990 to 2010–2039 there is a decrease of 25% (19,142 km^2 to 14,319 km^2) across the Fair to Excellent coffee suitability niche categories. Over the same period there is an increase of 85% (from 3,312 km^2 to 6,123 km^2) in the Excellent category, which accounts for the corresponding decreases in the Fair and Good categories (Figs 4 and 5; Supplementary Figs 7 and 8). Under Full Migration (A) there is a 48% increase (44,820 km^2 to 66,158 km^2) in the Fair to Excellent categories over this period (Box 2; Table 1; Figs 4 and 5). A projection with profound implications is the early loss (2010–2039) of almost the entire Bale coffee area and eastern parts of the Sidamo coffee area (Figs 2 and 3). This outcome is consistent across all three GCMs, and all migration and emission scenarios (Figs 2 and 3). This result appears dramatic given that much of this area currently falls within the Excellent coffee niche suitability category. In the Discussion, we offer a possible explanation for this critical finding.

Projections 2010–2039 to 2070–2099. Over the rest of this century (until 2099), the models forecast a general reduction (km^2) in coffee niche suitability, but the degree of reduction is highly dependent on the migration scenario (Box 1; Table 1; Figs 4 and 5; Supplementary Figs 5, 7 and 8). Under the No Migration (D) scenario and the middle range projection (Fig. 5) there is a 21% decrease (from 14,319 km^2 to 11,259 km^2) in the suitable coffee niche, from 2010–2039 to 2070–2099. We also see a similar reduction under the Full Migration (A) scenario, where there is a 22% decrease (from 66,158 km^2 to 51,280 km^2) over the same period (Fig. 5). For both No Migration (D) and Full Migration (A), the most obvious difference is the substantial decrease in the Excellent category: 82% (from 6,123 km^2 to 1,115 km^2) for No Migration (D), and 72% (from 14,585 km^2 to 4,052 km^2) for Full Migration (A) (Table 1; Figs 4 and 5), from 2010–2039 to 2070–2099. During 2040–2069, coffee suitability holds quite well, due to niche potential at higher elevations (as the higher ground provides suitability for coffee), for Full Migration (A) and No Migration (D) and most of the other migration scenarios (Figs 2–5). Most of the increases and stabilities in suitability are distributed in the main South West Zone (Figs 1–3 and 6). The Arsi, East Hararge and West Hararge coffee areas (Harar Zone) do not show any niche suitability, for any of the modelling, for any future time period, and this result receives strong model agreement. Environmentally, they are ill suited to coffee growing now and do not improve in the future (Figs 1–3 and 6). Under the Full Migration (A) scenario, new areas of suitability develop, especially in the Amhara, Benishangul–Gumuz and Rift South coffee areas (Figs 1–3), mostly in the Fair and Good categories, but with lower model agreement (Figs 2 and 3).

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Full Migration versus No Migration. Comparing Full Migration (A) to No Migration (D) over the three future time periods, the percentage differences in the potential coffee niche area are substantial: 2010–2039, 462% (44,820 km^2 to 14,319 km^2); 2040–2069, 450% (58,036 km^2 to 12,897 km^2); and 2070–2099, 455% (51,280 km^2 to 11,256 km^2) (Table 1; Figs 2–6; Supplementary Table 1). This also demonstrates that, in Ethiopia, considerably more land could be used to grow coffee than is currently the case.

Discussion

Modelling considerations. The outcomes of our projections should take into account the assumptions and uncertainties associated with SDMs generally[41], within the regional context[25], and the projection of SDMs with climate change[41]. We have done our utmost to represent assumptions and uncertainties. Predicting future climate with any great certainty is not possible, but by using multiple climate models it is possible to make future projections assuming certain pathways of greenhouse gas emission. These are highly uncertain and cannot be validated, since we have no analogue for future climate. However, climate model projections provide useful estimates of potential future conditions[41], which we can use to explore the sensitivity of coffee production. By comparing different climate models and exploring reasons for the projected change in the coffee farming suitability niche, we can start to understand the vulnerabilities of coffee growing, at least in terms of exposure[35,36], and the level of confidence in the projected change of the niche.

Projections 1960–1990 to 2010–2039. Projections from the recent past (1960–1990) to present/near future (2010–2039) under the No Migration (D) scenario (Fig. 3) agree with our on-the-ground observations for climatic coffee farming suitability, the overall productivity of specific areas[42] and climate station data. Specifically, areas categorized by us as Unsuitable or Marginal generally have poor and inconsistent harvests, produce lower quality coffee and in extreme circumstances (for example, drought episodes) coffee trees experience severe stress or death. We present three examples to illustrate this. (1) In the Zege Peninsula, near Bahir Dar (on the shores of Lake Tana), coffee farming is problematic, with good harvests only every five years. The farmers report (personal communication) that there has been a long-term decline in productivity, from good harvests every year or two in the 1930s, to good harvests every five years (since the late 1990s). We assess the suitability of the Zege coffee locality as Marginal (1960–1990) to Fair (2010–2039), and then Unsuitable (2040–2099), with very strong SDM model agreement (Figs 2 and 3). The main climate constraint for Zege is not the amount of total annual rain, but rather the long dry season (Supplementary Fig. 4). (2) In the central and eastern parts of Wellega coffee area, where the SDM (1960–1990) categorizes suitability as Marginal, farmers and intervention workers report (personal communication) increasingly inconsistent harvests (a good harvest every three years or so), which they attribute to a shift in less rain from the late 1970s and mid-1980s. (3) For the Harar Zone, the niche is categorized as Unsuitable (Figs 1–3), which is a fair representation of conditions there at the present time: coffee farming is mostly suboptimal unless improved agronomy is practised (for example, irrigation, terracing), where the local or micro-climate is more suitable, or where the water table brings sufficient moisture to the soil. During the course of our field survey work we received numerous anecdotal reports (from farmers and coffee sector representatives) of a long-term decrease in rainfall over the Harar Zone and a steady, long-term decline in coffee farming. It seems clear, however, that the conversion to the narcotic khat (*Catha edulis*) has also had a considerable influence on declining coffee production in the Harar Zone. Since at least the 1960s, farmers have moved to growing this more lucrative crop at the expense of coffee farming and best-practice coffee agronomy. Given that there are also no gains in niche suitability in the Harar Zone across any of the modelling to 2099 (Figs 1–3 and 6) and that the modelling is in strong agreement (Figs 2 and 3), it seems that Harar coffee production will continue to decline unless considerable interventions are made. Overall, our modelling projects low-value categorizations (Unsuitable, Marginal, Fair) for the 1960–1990 to 2010–2039 time periods, for areas that are currently suboptimal for coffee farming. One unexpected exception is the Bale coffee area and the eastern part of the Sidamo coffee area (Figs 1–3 and 6), which is projected to be no longer suitable for coffee by 2039. Most of these two areas currently fall within the Excellent niche category. This result has strong to very strong model agreement (Figs 2 and 3). Our explanation for the loss of the Bale area and the climate mechanisms behind declines and increases in coffee suitability are discussed below.

Projections 2010–2039 to 2070–2099. As the century progresses (2010–2039 to 2040–2069 to 2070–2099) the projected outcomes are profound, depending on the migration scenario (Fig. 5). By the end of this century the current coffee-growing niche of Ethiopia could decrease by 39–59% (of the original area; 41–61% suitable area remaining), under our most restrictive migration and emission scenarios (the low-range (area in km^2) outcome, under migration scenario E and emission scenario A2) if no interventions are made (Table 1). The scenario of No Migration (D) (A1B = 45–64% remaining) most closely resembles a 'do nothing' scenario, although forest and tree canopy cover would have to remain stable (no deforestation or afforestation). At the other extreme, under the Full Migration (A) scenario (emission scenario A1B), there would be substantial gains with the potential for a more than fourfold increase in coffee farming area compared to the No Migration (D) scenario.

The main reason for the substantial increase in the area for coffee suitability in 2010–2039, under the Full Migration (A) scenario, is due to higher elevation areas coming into suitability. This is seen predominantly in the South West Zone (Fig. 1), where a huge area (in excess of 15,000 km^2) within the south-western highlands comes into suitability in 2010–2039. After 2010–2039, an elevation ceiling (literally) is reached, resulting in a decline from there onwards. There are of course interactions with rainfall (adding more nuanced changes), but the dominant climatic factor for the expansion is temperature, which is manifest as an upward elevational shift. An elevation profile across the South West Zone (Fig. 6b) illustrates this topographical expansion.

Particularly vulnerable coffee areas over these two time periods, under any migration scenario, include large parts of Wellega, the northern part of Illubabor and Bench-Maji (Figs 1–3 and 6), with variable but mostly strong SDM model agreement for these projections (Figs 2 and 3). All of the five circumscribed coffee zones (Fig. 1) could be negatively influenced to some extent (Figs 2 and 3), particularly at lower altitudes (Fig. 6). The main South West Zone has the most inherent resilience, mainly due to the potential for the coffee niche to improve in suitability at higher elevations (Figs 6 and 7). Across Ethiopia, the most climatically suitable part of the overall niche (the Excellent category; Box 2) is projected to drastically decline in the long-term (Figs 2–5).

Identifying the drivers of change. There has been considerable focus on the influence of increasing temperatures and supra-optimal temperatures on coffee production[8,43]. It is clear from our study, however, that rainfall is also a major contributing factor; as well as this, field observations, climate station data and our weather station recordings show that temperatures rarely reach the extreme limits for Arabica coffee[43] in Ethiopia. Analysis of the BIOCLIM[34] layers reveals that a combination of rainfall, temperature seasonality

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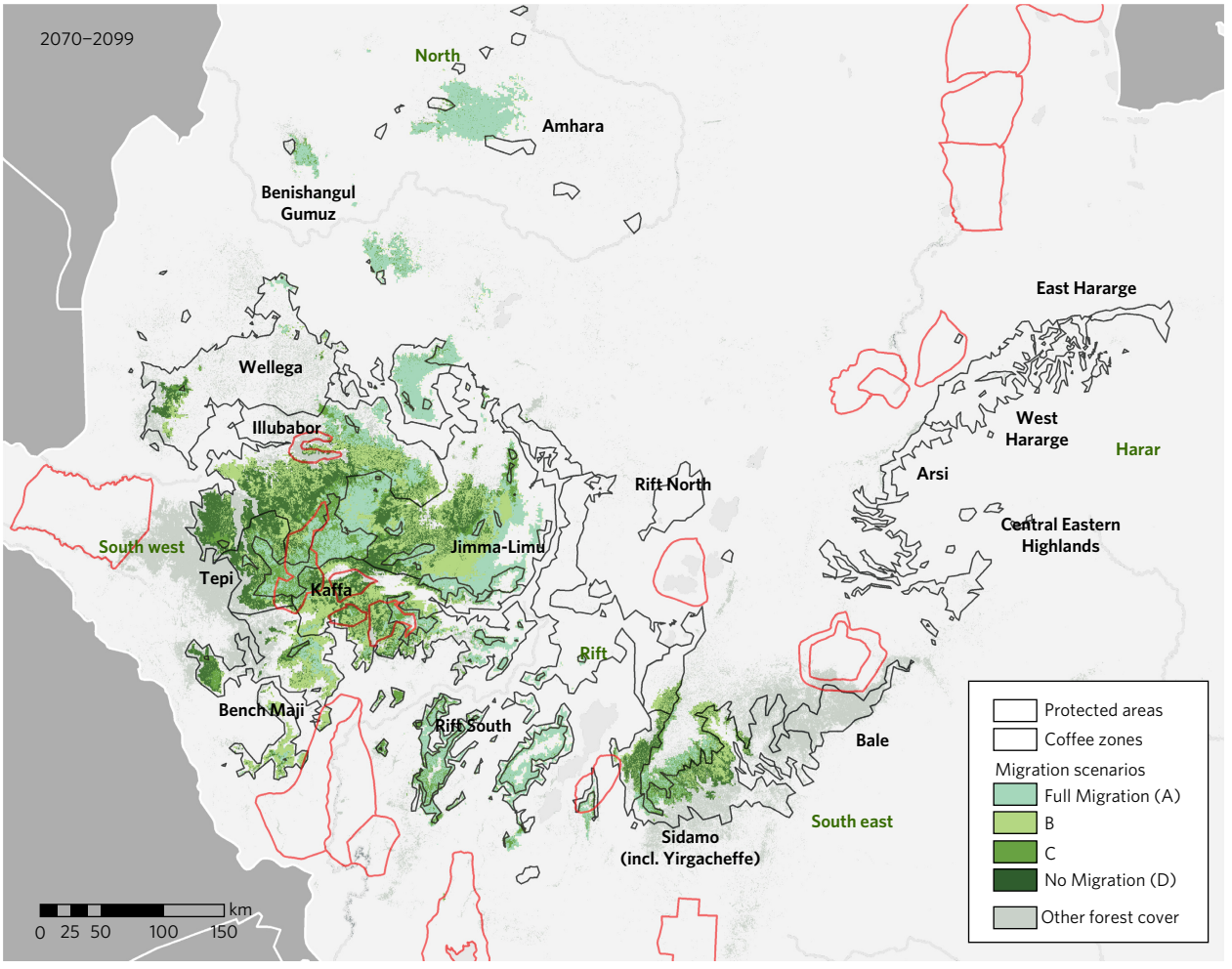


Figure 7 | Projections for coffee suitability 2070–2099 (emission scenario A1B) for scenarios Full Migration (A) and No Migration (D), with main coffee areas (black lines; see Fig. 1) and protected area boundaries[53] (red lines). Migration scenario A (Full Migration (A); green-blue) represents new coffee suitability niche for 2070–2099. Migration scenario B (light green) represents 1960–1990 niches that persist into 2070–2099. Migration scenario C (mid-green) represents new coffee suitability niche for 2070–2099 (as in migration scenario A), but with present-day forest cover. Migration scenario D (No Migration (D); dark green), 1960–1990 niches that still persist into 2070–2099 (as in migration scenario B), but with present-day forest cover. Grey represents other forest cover (with no end of the century coffee niche predicted). Figure 7 should be reviewed with model variability (Fig. 2.). Note, migration scenarios E and F are not represented on this map as they are too small to be visible at this scale.

and annual temperature (east and west of the Rift Valley; Supplementary Tables 2 and 3) were contributing most to the SDMs. By comparing these bioclimatic variables against each of our GCM projections (for emission scenario A1B), we were able to identify the main drivers in our models for change for each of the major coffee zones (Figs 1–3, for context; Supplementary Figs 9–12 show the trends for each zone). Across the entirety of the coffee landscape, the temperature BIOCLIM (BIO1) shows projected temperature increases of 2.7–3.2 °C (under emission scenario A1B) from 1960–1990 to 2070–99 (Supplementary Fig. 9), which is in good agreement with historical records (1960s onwards) and temperature projections from other sources (see Introduction). Temperature seasonality (BIO4) generally increases (Supplementary Fig. 10). Critically, the rainfall BIOCLIMs (BIO12 and BIO18) show little change across this century (Supplementary Figs 11 and 12). Thus, the total rainfall for each area experienced in the present day is key to understanding future suitability, as any increases and decreases in rainfall are mostly projected to be negligible to slight. Harar does show some decline in rainfall towards the end of the century, but the GCMs are in poor agreement (varying in decline of 250, 100 and 0 mm to the end of the century). Any decreases in rainfall for Harar would compound the already unsuitable coffee niche in this area, particularly if temperature increases continue to track future projections. To summarize, the key influencing factors can be viewed as a relatively simple interaction between rainfall and temperature: coffee areas that start with low rainfall cannot tolerate an increase in temperature, especially as rainfall is not projected to change by any considerable amount; temperatures are projected to increase steadily and substantially. If Ethiopian rainfall declines continue (see Introduction), in contrast to the negligible changes in precipitation observed in our projections (Supplementary Figs 11 and 12), they would further amplify the temperature-driven changes identified here. The Harar Zone and some locations within the South East Zone (the latter includes the coffee areas of Bale and Sidamo) have the lowest total rainfall at the present time (<1,300 mm), giving these areas little potential to deal with any temperature increases. In Harar and the South East zones, air temperatures tend to reach a seasonal maxima between January and May, that is, just before or during the onset of the spring rains (and coffee flowering time). These areas would be particularly sensitive to warming and evapotranspiration increases at the end of the dry season, for example, between November and March. This is consistent with projections indicating that increases in potential evapotranspiration may reduce the effective length of the African growing seasons[44].

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The Rift and South West zones have greater rainfall (1,320–1,690 mm) and therefore greater scope to tolerate temperature increases. Areas that are presently too cold (the North Zone and parts of the South West Zone, at higher altitudes), but have enough rainfall, will start to come into suitability as temperatures increase.

A better understanding of the critical relationship between low rainfall (and a corresponding soil moisture deficit) and high temperatures is starting to emerge from our in-country observations of plant stress, in conjunction with the use of climate data logging equipment. At the beginning of the year (January to March), we observe low rainfall and steadily increasing temperatures, resulting in low soil moisture levels, which in some cases reach or exceed the permanent wilting point. For example, in the Bench Maji coffee area we recorded severe plant stress in March (2015), after two months' total rainfall of less than 10 mm per month, an average temperature (based on 1 reading per hour) of 24 °C (minimum 16.4 °C; maximum 34.5 °C) and a volumetric soil moisture content of c. 20%, and soil water potential values of −400 kPa to −1000 kPa (both recorded at 40 cm soil depth). Arabica coffee will perform well in areas with higher temperatures than Ethiopia, but only if there is sufficient rainfall, especially if there are few, short or no periods of the year with a soil water deficit, for example as found in Panama and Costa Rica[45,46]. However, it should be clear that none of our projections would lead to a comparable environment for Ethiopia, given that rainfall is not projected to increase by any considerable amount.

CMIP5 versus CMIP3. In their overview of CMIP5, Knutti & Sedláček[39] compare CMIP5 and CMIP3 and state: "The spatial patterns of temperature and precipitation change are also very consistent. Interestingly, the local model spread has not changed much despite substantial model development and a massive increase in computational capacity." Our SDM results show no considerable differences between A2 and A1B, so if we see scenarios that fall within our present A2 and A1B we would expect similar results. Following Knutti & Sedláček[39] and comparing RCP8.5 with A2, we are provided with an indication of likely differences. The only substantial difference seen is an increase in annual mean temperature (BIO1), with an average additional increase of 0.9 °C (Supplementary Fig. 9), and an increase in temperature range between GCMs. We see some difference in rainfall between A2 and RCP8.5, with projections for increased rainfall (North and Harar zones), but with large disagreement between GCMs. These increases are unlikely to be sufficient to compensate or override projected severe temperature increases, although in the North Zone it is possible that some areas could move to higher suitability under this pathway (Supplementary Figs 11–14 and 16–17). The larger increase in temperature observed for RCP8.5 would indicate that both the A2 and A1B scenarios could be more conservative, compared to RCP8.5. It is also possible that the North Zone, which comes in as a new area in our CMIP3 future predictions, could come into better conditions under RCP8.5, but the increase in rainfall is slight and highly variable (Supplementary Figs 11 and 12). It should be reiterated that RCP 8.5 is the most extreme emissions scenario of the new CMIP5 pathways. Reviewing all of the RCPs for CMIP5 (which for the first time includes a low-emission mitigation scenario), these pathways are likely to deliver a broader range of outcomes. Overall, and as demonstrated by Knutti & Sedláček[39], CMIP5 scenarios give higher warming compared to CMIP3. If temperature change trends track according to (CMIP5) RCP8.5, we would see an amplification of the negative changes identified here using CMIP3.

Other influences. Our modelling does not include the potential influence of elevated CO_2 concentrations in the atmosphere, even though it has been shown that this may have a beneficial physiological influence on coffee, due to improved (leaf) water-use efficiency, which may mitigate high temperatures, at least where there is unrestricted water supply and high relative humidity[43]. Free air CO_2 enrichment experiments show that trees are more responsive than herbaceous plants to elevated CO_2[47] and that elevated CO_2 benefits plant species under drought conditions[48,49], although research indicates that the influence of CO_2 enrichment for crop production may be over-emphasized[50]. If projected increases in CO_2 prove to have a substantial role in mitigating the impact of drier, warmer conditions on coffee production, then our projections of climate exposure could be over-estimated. However, in Ethiopia we observe that drought (water stress) is one of the major causes of crop failure for coffee, and severe drought (lethal water stress) the most significant climate-related cause of plant fatality. We argue, therefore, that while there could be benefits from elevated atmospheric CO_2, drought (in its duration, timing and severity) may far outweigh these gains in the longer term. One might also contend that the forest will change as the climate changes, including responses to elevated CO_2. In this study, we review changes in niche and not forest, although our scenario of Full Migration (A) would encompass a broad spectrum of vegetation change (species and forest composition) within the humid forest vegetation class (MAF and TRF[6]). As well as increasing drought stress, high deforestation rates[5] and particularly their influence on local and regional climate are likely to override the benefits of atmospheric CO_2 enrichment for forest performance and survival and the physiological behaviour of Arabica coffee. We also have little knowledge about the potential influences of pests and diseases, although these are likely to have a compounding negative influence under a warming climate[25,51].

Migration scenarios and interventions. Under the Full Migration (A) scenario, there would be substantial potential to increase coffee farming and thus production volumes. As outlined above, comparison between Full Migration (A) and No Migration (D) (no migration, no forest loss) scenarios shows that the potential to increase the coffee growing area, over the three future time periods (2010–2039, 2040–2069 and 2070–2099), is at least fourfold (>400%), although the niche peaks in 2010–2039 (Table 1; Figs 4–7; Supplementary Table 1). Most of this change comes from up-slope migration to higher elevations. Under Full Migration (A) (emission scenario A1B) there would be a projected altitude shift for overall coffee suitability of 32 m per decade, from 1960–1990 to 2070–2099 (Fig. 6), with a considerable change in the extreme upper limits to 2,800–3,300 m (from 2,200–2,600 m). The emergence of coffee suitability areas at higher altitudes (to those existing now) is projected over a large area of the south-western Ethiopia plateau, but also in areas of the North Zone (Amhara and Benishangul–Gumuz coffee areas), Rift Zone (Rift South area) and South East Zone (Sidamo coffee area), although with different levels of model agreement (Figs 2 and 3). For the Full Migration (A) scenario to be realized, significant intervention would be required, including the planting of shade cover or the restoration of humid forest cover for areas with little or no present-day forest cover (Fig. 7). A concerted effort would be needed to identify and establish new coffee areas at higher altitudes, with particular attention placed on competing land-use issues (for example, existing land-use ownership, nature conservation sites), soil and micro-climate suitability and access to roads and other infrastructure. Shifts could also occur without major intervention, as farmers realize the potential for growing coffee in their upland areas. Field observations made by us in 2015 show that locations in the North Zone are already being developed as new coffee areas (in correspondence with our projections; Fig. 2), at altitudes in excess of 2,500 m (not previously seen for coffee

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farming in Ethiopia), indicating that assisted migration is already underway.

Resilience built via the migration of coffee farms could be supplemented with (location- and time-specific) improvements in coffee productivity (kg per hectare; for example, by increasing soil fertility and pruning) and quality (kg per $; for example, better harvesting and post-harvest processing), in order to offset unit area reductions in environmental suitability. In addition, there is scope for investing in locally appropriate, cost effective agronomy adaptations (such as mulching, irrigation, improved shade management and terracing). Irrigation would provide the single most effective adaptation measure, especially where implementation costs are low, for example, the diversion of nearby streams and rivers. Our projections would serve to provide a framework for the likely success, timing, duration and location of interventions.

Wild coffee forests. Ethiopia's wild coffee forests have considerable fundamental value as the main storehouse of *C. arabica* (Arabica coffee) genetic resources[25], with specific benefits for the coffee sector, locally, regionally and globally[52]. Most directly, indigenous Arabica coffee plays a key role in Ethiopian coffee production as an important source of planting material for farms via seed and seedlings. Protection of these resources should thus be seen as a key part of a resilience strategy. Using all migration scenarios (to 2070–2099), but selecting scenario E to represent the most resilient areas (refugia), provides an indication of which protected areas might have value as reserves for coffee genetic resources (Fig. 7). This exercise identifies protected areas in Kaffa (Kaffa Biosphere Reserve) and northern Illubabor (Yayu, a UNESCO registered Coffee Forest Biosphere)[53], although Yayu would have limited long-term potential unless contiguous areas at higher altitudes are included in the delimitation of its core area. Another important consideration is the preservation of specific coffee origins (and their unique flavour profiles), some of which are identified in the modelling as highly susceptible to negative climate change influences, including the coffees of Harar and Bale.

Summing up. Timely, precise, science-based decision making is required now and over the coming decades, to ensure sustainability and resilience for the Ethiopian coffee sector. Our projections show an overall negative influence, due to climate change, across this century for the present coffee growing landscape. Despite this, there is the potential to increase the area where coffee can be grown (by at least fourfold) via relocation and expansion, even if climate change tracks to our projections, although this would have to be done in combination with forest conservation and re-establishment. We also identify key coffee areas that could be climatically resilient, even without major intervention, at least until the end of this century.

Methods

Mapping the extent of humid forest in Ethiopia. A map of humid forest cover (TRF/MAF[6], and comparable agroforestry environments; Supplementary Fig. 6) was produced from Landsat 8 imagery (http://landsat.usgs.gov/landsat8.php)[26], downloaded for December of 2013 to February of 2014 (http://earthexplorer.usgs.gov (38 images covering 24 scenes)). The images were atmospherically corrected using the Fast Line-of-sight Atmospheric Analysis of Hypercubes algorithm (FLAASH) in ENVI 5.1 (ref. 54) to obtain surface reflectance values. To produce a cloud-free composite, the images were processed to identify clouds and cloud shadows using the Fmask 3.2 algorithm[55]. ERDAS Imagine 2013 was used to produce Normalised Difference Vegetation Indexes[56] from the surface reflectance cloudless composites. Finally, we produced a Normalised Difference Vegetation Index composite using two thresholds to identify the humid forest.

A set of 300 training data points were used to identify the most appropriate thresholds and the individual maps were combined in ArcGIS ver. 10.1 (Environmental Systems Research Institute (Esri)). Testing of the final map yielded an accuracy assessment of 97%. The humid forest map was uploaded to Google Earth for review, as well as large-format mobile phones (Samsung Note II, GT-N7100) using Locus Map Pro 3.1, Asamm Software, Praha, for validation during eight fieldwork trips (2014–2016), with an emphasis to identify and remove non-coffee production areas (for example, tea, mango, avocado plantations and commercial forestry).

Point data and ground-truthing. We collected 3070 data points (Supplementary Fig. 3), of which 1624 were coffee presence data points (1446 non-coffee points), comprising 824 historical (1941–2001) and 800 contemporary (2013–2015) points (with coffee production type, forest cover and condition, and global positioning system (GPS) data recorded). To reduce sampling bias and sampling errors, the ground data was filtered: historical data points collected before 2001 (early-generation GPS, herbarium specimens and literature records) with an accuracy lower than 1 km were rejected; multiple points falling within a 1 km^2 grid were reduced to a single point; any points covering locations with significant interventions (all irrigated and high water table areas) were removed. This left 381 points to build the final SDM. Many of the data points appear to lie close to roads, although a considerable amount of data was collected on foot (c. 40%). There were no indications of a road-like bias in our SDMs. In well-sampled studies, sampling along roads should not represent a bias issue[57], especially where roads cut across numerous environmental gradients, as in Ethiopia. Moreover, the niche and landscape were very well sampled (Supplementary Fig. 3). We double-checked to see if our sampling would show any significant sampling bias by comparing histograms of elevation versus percentage sampling. The range of elevations sampled by the 3,070 data points was 426–3,877 m, which is much greater than the range (991–2,263 m) for the 381 points used for the SDMs. Both histograms showed consistent sampling across 250 m elevation bands.

In addition to the 3070 original points, an additional 1028 points for coffee presence and absence were collected after the initial modelling (2015). These points were used to informally validate the modelling and remote sensing, although no mapping or analyses were undertaken with these data. The 800 contemporary data points (2013–2015) and the additional 1028 data points (2015–2016) were collected during ten field missions, covering c. 30,000 km by road and on foot (plots and transects), across almost the entire coffee landscape of Ethiopia. During our fieldwork, we also informally interviewed farmers for perceived changes in coffee farming, on a year-by-year and generation-by-generation basis.

SDM—the niche. There has been much discussion about the actual niche represented by an SDM and particularly the question over realised niche versus fundamental niche. Most SDM studies identify the realised niche[58]; the closer the realised niche gets to the fundamental niche, the better the projections are likely to be. When using bioclimatic variables, the results will tend towards the fundamental niche, especially when extrapolating to new areas (for example, introduced ranges) or future climates[58,59]. In this study, the niche-only scenarios (A, B and E), combined with exhaustive ground validation, show that our SDMs are very close to representing the fundamental niche, that is, where coffee grows and is farmed. Our niche and forest (migration) scenarios (C, D and F; Supplementary Fig. 5) preserve the relationship to the fundamental niche; applying the humid forest mask also means that we are closer to the realised niche than using an SDM alone.

SDM—division into climatic groups. After running preliminary models for the present day, investigating climate profiles, and considering the biology of Arabica coffee in Ethiopia, it became clear that we should treat east and west of the Rift Valley (Fig. 1) separately. The rainfall pattern east of the Rift Valley is bimodal, and in the west it is unimodal (see Supplementary Fig. 4). Molecular[60–62], morphological[63] and physiological data[64] support Arabica coffee differentiation either side of the Rift Valley. Thus, for our modelling, we treated east and west independently, running the models for each and combining only at the end of the procedure to provide final modelling outputs.

SDM—selection of environmental variables. We examined the full BIOCLIM dataset[34] of 19 variables, independently, east and west of the Rift Valley. Paired dataset correlations and boxed plots were reviewed and we examined which variables had significant influence on the Generalised Linear Models (GLM) and Generalized Additive Models (see below). For each BIOCLIM variable, we ran an analysis of variance (ANOVA) test by examining output model results for our validation points and comparing these to the pseudo-absence points. We also ran models using random pairs of variables to investigate the best variables for model fit (see below). Finally, we examined the resultant BIOCLIM variables and reduced the selection to those that were significant in the above tests, not highly correlated (as pairs) and which represented the ecological requirements of Arabica coffee. By comparing the results independently for east and west of the Rift Valley, we reduced the 19 BIOCLIM variables to nine (Supplementary Table 4), for use in our modelling. The same variables were used for the east and west split, to allow our models to be comparable.

SDM—processing. Using the selected environmental variables (see above), we ran the data (381 ground points) in the Biomod2 R package, version 3.1–64 (ref. 65), using six modelling methods (GLM, Generalized Boosted Regression Models, Generalized Additive Models, Multiple Adaptive Regression Splines (MARS), Random Forest and Maximum Entropy (Maxent) software version 3.3.3 (refs 65–68) to produce an ensemble model for either side of the Rift Valley. Each of the models

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used the nine selected environment variables to maximise its fit to the output prediction. We largely followed established methodologies[65,69–71] for model evaluation, runs, replications and combination. We used the default setting in Biomod2, except for increasing the number of iterations for GLM and Maxent, to reach convergence. Three sets of background or pseudo-absence data were generated. Ground control data, both presence and background for each of the three sets, was split randomly ten times with a ratio of 70:30 to build training and testing data, respectively[72]. Model outputs from Biomod2 were evaluated by viewing the actual results and using sensitivity, specificity, True Skills Statistics (TSS), Cohen's Kappa statistic (KAPPA) and relative operating characteristic curve for east and west of the Rift Valley models (see Supplementary Information). Following Araujo & New[70] and Thuiller *et al.*[69,71] we took the six individual models to produce an ensemble prediction for either side of the Rift Valley, using the suggested model evolution threshold of 0.7 (using TSS), to remove poorly performing models (although no models were removed during this process, as they all exceeded this threshold). We also implemented proportional weighted overlay, to give better fitting models a higher weight. During the statistical evaluation of the six models, expert review was used to make sure that they were in agreement with the biotic and abiotic requirements for Arabica coffee. The testing and training data were assessed and reviewed to give the relative importance of the variables used in each developed model, model sensitivity and specificity, as well as overall model performance[72]. All six niche model methods performed exceptionally well (over 90% for specificity and sensitivity for each model).

There are two assumptions associated with the models for 1960–1990: (1) because the 2014 TRF/MAF[6] forest cover (see Supplementary Fig. 6) was used with 1960–1990 data, the surface area will be underestimated, as there has been considerable deforestation since the 1960s[5]; and (2) we assume that the suitable coffee niche, if forested or having sufficient shade cover, is being used for coffee production of some description[25].

SDM—evaluation. Model outputs from Biomod2 (ref. 65) were evaluated by viewing the resultant maps and using the statistics; sensitivity, specificity, TSS, KAPPA and relative operating characteristic curve for east and west of the Rift Valley. For our purposes, sensitivity and specificity was the most useful and easiest to use metric, but we reviewed all statistics. All six niche model methods performed very well (over 90% for specificity and sensitivity), but east of the Rift Valley showed slightly lower specificity values, compared to west (this is not surprising as the sample for the east is much smaller). GLM and MARS showed the lowest scores (90–93% for GLM and MARS for specificity), which is still very good, but suggests they are not fitting the data as well as other models. Final models were produced from ten runs and three replicates. We checked the outputs visually to see if there was a noticeable difference between model runs (which may suggest problems, for example, overfitting or incorrect models).

SDM and WorldClim—validation. The ensemble SDM was loaded onto four large-format, GPS-enabled mobile phones (Samsung Note II, GT-N7100), using Locus Map Pro 3.1, Asamm Software, Praha, for validation during seven fieldwork trips (2015 to 2016). This activity revealed excellent correspondence between the ensemble SDM and coffee farming areas; the SDM predicted coffee farming activity to within a 1 km radius of each validation location.

As a means of checking the WorldClim[34] precipitation data, we compared precipitation data from 27 weather stations over a 30-year period (1984–2014) (National Meteorology Agency Ethiopia) against the WorldClim[34] data (1960–1990). We found acceptable to excellent agreement between the two data sets, when visualized as c. 30 year averages for numerous locations. Climate profiles (30-year period; 1984–2014) for total monthly rainfall and average monthly temperature (minimum, median and maximum) for an additional 20 weather stations (National Meteorology Agency) situated within, or adjacent to, coffee growing areas, were also found to be in good agreement with 1960–1990 WorldClim[34] data. Six examples are provided in Supplementary Fig. 4. At Yayu (Illubabor), Ashi (Wellega), Gesha (Bench-Maji), Yirgacheffe and Yirga Alem (Sidamo), Bale (Bale) and Gololocha (Arsi) (see Fig. 1) we installed (2013–2016) proprietary data-logging equipment (Tinytag Plus 2—TGP-4500, with Stevenson type screen (ACS-5050), both from Gemini Data Loggers), to measure air temperature and relative humidity (RH%). At Ashi, Gesha and Bale we also installed soil temperature probes (Tinytag Plus 2—TGP-4510, Gemini Data Loggers), soil moisture (10HS) and soil water potential sensors (MPS-6) connected to EM50 digital data loggers (all from Decagon Devices) at 20 and 40 cm soil depths and low resolution rain gauges (ECRN-50, Decagon Devices). The logging interval was every hour on the hour for Tinytag Plus 2 and twice daily for the Decagon equipment. The data was not analysed for this study, but simply used to ground-truth WorldClim[34] data and the coffee niche and to better understand the climatic variables causing physiological stress in coffee.

SDM—assessment of climatic variables. We examined the BIOCLIM[34] data to see which bioclimatic variables were contributing most to the SDMs, by summarizing the contribution of each variable for each of the six niche modelling methods (Supplementary Table 2 and 3), for east and west of the Rift Valley. For the east, the most important were temperature seasonality (BIO4) and precipitation of the warmest quarter (BIO18); and the west, annual mean temperature (BIO1) and annual precipitation (BIO12).

Selection of GCMs. The evaluation and selection of GCMs for a study area and set of circumstances is a challenging activity[24,73,74]. Ideally, we would have used all GCMs to assess the full range of outcomes, but selected three in order to keep processing time and storage to a manageable level and to reduce redundancy (for example, where GCMs were in agreement). To make our selection, we processed all 23 GCMs available for the study area, excluding models that did not fit our future time periods (2010–2039, 2040–2069 and 2070–2099). We then reviewed the projections for each of the contributing BIOCLIM layers, for eight coffee locations either side of the Rift Valley, as a representative sample of the of the coffee farming landscape: for the South West Zone (Yayu (Illubabor), Dembi Dollo and Ashi (Wellega)); South East Zone (Bale (two sub-locations), Yirgacheffe and Yirga Alem (Sidamo)); and Harar Zone (Gololocha (Arsi)); an example for one of these locations (Ashi) is shown in Supplementary Fig. 15. On reviewing these graphs, we rejected GCMs that were highly anomalous for temperatures and anomalously high or low values for precipitation; an emphasis was placed on the 2010–2039 period, where anomalies are more easily assessed. We selected a representative GCM for those showing similar results across the nine BIOCLIMs, two emission scenarios and four time intervals. This still left us with eleven GCMs from which we choose three (BCCR-BCM2.0, CSIRO-MK3.5 and GFDL-CM2.1) to represent climatic changes over time (for the subset of 11 GCMs; across the nine BIOCLIMs).

GCM data downscaling. The original ground resolution for the GCMs was approximately 200 km. To make this data more useful for SDM and to see variation at higher resolutions, we used downscaled GCMs[34,75,76]. We employed the downscaled (Delta method of the Intergovernmental Panel on Climate Change (IPCC) AR4 (ref. 76)) climate models from CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) (http://ccafs-climate.org/data_spatial_downscaling/ and http://www.ccafs-climate.org/data/). The downscaled method used by CCAFS is based on thin plate spline interpolations of deltas (anomalies) of the original low-resolution GCM outputs. These deltas are applied to the WorldClim[34] data (the same data we used for our 1960–1990 SDM) at a resolution of 30 arc seconds (approximately 1 km^2 cells size for Ethiopia) by interpolating between GCM cell centroids[76]. The 19 bioclimatic indices (BIOCLIM)[77] were calculated by CCAFS from the resultant rasters.

GCMs—modelling future projections. Our three selected GCMs were: (1) BCCR-BCM2.0—BCCR, Univ. of Bergen, Norway (BCM Version 2); (2) CSIRO-MK3.5—Centre for Australian Weather and Climate Research (Mark 3.5); and (3) GFDL-CM2.1—GFDL USA (Coupled Climate Model 2.1). The future SDM variability of the selected GCMs is illustrated in Figs 2 and 3. We used two CO_2 emission scenarios, A1B and A2: A1B reaching 13.5 giga tonnes of carbon (GtC) by 2099; and A2 reaching 29.1 GtC; this is against a baseline of 9.8 GtC (in 2014/15). The projections (areas of coffee-growing suitability given as percentages and km^2) produced from the three GCMs were categorised into three classes: low, middle and high (Table 1). For the Results and Discussion, we provide percentages and area measurements (km^2) for the middle-range outcome, based on the three GCMs (Table 1; Supplementary Table 1). The GCM CSIRO-MK3.5 predominately produced the middle-range outcomes; BCCR-BCM2.0 tended to produce low-range outcomes and GFDL-CM2.1 the higher ones, although these switched between low, middle and high, depending on the suitability category and time intervals across this century.

The future projections were modelled in the Biomod2 package Ensemble Forecasting[65], which projects the ensemble recent past and current model in space and time. The projection was performed on the nine BIOCLIM variables as identified above. Future models were run for each GCM, for east and west of the Rift Valley and over three time periods (2010–2039, 2040–2069 and 2070–2099; Supplementary Fig. 1), giving 18 future projections (two regions, over three dates and three GCMs) as a final output.

Combining SDMs and GCMs—analysis and mapping. The outputs from the four time periods (1960–1990, 2010–2039, 2040–2069 and 2070–2099) were imported into ArcGIS ver. 10.1 (Esri), with the spatial analysis extension, for further analysis and visualization. The Rift Valley separation, from each modelling stage, was combined using the raster calculator tool to give the maximum suitability value for each pixel, giving 19 models for the final analysis (one time period (1960–1990) plus three GCMs × two emission scenarios, across three further time periods). To visualise the SDM variability, the projections were processed to show the range of SDM values and these ranges were categorised into three classes: (1) Very Strong, model variability 0 to 200; (2) Strong, 200 to 400; and (3) Weaker, 600 or higher. Very strong (solid colours, with no overlay) shows where the model class (Excellent, Good, Fair, Marginal and Unsuitable) is unlikely to change, except at the edge of the ranges. Strong (overlaid with dots) shows where a class could change up or down by one class (for example, Good could range from Excellent to Fair). The Weaker class (diagonal lines) is where classes could change by more than one class; the largest range is 610, indicating a movement of up to one and a half classes. We adopted the same symbology as used in a widely read IPCC report[22], although it should be noted that we used it for SDM variation not GCM variation (as in the IPCC report). We

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also calculated the median for each model, which was used only for visualization of the results (Figs 2 and 3).

Categorisation of projection maps. To provide area measurements (in km^2) for each category (Unsuitable, Marginal, Fair, Good, Excellent), we needed to threshold the continuous SDM values (those between 0 and 1,000). To achieve this, we examined the SDM values for our ground point data (ground control, absence and pseudo absences data), by comparing TSS and the cumulative percentage of points to give us our initial threshold. This was further subdivided to give a total of five categories (Supplementary Fig. 2; Supplementary Information).

Migration scenarios for climate change projections. The six migration scenarios (Box 1; Supplementary Fig. 5) were processed in ArcGIS, using simple map algebra, summarized, with the following processing: (A) no processing; (B) all models cookie-cut with 1960–1990 suitable niche (all areas outside of the 1960–1990 niche were clipped for all dates); (C) as A but cookie-cut with forest cover; (D) as B but cookie-cut with forest cover; (E) as B but 2040–2069 cookie-cut with 2010–2039 suitable niche and 2070–2099 cookie-cut with 2010–2039 and 2040–2069 suitable niche; (F) as E but additionally cookie-cut with forest cover. The forest cover niche models were resampled at 30 m resolution using a simple nearest-neighbour resampling (to preserve the original model resolution of 1 km^2).

Analysis of regional trends and drivers. To understand the trends and the main drivers for climate change outcomes we produced graphs of change for the most influential BIOCLIMs. Supplementary Figs 9–12 show the trends for each of the five coffee zones (Fig. 1), from 1960–1990 to 2070–2099. The most influential BIOCLIMs were: temperature seasonality (BIO4), precipitation of the warmest quarter (BIO18), annual mean temperature (BIO1) and annual precipitation (BIO12). We calculated the mean, max, min and range for each zone, for CMIP3 scenarios A1B and A2, the three GCMs and all four date periods.

CMIP3 versus CMIP5. Our projections are based on the WCRP's CMIP3 multi-model dataset[37]. The newer and more developed WCRP CMIP5 multi-model ensemble[38] was released as a downscaled dataset after the project research period. A direct comparison between CMIP3 and CMIP5 is not straightforward, as CMIP3 uses emission scenarios, whereas CMIP5 uses RCPs[39]. Following the methods of Knutti & Sedláček[39], we compared CMIP5 RCP8.5 against CMIP3 SRES scenario A2, which represents the two scenarios with the highest temperature changes. Supplementary Figs 15 and 16 show a comparison of the GCM robustness across Africa for CMIP5 (RCP8.5) vs CMIP3 (SRES A2) based on Knutti & Sedláček[39]. For further comparison, we included CMIP5 RCP8.5 in the same analysis that we used to represent the five coffee zones (Fig. 1) for CMIP3 A1B and A2 (Supplementary Figs 9–12). Both the GCM and the downscaling methods (Delta method[76] IPCC AR4[78] to Delta method IPCC AR5 (ref. 79)) were updated when moving from CMIP3 to CMIP5. Where possible, we used the most up to date version of each GCM: GFDC-CM2.1 and CSIRO-MK3.5 for CMIP3 scenarios A2 and A1B were updated to GFDL-CM3 and CSIRO-MK3.5 for the CMIP5 scenarios, respectively. There was no updated GCM for BCCR-BCM2.0, so we used BCCR-CSM1.1m to give us an output level for comparative purposes. The period 2010–2039 was not available for CMIP5, so we substituted the period 2020–2049.

Data availability. The data that supports the findings of this study are available from the corresponding author upon request. The supply of ground point data is restricted, as ownership is shared across the authorship and externally.

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Author contributions

J.M. and A.P.D. conceived and led the study; A.P.D. and J.M. led the project; all authors collected data; J.M., A.P.D., J.W., S.B. and T.W. analysed and processed the data. J.M. and A.P.D. wrote the paper with contributions from all authors.

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Correspondence and requests for materials should be addressed to J.M. and A.P.D.

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C. Conclusion

Earth Observation by Remote Sensing has proved to be instrumental for addressing the observation needs of the plant conservation community across multiple scales. Its importance from collecting and processing very high resolution data for local conservation projects to help determine conservation status of a country's unique ecosystem to tracking and reporting on global plant conservation targets has been demonstrated. The amount, quality and accessibility of Earth Observation data is ever increasing. The opening of Earth Observation data archives, the recent proliferation and access to UAVs and recent/upcoming satellite missions are constantly adding to the records of the Earth. The constantly growing academy of Remote Sensing, making use of cutting edge methodologies and algorithms, allows for the faster and more accurate processing of Earth Observation data affording the assimilation of yet more. Throughout the papers comprising this thesis, Remote Sensing technology has been applied to address the observation needs of the plant conservation community across scales. But this is only a small sample of what can be achieved. The further development of these technologies in fields such as plant health and plant resilience to environmental changes, could be a major contribution to plant science. However, the plant conservation community has a long way to go to achieve the full potential of these technologies. This research has identified the main barrier hindering the realisation of this potential: There is a generalised lack of awareness amongst plant conservation scientists and practitioners of what Remote Sensing has to offer. There are indeed compelling reasons for this, including the fast-evolving pace of these technologies, the vast amount of available data constantly been created as well as the need of specific technical skills which are generally not very appealing to plant scientists. Nevertheless, in order to overcome this barrier and encourage the plant conservation community to be more involved with RS an effort has to be made on both sides. On one side the RS community needs to make EO data more readily available. Satellites missions need to be translated into "conservation useful" information and be kept regularly updated. Global land cover products (Gong et al., 2013), vegetation maps and deforestation datasets (Hansen et al., 2013) are of great value for plant conservation practitioners but

also other useful data sets largely derived from satellite data such as threats to plant diversity (Joppa et al., 2016) will need to be created and regularly updated.

On the other hand, the plant conservation community needs to embrace these technologies. Plant scientists have a history of rejecting technology, only in the last few years GPSs and mobile technology have been slowly introduced to botanical surveys and field collection campaigns. Remote Sensing needs to also be part of the "botanist toolkit". Plant scientists need to make use of these technologies, but more importantly they need to be aware of future developments to be able to successfully design research and conservation projects. The forthcoming Sentinel satellites part of the Copernicus programme comprising radar and optical sensors, radiometers and spectrometers. The planned NASA Global Ecosystem Dynamics Investigation (GEDI) that will provide the first global, high-resolution space borne LiDAR. Commercial cube satellites, miniaturised sensors on board of UAVs… These are just a few of the imminent developments that will revolutionise the way we monitoring plant diversity.

It is essential that Botanical Gardens and plant conservation organisations start valuing these skills and plant conservation training programs include Remote Sensing in their curriculum so plant conservationist can start speaking remote sensing. More dialogue between the conservation and remote sensing community has long been called for (Kuenzer et al., 2014; O'Connor et al., 2015; Pettorelli et al., 2016a, 2014b) and attempts to bring together members of the conservation and the RS community (Skidmore et al., 2015) has also been sought. But until there is real understanding between both communities final goals will not be achieved. Dialogue yes, but we need people speaking both languages!

This thesis aims to pave the way for the plant conservation community to realise the full potential of Earth Observation by Remote Sensing for the analysis and conservation of global plant diversity. It is unique and novel since it address the needs and priorities of the plant conservation community as a separate entity from the general conservationist whom are largely focus on the animal kingdom. This thesis provides examples and guidance to fulfil the goal of realising the full potential of Remote Sensing for the conservation of plant diversity, exploring exciting future developments and applying

them to real plant conservation projects. I hope this research inspires the plant conservation community to embrace Remote Sensing technology to help stem future plant diversity loss.

D. References

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E. Appendices

1. Appendix I:

Questionnaire use in the "Remote Sensing use across Kew's science directory" survey

Survey carried out from January to March 2016

Remote Sensing use across Kew's science directory:

BACKGROUND

The beginning of this century has experienced a dramatic increase in the availability and quality of Earth Observation (EO) data. A sophisticated network of satellites along with newly developed aerial platforms are capturing data and adding it to a timeline of a consistent record of the Earth. Some of this has already been successfully used for biodiversity conservation.

Still, there is a limited use of Remote Sensing (RS) techniques and Earth Observation data within the plant science and conservation community. The reasons for this might include technical constrains such as data suitability, costs related to data collection or the capacity needed to process this data. However, it may be also due to a lack of awareness of these technological developments and how they can directly contribute to the conservation of plants across different scales.

For the full potential of RS and EO data to be achieved the exact reasons for its limited used need to be identified. Royal Botanic Gardens, Kew is placed in a unique position to be the population target. Kew is a world leader organisation in plant science and conservation, being one of the most important global resources for plant and fungal knowledge. It has one of the largest and most diverse collections of plant and fungal specimens (living and preserved) in the world, as well as the largest *ex situ* plant conservation programme in the world (The Millennium Seed Bank Partnership)

The overall aim of this survey is to identify the challenges and limitations on the use of Earth Observation data and Remote Sensing techniques across the organisation and to explore the opportunities provided by these technologies for the conservation and analysis of plant diversity. Results from the survey will constitute the backbone of the research on "Remotely sensed solutions for plant science and conservation"

OBJECTIVES

The objective of this organisational survey is to gather information regarding the use of Remote Sensing technologies and Earth Observation data for plant science and conservation across Kew's science directorate. It aims to investigate the following:

- Awareness within the organisation of the advances in RS technologies and the increased availability of EO data
- Current uses and applications of RS/EO for plant sciences and conservation
- Limitations on the use of RS/EO across the organisation (Reasons why EO/RS might be limited)
- Specific needs for EO derived data products
- Challenges when using RS/EO for plant sciences and conservation
- Opportunities for further development

SURVEY METHOD

It will be a combination of email and personal interviews. A simplified survey questionnaire (using mainly closed-ended questions) will be emailed to all science staff (not in support or technical roles) within the science directory to get an overview of how widely spread the use of RS is within the organisation. A more detailed questionnaire will be then used to guide personal interviews with a smaller group (sample size around 10% of the population). This sample will be chosen (non-randomly) amongst the more experienced users to get a deeper understanding on the specific uses, limitations, challenges and opportunities for further development.

The time scale for completion of this survey will be 3 months. Deadline for completion will be the end of June 2016

SEMI-STRUCTURED INTERVIEWS

BACKGROUND SECTION

1. Name (Optional):
2. Position (Optional):
3. Is your job directly related to the conservation of plant diversity? How?

AWARNESS SECTION

4. How would you rate your knowledge/ level of awareness of EO data and RS techniques (Highlight or circle one)
   Nil _____ / Low _____ / Medium _____ / High _____ / Very High _____

5. Are you aware of any of the following technical developments (tick where appropriate):

Google Earth display of satellite images, elevation and maps on a virtual Globe	
Availability of very high spatial resolution satellite data (i.e. WorldWiew)	
New constellation of satellites such as Landsat8 and Sentinels	
Opening of Earth Observation data archives extending back to 70's	
Global elevation data at 30m resolution	
Global deforestation dataset (2000-2012) at 30 m resolution	
EO climate datasets (TRMM…)	
Value-added data products (i.e. Vegetation Indices, Fires…)	

USES SECTION

6. Do you use EO data for plant diversity conservation? (Highlight or circle one)
   Yes _____ / No _____

   If Yes,

   6.1. Where you obtain your data from:

Freely available	
Commercial providers (do you purchase your data?)	
From other organisations	

   6.2. How often do you use the data: (Highlight or circle one)

   Daily _____ / Weekly _____ / Monthly _____ / Yearly _____ / Occasionally _____

7. Tick if any of the following applications are relevant to your work/research. Tick all applicable. Add other you may feel relevant

Plant/ecosystem conservation assessments	
Vegetation/ ecosystem mapping	
Land cover change - Deforestation and vegetation degradation	
Resilience - Vegetation dynamics / seasonality studies	
Assessment or management of protected areas	
Spread of invasive species	
Plant Health	
Ecosystem services (Amount of biomass, Carbon storage, climate change)	
Development of environmental layers/variables for modelling	
Baseline data for general mapping	
Support for field work planning and sampling design	
Other (please describe) :	
…	

LIMITATIONS SECTION

8. Please give reasons why there might be limitations in the use of EO data for your research. Tick all applicable. Add other you may feel relevant

Cost of data	
Cost of equipment	
Data accessibility (where to obtain the data)	
Lack of understanding the type of data useful for a specific application	
No qualified personnel for data processing	
Cost of personnel for data processing	
Insufficient data availability	
Lack of validation data	
Insufficient spatial resolution of remotely sensed data	
Algorithms for processing data not sufficiently developed	
Methodologies for data collection are not harmonize	
Remotely sensed information is difficult to incorporate into monitoring	
Methodologies are not realistic to my specific problems	
Other (please describe) :	
…	

NEEDS SECTION

9. Any specific tools you would like to see developed which would help/increase the use of RS/EO in your research

10. What is the level of processing of the remotely sensed information that you use (from raw RS images to EO data to final maps)

Raw RS images	
Calibrated data	
Off-the-shelf data products (processed to metrics)	
Mapping products for direct used in a GIS	
Final maps (google maps, pdf, print outs …)	

11. How do you see RS/EO contributing to your own (or your department) research?

FUTURE OPPORTUNITIES

12. How do you see RS/EO can contribute to Kew's strategic outputs? Please rate for each output. 1: Low, 2: Medium or 3: High.

Plants of the World Online Portal	
State of the World's plants	
Tropical Important Plant Areas	
The plant and Fungal Trees of Life	
Banking the world's seeds	
Useful Plants and Fungi Portal	
Digitising the collections	
Training the Next Generation of Plant and Fungal Scientists	
Sciences in the Gardens	

Potential candidates for RS/EO interview across Kew's science directory:

- Biodiversity Informatics & Spatial Analysis
- Collections
- Conservation
- Comparative Plant & Fungal Biology
- Identification and Naming
- Natural Capital and Plant Health

Extended Questionnaire (Personal Interviews):

13. I will give an introduction of RS/EO in line with their level of awareness. Potential RS/EO applications (tick if relevant to your research and/or any more to add) → This is to aid discussion

Plant/ecosystem conservation assessments	
Vegetation/ ecosystem mapping	
Deforestation and vegetation degradation	
Vegetation dynamics / seasonality studies	
Assessment or management of protected areas	
Spread of invasive species	
Plant Health	
Ecosystem services (Carbon storage, climate change)	
Development of environmental layers/variables for modelling	
Baseline data for general mapping	
Support for field work and statistical spatial sampling design	

14. How do you see RS/EO contributing to your own (or your department) research?
    - Scale, resolution or level of detail relevant to your research
    - Temporal component (EO data archives, monitoring systems, future projections) relevant to your research
    - Applications to any specific plant species/ taxon/ ecosystem
    - Any specific tools you would like to see developed which would help/increase the use of RS/EO in your research

15. Limitations and challenges of the use of RS/EO to your research (Accessibility of data, cost, computing required, steep learning curve)
16. Future opportunities (how RS/EO can help in your research)

2. Appendix II:

Supplementary information for Paper 5: Resilience potential of the Ethiopian coffee sector under climate change

Further description of the Remote Sensing methods developed for the paper: "Resilience potential of the Ethiopian coffee sector under climate change"

nature plants

SUPPLEMENTARY INFORMATION

VOLUME: 3 | ARTICLE NUMBER: 17081

In the format provided by the authors and unedited.

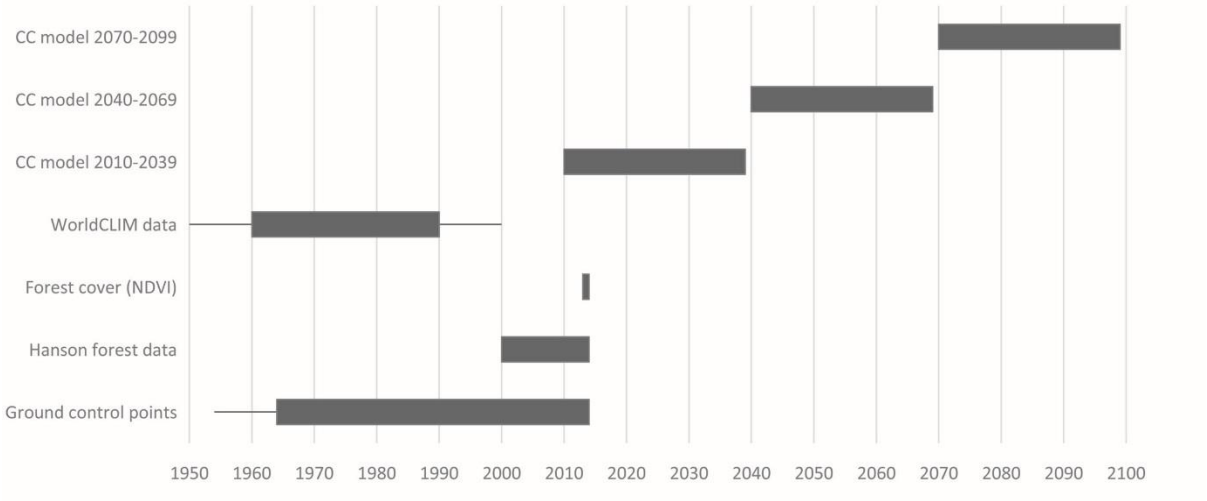
Resilience potential of the Ethiopian coffee sector under climate change

Justin Moat[1,2]*, Jenny Williams[1], Susana Baena[1,2], Timothy Wilkinson[1], Tadesse W. Gole[3], Zeleke K. Challa[3], Sebsebe Demissew[1,4] and Aaron P. Davis[1]*

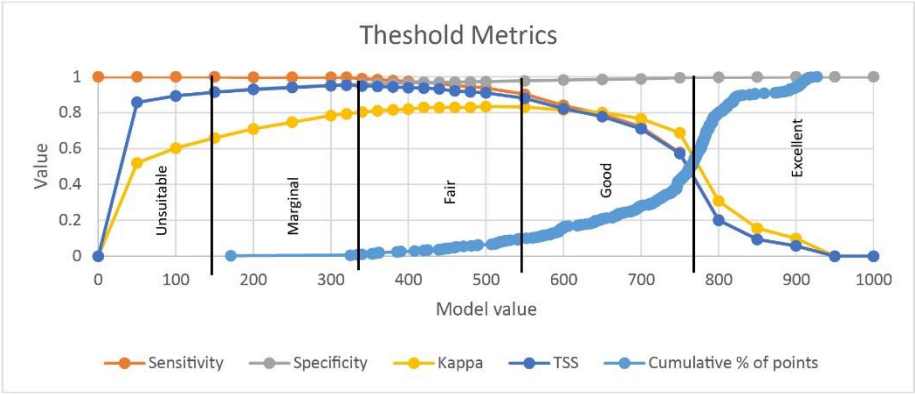
[1]Royal Botanic Gardens, Kew, Richmond, Surrey TW9 3AE, United Kingdom. [2]School of Geography, University of Nottingham, Nottingham NG7 2RD, United Kingdom. [3]Environment and Coffee Forest Forum (ECFF), PO Box 28513, Addis Ababa, Ethiopia. [4]The National Herbarium, Department of Plant Biology and Biodiversity Management, College of Natural Sciences, Addis Ababa University, PO Box 3434, Addis Ababa, Ethiopia.
*e-mail: j.moat@kew.org; a.davis@kew.org

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SUPPLEMENTARY FIGURES



Supplementary Figure 1.Date ranges for study datasets. Whiskers represent limited data availability in that period. Note. CC model = climate change model.



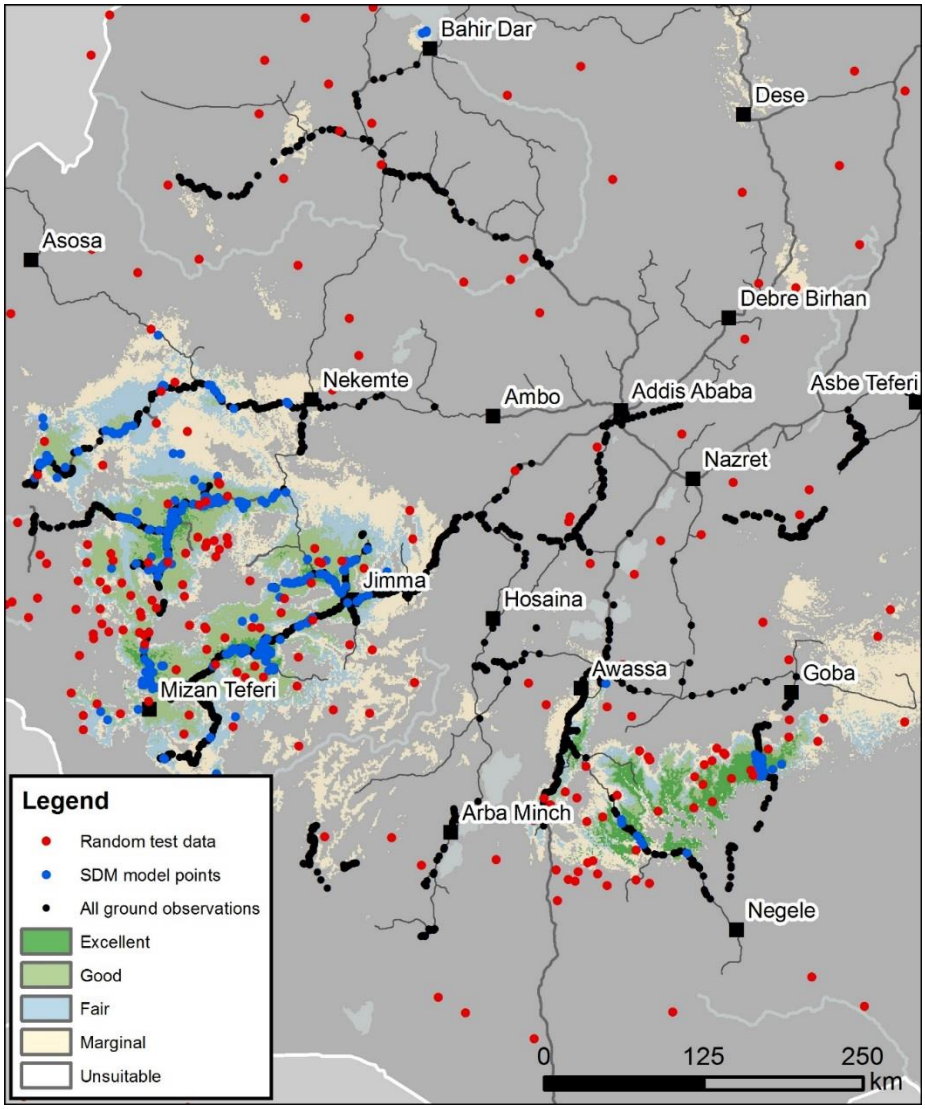
Supplementary Figure 2. Graphs of five threshold statistics vs. model values. See Box 1A for explanation of environmental niche (coffee suitability) categories (Unsuitable, Marginal, Fair, Good and Excellent). Thresholded values and statistics used for SDM classification. Y value = threshold statistic value, X = SDM model value (from 0 unsuitable to 1000 excellent). Actual categories used for cut offs are highlighted with vertical black lines. Threshold metrics for categorising model suitability (statistic with maximum model threshold values in parentheses): Kappa (504); True skills static TSS (324); Sensitivity=Specificity (424); accumulative percentage of ground observation points 100% (177); 99% (353); 95% (462); 90% (552); 65% (737); 50% (764); 35% (780); 25% (792); 10% (840); 5% (904); 1% (914).

Notes for Supplementary Figure 2.

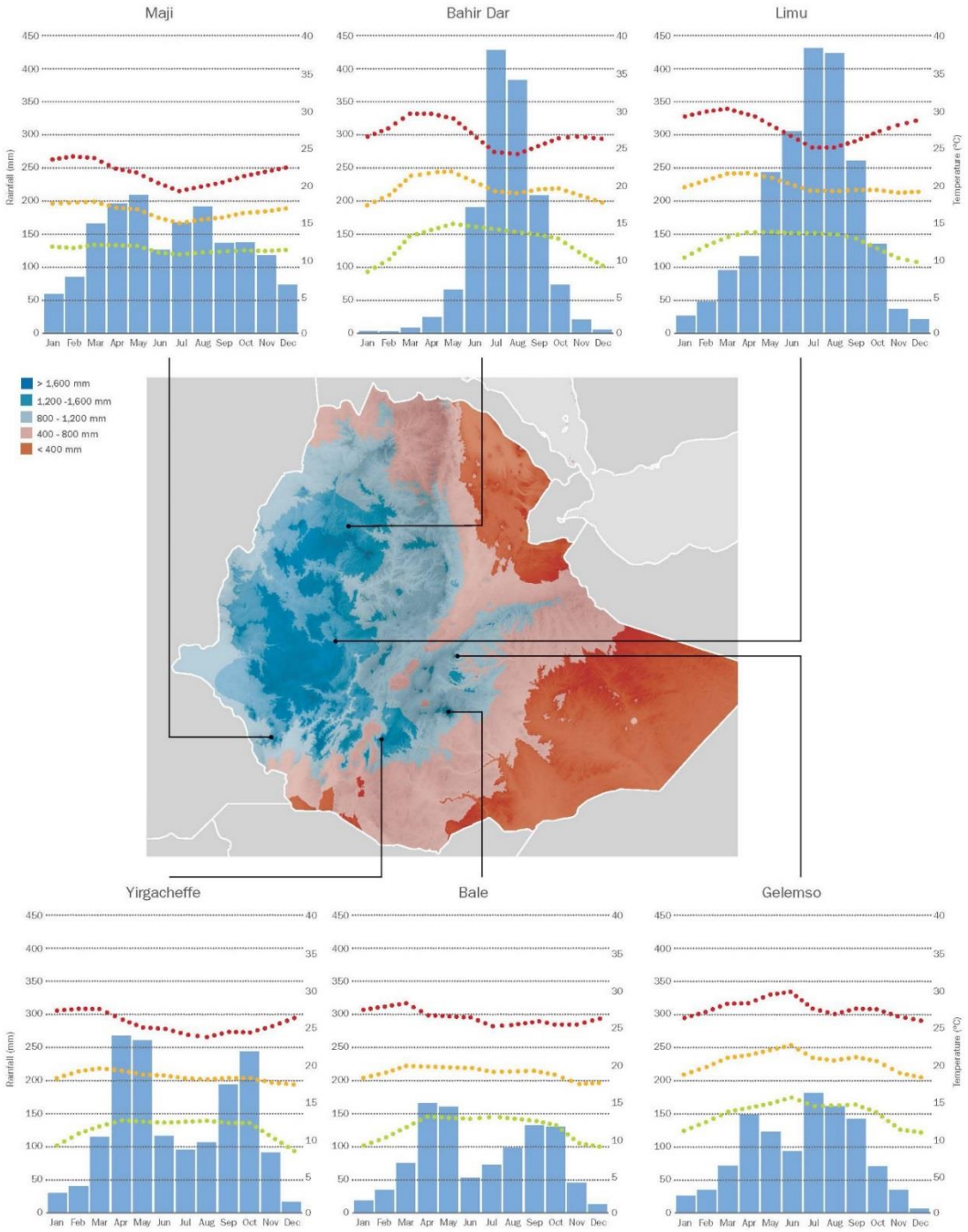
To allow the data to be easily presented and analysed we needed to categorise the SDM values. To do this we examined and calculated various thresholds as normally applied to SDMs.This was calculated using the ground-data localities (east and west of the Rift Valley) and the pseudo absences produced as part of the Biomod2 model development. We calculated Kappa coefficient, TSS, balance of sensitivity and specificity as well as accumulative thresholds of; 99%, 95%, 92%, 65%, 35% and 10% of the ground data point localities.

For the bottom threshold we chose 99% (353 ground data points) as this is a conservative balance between all the thresholds (Kappa 504, specificity=sensitivity 424, 99% 353 points and TSS 324 points), which resulted in losing only four ground control points. Not all values are able to fit all the models, for a number of reasons: there are no variables in the model to describe the specific ground-data locality points; we do not have the resolution to describe these localities or the local conditions are not represented (e.g. ground water, microclimate).

The upper thresholds are used for descriptive purpose only. From the histogram we can see that there are many localities (ground-data points) from 750 to 840, and so it would seem prudent to add a boundary here (35% of ground-data points (780)). To give a differentiation at the lower limits (between 353 and 780 ground-data points) the third threshold was set at 550, giving thresholds at 353,550, and 780. We have also placed a lower threshold at 171, and although it is a relatively artificial boundary, it does correspond with our lowest test locality (and is approximately between our lowest modelled value of 7 and our threshold 353). This allows us to see changes in the lower predicted categories.



Supplementary Figure 3. Ground control and test points used in this study overlaid on suitable niche. Black dots = all ground observations (3070 points), including coffee, non-coffee, cultivation, historic collects etc.; blue dots = final points used to produce models (381 points of the original 3070); red dots = random test locations (150 in forest/SDM and 150 outside), used to independently test accuracy of forest cover and SDM.



Supplementary Figure 4. Annual rainfall map of Ethiopia (background) and charts of rainfall (blue bars) and temperature (red maximum, average orange, green minimum) profiles for six coffee growing locations (present day). Bi-modal rainfall pattern (east of Rift Valley: Yirgacheffe, Bale and Gelemso); uni-modal rainfall (west of Rift Valley: Maji [slight rainfall bi-modality], Bahir Dar and Limu). Graphs based on historical climate data (30 year averages 1960–1990) from WorldClim[1], verified for accuracy using weather station data (30 year averages), for Bahir Dar, Limu, Yirgacheffe, and Gelemso. Background annual rainfall map of Ethiopia also from WorldClim[1].

Notes for Supplementary Figure 4

Bahir Dar. Sufficient annual rainfall, but the dry season (October to February/March) is too long and too dry and coincides with highest temperatures. The bulk of the rain falls in the main wet season (May/June to September). Coffee suitability is Marginal (coffee growing possible but often problematic, with poor and very inconsistent yields) and is often negatively influenced by drought during the dry season.

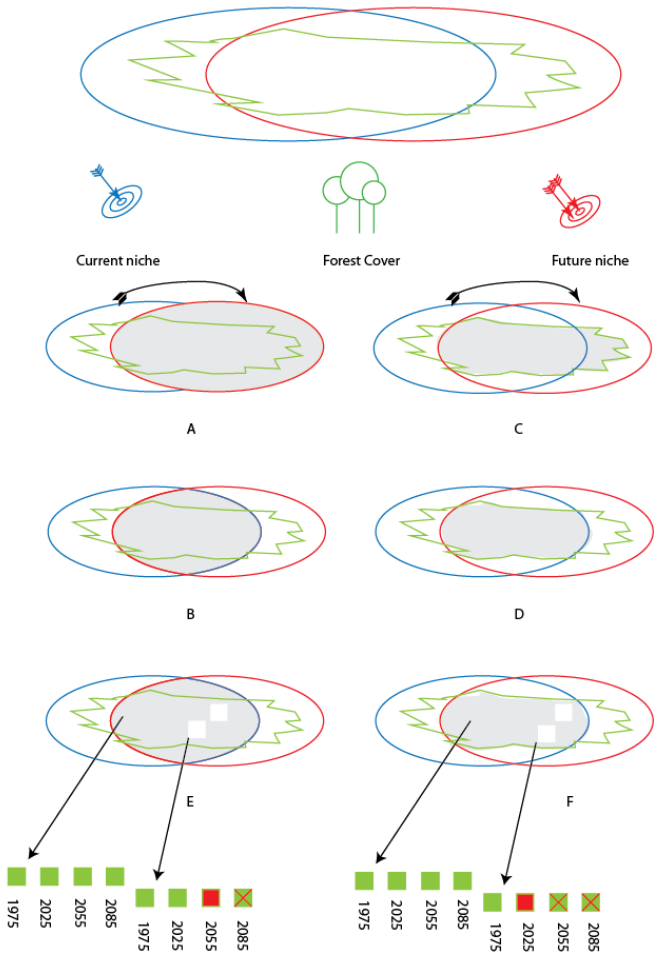
Limu. Sufficient rain throughout the dry season (October to February), and good rains in main wet season (May/June to September). Highest temperatures coincide with sufficient rainfall. Coffee suitability is Excellent (coffee production good to excellent, with the potential for consistent, high quality yields).

Maji. Sufficient rain throughout the dry season (October to February), and good rains in the main wet season (May/June to September). Highest temperatures coincide with sufficient rainfall. Slight bimodality to main season rainfall pattern. Coffee suitability is Excellent (coffee production good to excellent, with the potential for consistent, high quality yields).

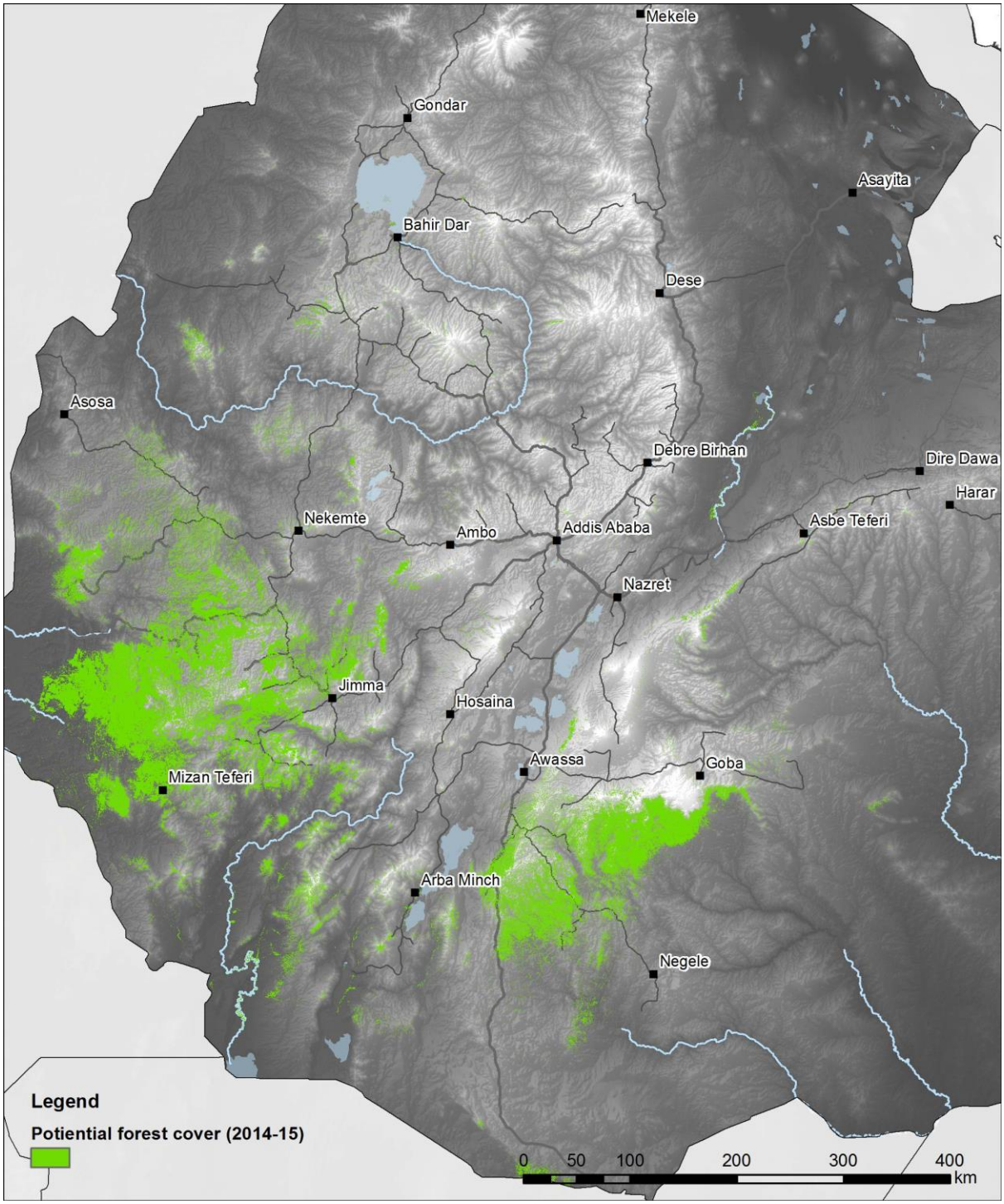
Gelemso. Barely sufficient rain throughout the dry season (October to February), and low rainfall in the main wet season(s) (April to September). Highest temperatures may not always coincide with sufficient rainfall. Coffee suitability is Unsuitable to Marginal (coffee growing is possible but often problematic, with poor and inconsistent yields), especially without intervention (e.g. irrigation).

Bale. Barely sufficient rain throughout the dry season (October to February), and low rainfall in the main wet season(s) (April to September); low rainfall is somewhat offset by lower temperatures. Coffee suitability is Good to Excellent (with the potential for consistent, high quality yields). Yield and quality may be negatively affected in some years (during adverse weather conditions, especially low rainfall).

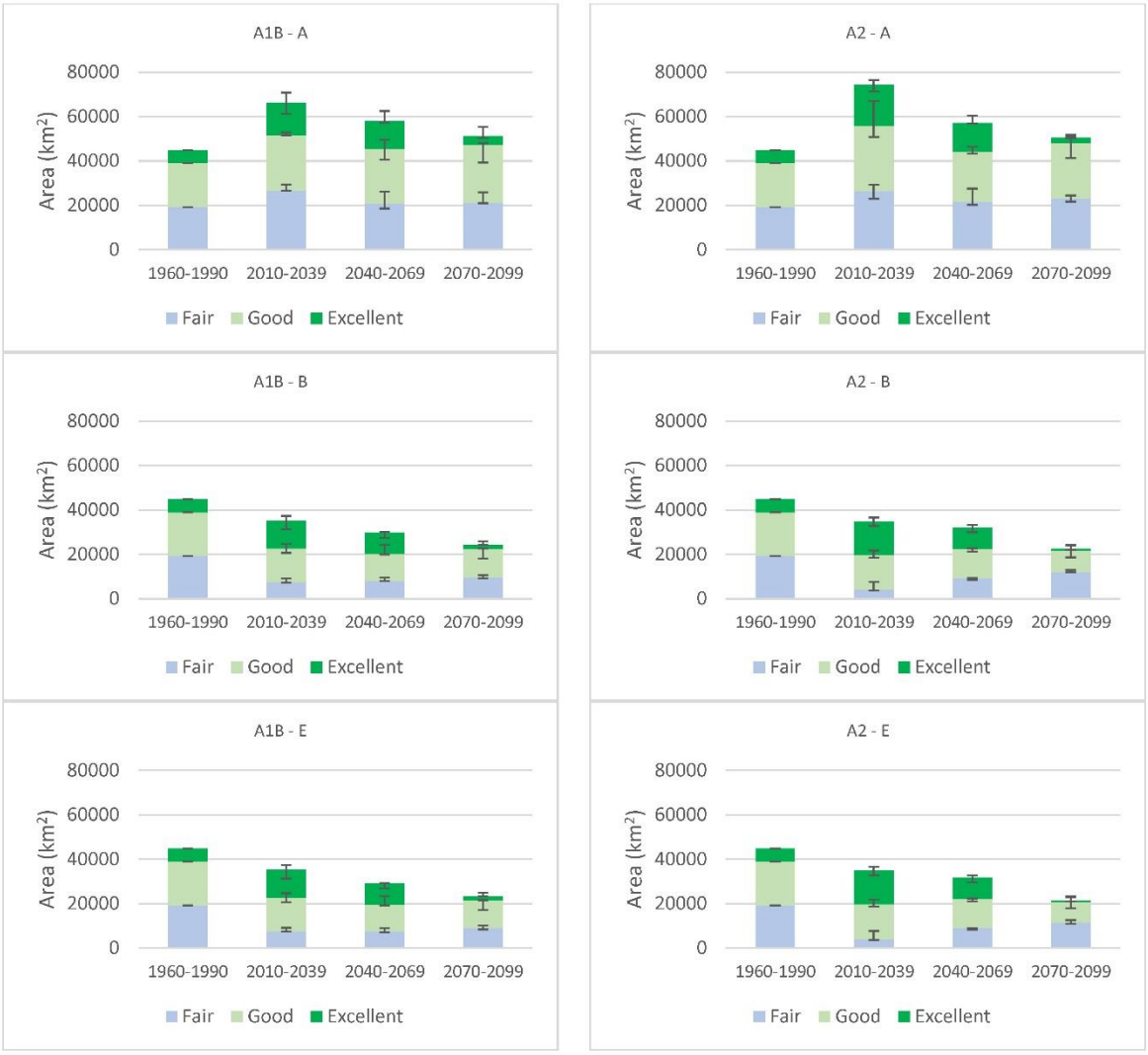
Yirgacheffe. Sufficient rain throughout the dry season (November to February), and sufficient rainfall in the main (and slightly extended) wet season(s) (April to October). Highest temperatures usually coincide with sufficient rainfall. Coffee suitability is Good to Excellent, with the potential for consistent, high quality yields. Yield and quality may be negatively affected in some years (during adverse weather conditions, especially low rainfall).



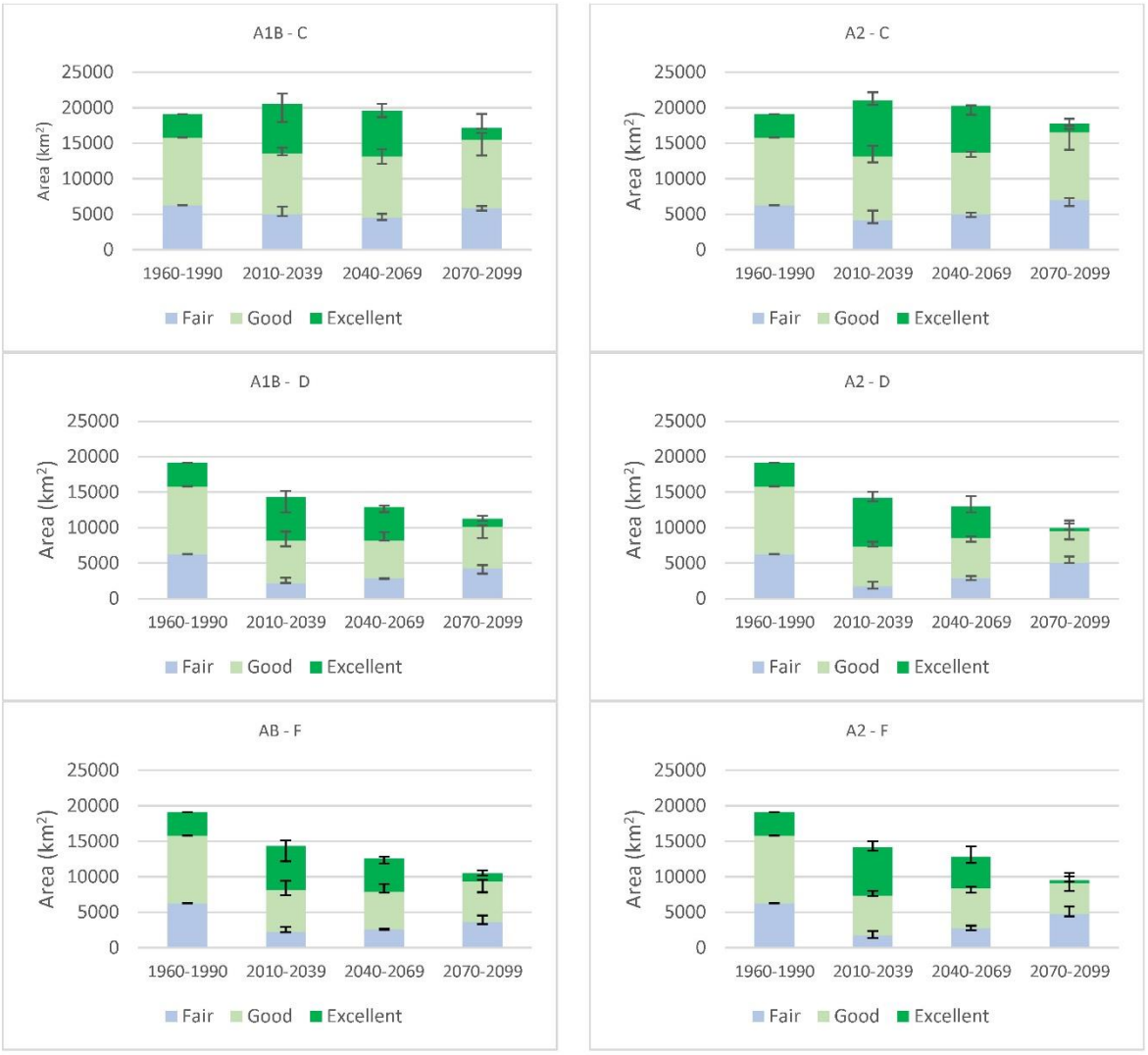
Supplementary Figure 5. Diagram for six future migration scenarios for Ethiopia coffee (farmed and wild), as used in the modelling. A, Plants can grow in any suitable niche (i.e. can move anywhere) [**Full Migration (A)**]. **B,** Plants can only grow only within known niche (i.e. can only move within presently predicted niche). **C,** Plants can only grow within suitable forest cover, within any suitable niche (i.e. can move within suitable forest). **D,** Plants can only grow within suitable forest cover and only in suitable known niche (i.e. restricted to present-day forest cover and suitable niches) [**No Migration (D)**]. **E,** Plants can only grow within suitable niche but only if niche does not drop outside of suitability during any 30-year time period. **F,** Plants can only grow within suitable forest cover and suitable niche, but only if niche does not drop outside of suitability during any 30-year time period.



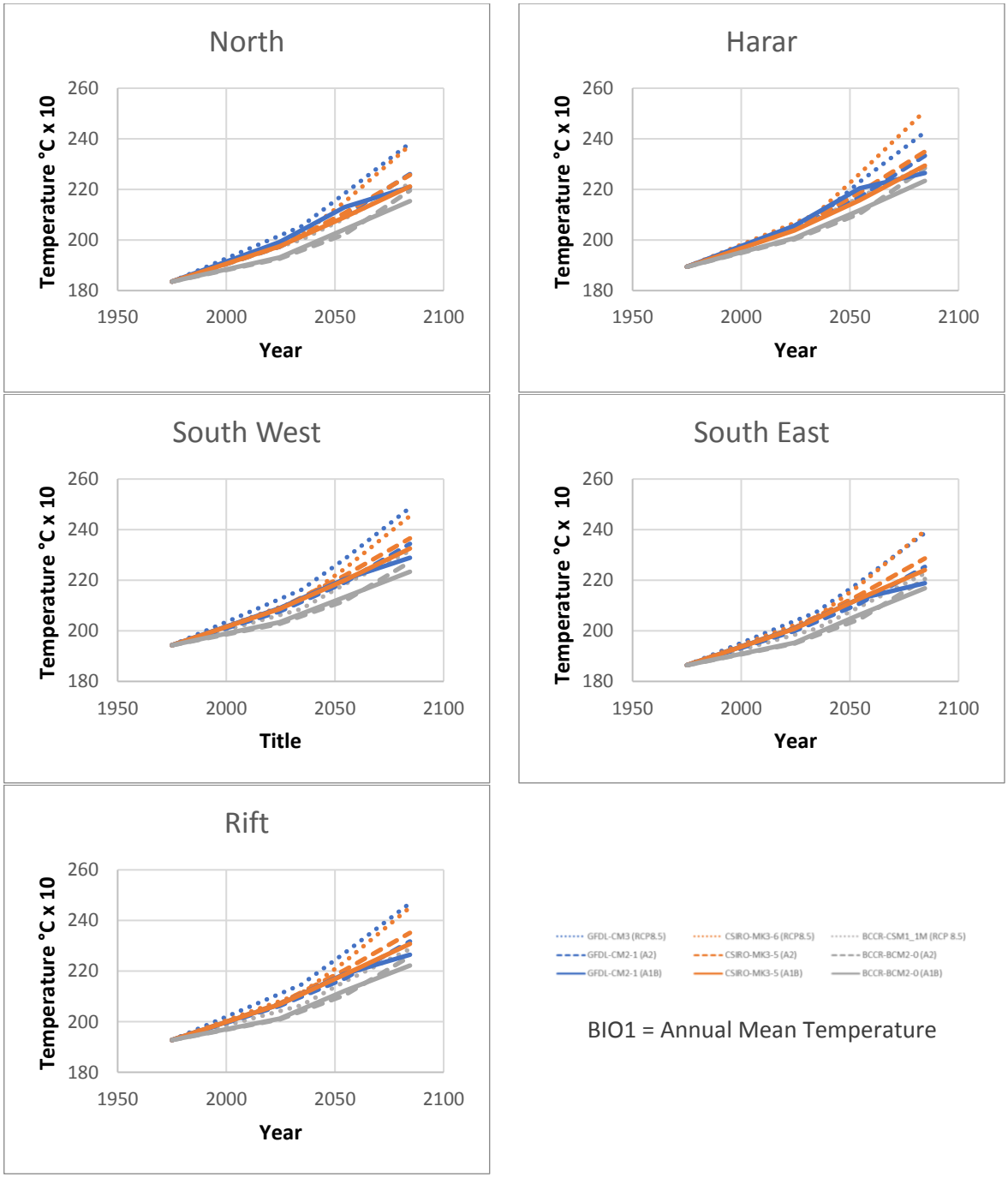
Supplementary Figure 6. Potential humid forest cover (2014–15) derived from Landsat 8 imagery. See Methods for details.



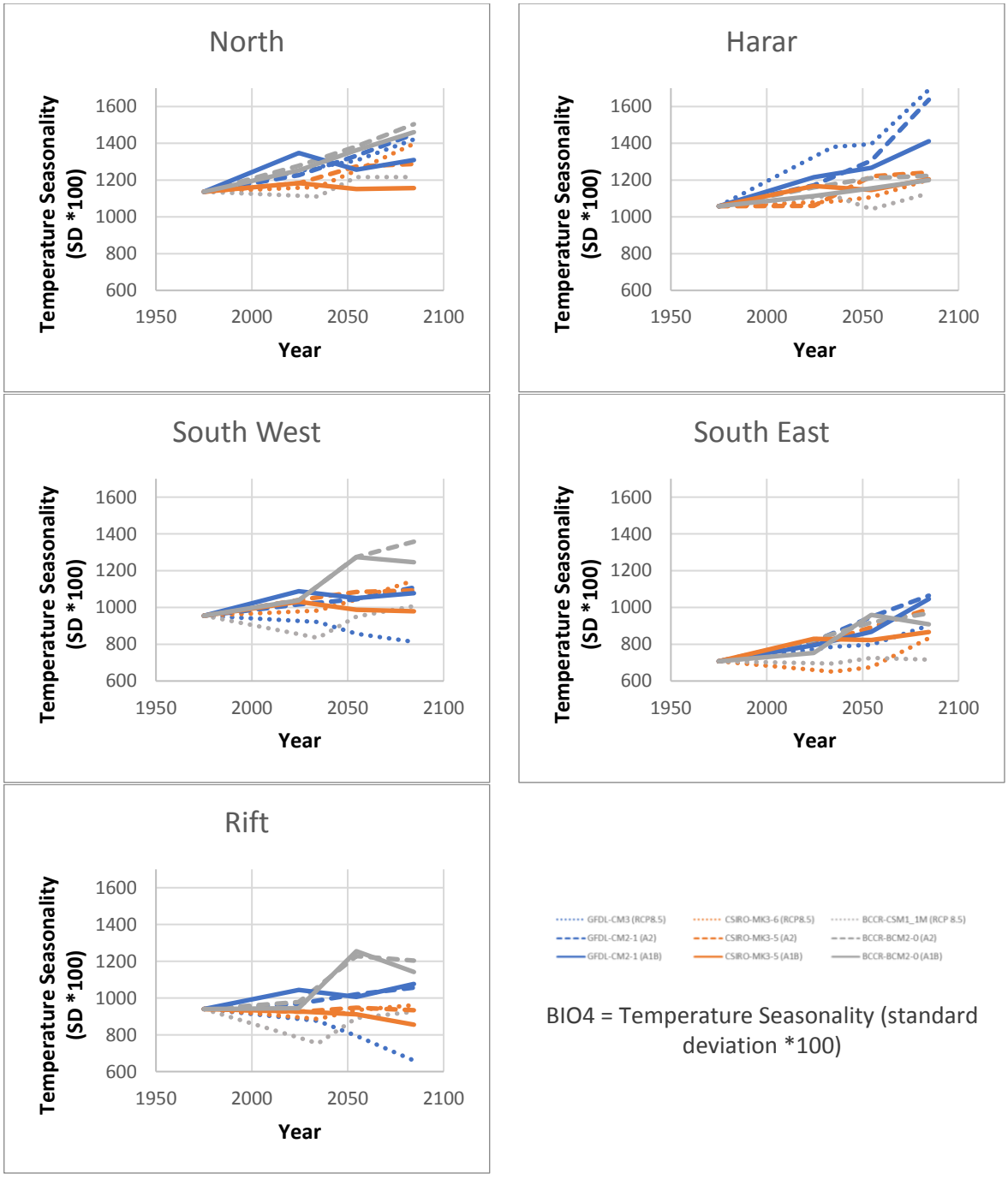
Supplementary Figure 7. **Future prediction for coffee suitability under scenarios A (Full Migration (A)), B, E, across emission scenarios A1B and A2.** Error bars represent the SDM area (km^2) model variability (low and high model outcomes) within the three General Circulation Models (GCMs): GFDL-CM2-1, CSIRO-MK3-5, and BCCR-BCM2-0. See Methods for further details.



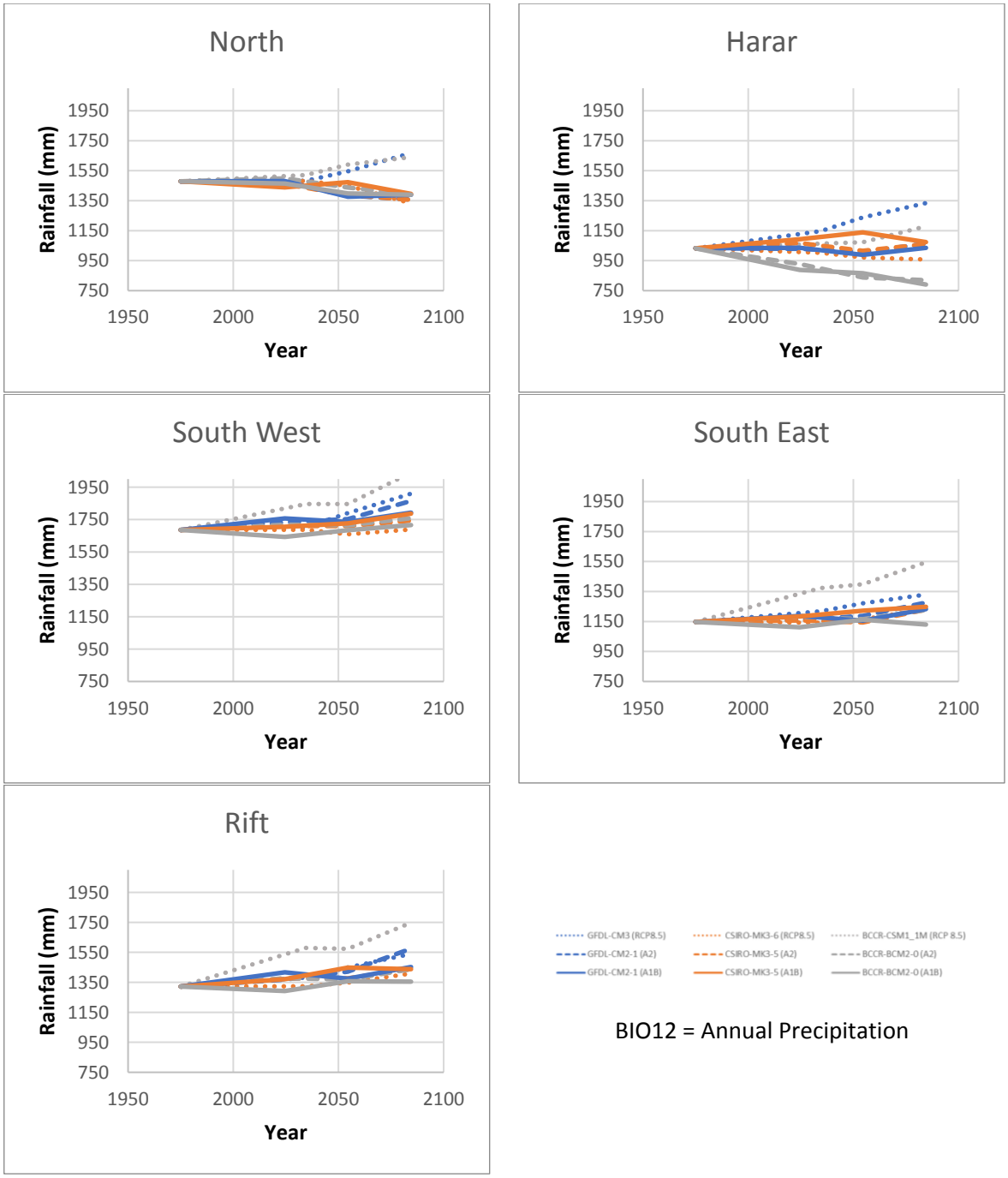
Supplementary Figure 8. Future prediction for coffee suitability under scenarios C, D (No Migration (D)), F, across emission scenarios A1B and A2. Error bars represent the SDM area (km^2) model variability (low and high model outcomes) within the three General Circulation Models (GCMs): GFDL-CM2-1, CSIRO-MK3-5, and BCCR-BCM2-0. See Methods for further details.



Supplementary Figure 9. Changes in mean annual temperature (BIOCLIM 1). Based on BIOCLIM data[1] (1960–1990), three GCMs, A1B, A2 emission scenario (CMIP3), and RCP 8.5 (CMIP5), for all coffee zones: North, Harar, South East, South West and Rift (see Fig. 1). See Methods for further details.

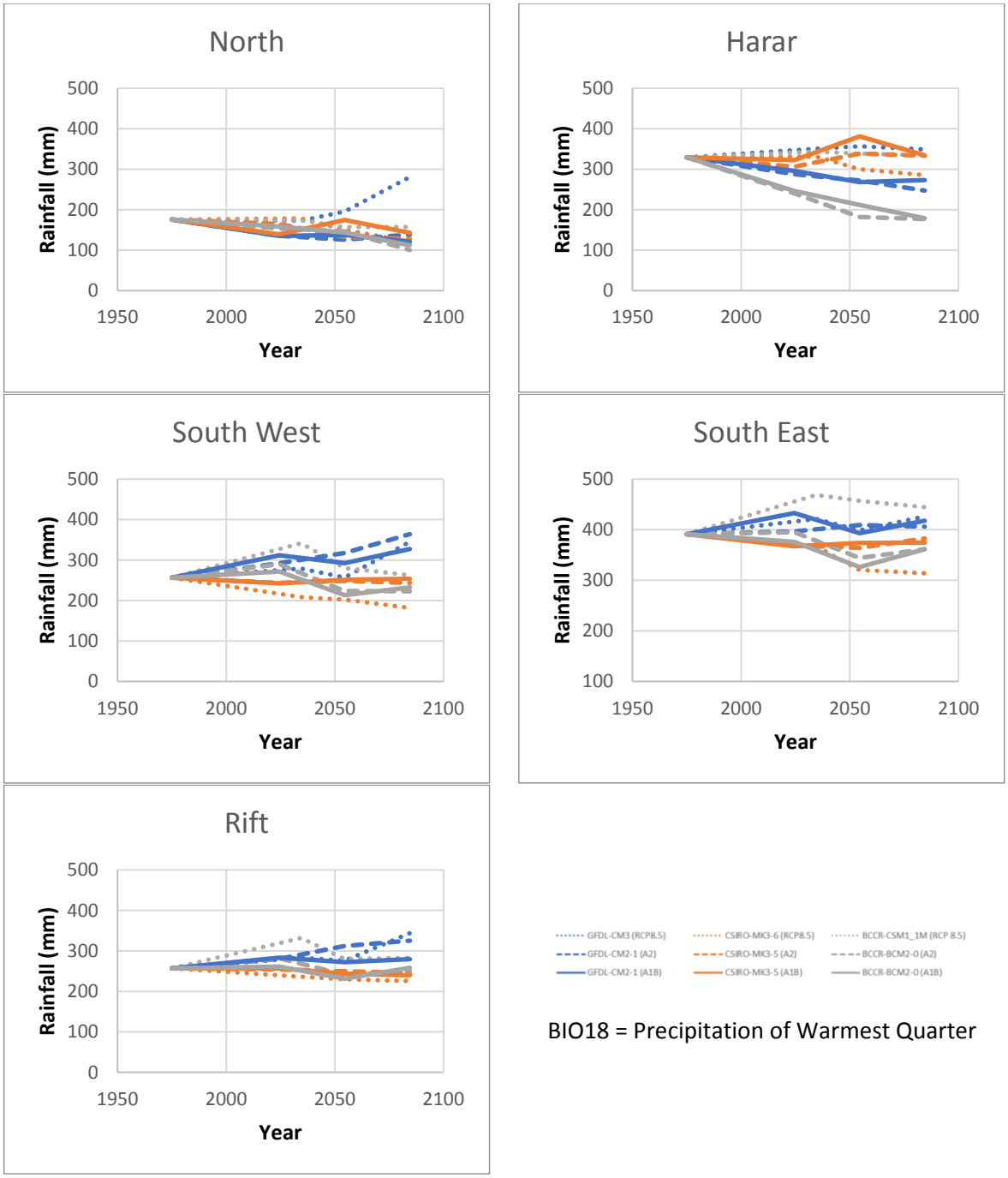


Supplementary Figure 10. Changes in temperature seasonality (BIOCLIM 4). Based on BIOCLIM data[1] (1960–1990), three GCMs, A1B, A2 emission scenario (CMIP3), and RCP 8.5 (CMIP5), for all coffee zones: North, Harar, South East, South West and Rift (see Fig. 1). See Methods for further details.



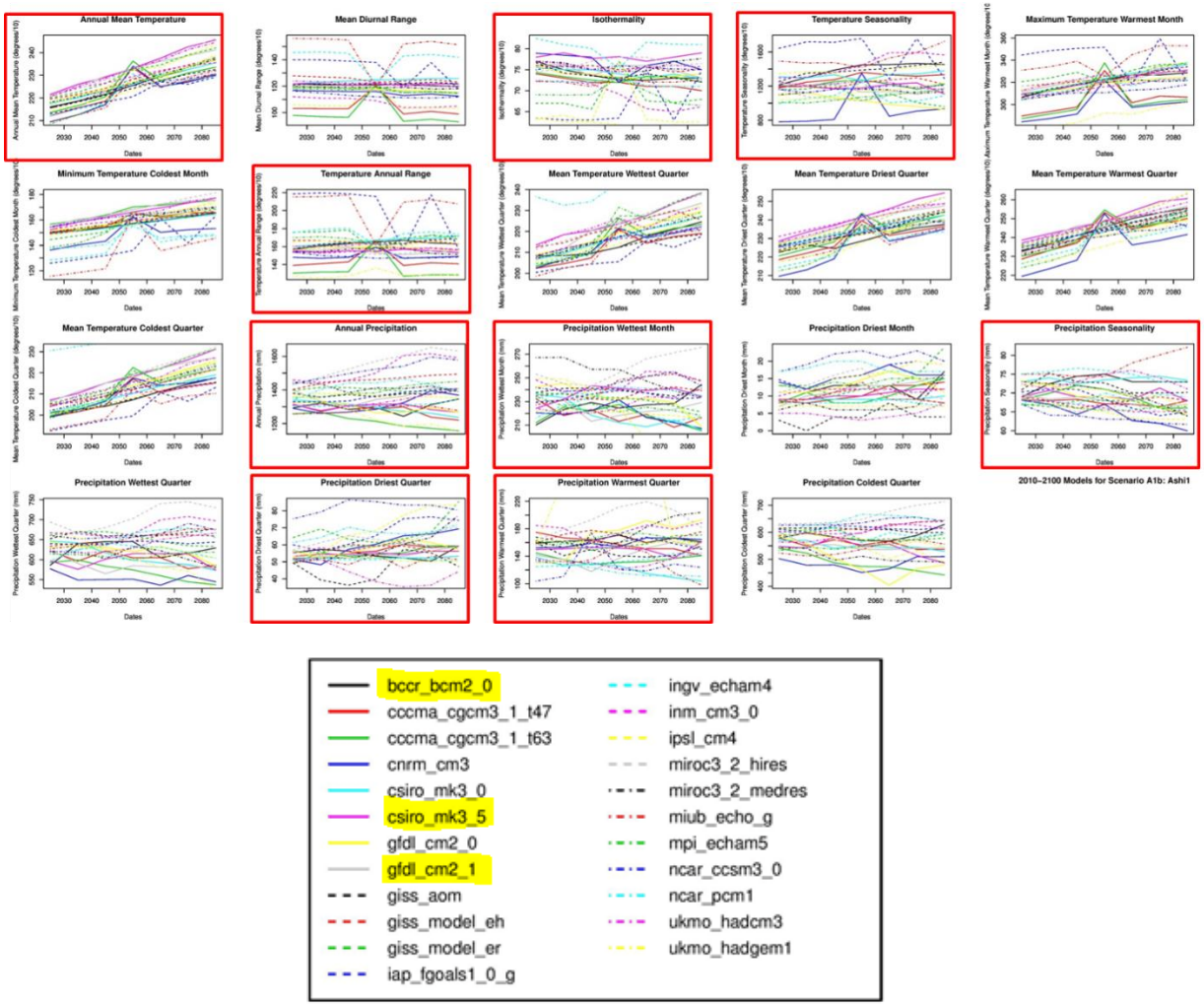
BIO12 = Annual Precipitation

Supplementary Figure 11. Changes in annual precipitation (BIOCLIM 12). Based on BIOCLIM data[1] (1960–1990), three GCMs, A1B, A2 emission scenario (CMIP3), and RCP 8.5 (CMIP5), for all coffee zones: North, Harar, South East, South West and Rift (see Fig. 1). See Methods for further details.

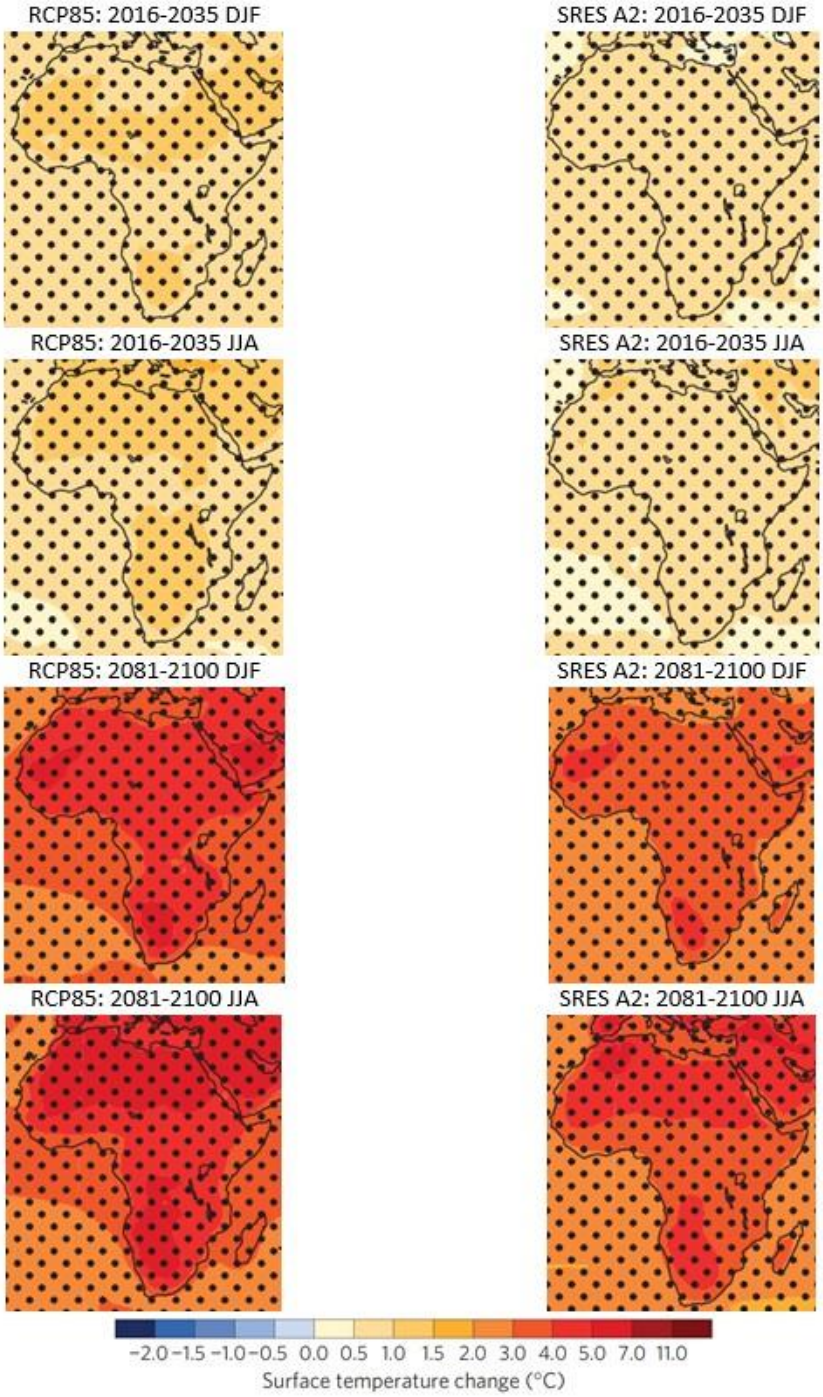


BIO18 = Precipitation of Warmest Quarter

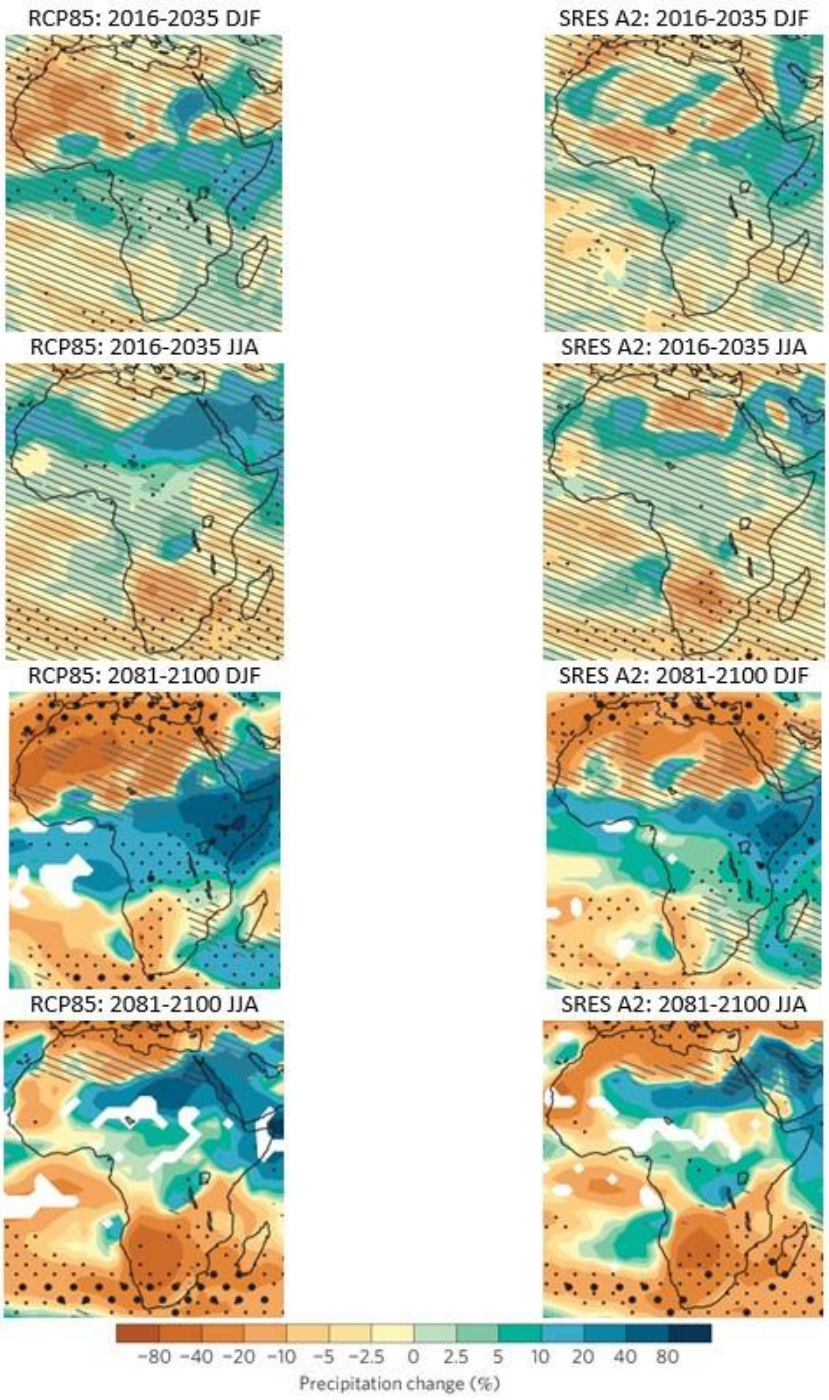
Supplementary Figure 12. Changes in precipitation of the warmest month (BIOCLIM 18). Based on BIOCLIM[1] data (1960–1990), three GCMs, A1B, A2 emission scenario (CMIP3), and RCP 8.5 (CMIP5), for all coffee zones: North, Harar, South East, South West and Rift (see Fig. 1). See Methods for further details.



Supplementary Figure 15. Example of GCM plots used to evaluate GCMs for the coffee landscape of Ethiopia. Plots for Ashi (Wellega coffee area). Highlighted in red are BIOCLIM[1] variables used for our SDMs. Key to GCM (lower box); highlighted in yellow are the three final models used. Mean temperature of the wettest quarter (third from left, second row down) model GCM ingv_echam4 (blue dotted and dashed line), is a good example of a possible erroneous dataset, which show a disjunct of over 2°C from of all other GCMs.



Supplementary Figure 16.Patterns of surface warming for CMIP5 vs CMIP3. Detail of Africa from Knutti and Sedláček Figure 2[2]. Patterns of surface warming. Multi-model mean surface warming for two seasons (December–February, DJF, and June–August, JJA) and two 20-year time periods centred around 2025 and 2090, relative to 1986–2005, for CMIP5 (left) and CMIP3 (right). Stippling marks high robustness, hatching marks no significant change and white areas mark inconsistent model responses.



Supplementary Figure 17.Patterns of precipitation change for CMIP5 vs CMIP3. Detail of Africa from Knutti and Sedláček Figure 3[2]. Patterns of precipitation change. Multi-model mean relative precipitation change for two seasons (December–February, DJF, and June–August, JJA) and two 20-year time periods centred around 2025 and 2090, relative to 1986–2005, for CMIP5 (left) and CMIP3 (right). Stippling marks high robustness, hatching marks no significant change and white areas mark inconsistent model responses.

SUPPLEMENTARY TABLES

Year periods	Migration scenario	Niche categories (km^2)				Total suitability (km^2) for Fair to Excellent – middle value from GCMs
		Marginal	Fair	Good	Excellent	
1960-1990	A	40,386	19,241	19,767	5,812	44,820
2010-2039	A	38,403	26,662	24,911	14,585	66,158
2040-2069	A	38,319	20,663	24,816	12,557	58,036
2070-2099	A	39,648	21,047	26,181	4,052	51,280
1960-1990	D	6,676	6,294	9,536	3,312	19,142
2010-2039	D	999	2,219	5,976	6,123	14,319
2040-2069	D	2,228	2,891	5,306	4,700	12,897
2070-2099	D	3,827	4,284	5,858	1,115	11,256

Supplementary Table 1. Availability of suitable niche in km^2 for Full Migration (A) and No Migration (D) scenarios, generated from the three GCMs, for emission scenario A1B. Only middle values shown (see Table 1 for all values).

Description	MAXENT	GLM	GAM	RT	GBM	MARS	No.in top 3
Annual Mean Temperature = bio_1	0	0.15	0.35	0	0	0.29	0
Isothermality (BIO2/BIO7) (* 100) = bio_3	0.05	0.12	0.24	0	0	0.04	0
Temperature Seasonality (standard deviation *100) = bio_4	**0.56**	**0.74**	**0.77**	**0.22**	**0.23**	**0.2**	**6**
Temperature Annual Range (BIO5–BIO6) = bio_7	0.31	0.38	0.41	0.04	0.01	0.08	2
Annual Precipitation = bio_12	0.03	0	0.59	0	0	0.04	1
Precipitation of Wettest Month = bio_13	0.18	0.55	0.59	0.01	0	0.24	2
Precipitation Seasonality (Coefficient of Variation) = bio_15	0.19	0.12	0.52	0.01	0.03	0.09	1
Precipitation of Driest Quarter = bio_17	0.09	0	0.32	0.01	0	0.25	0
Precipitation of Warmest Quarter = bio_18	**0.7**	**0.73**	**0.79**	**0.76**	**0.8**	**0.75**	**6**

Supplementary Table 2. Relative importance (TSS score) of BIOCLIM variables east of the Rift Valley. Major contributing BIOCLIM[1] variables highlighted in grey, for each of the six niche modelling methods.

Description	MAXENT	GLM	GAM	RT	GBM	MARS	No. in top 3
Annual Mean Temperature = bio_1	**0.22**	**0.32**	**0.48**	**0.06**	**0.42**	**0.2**	**6**
Isothermality (BIO2/BIO7) (* 100) = bio_3	0	0.05	0.11	0.05	0	0.04	0
Temperature Seasonality (standard deviation *100) = bio_4	0.01	0.04	0.11	0.02	0.01	0.05	0
Temperature Annual Range (BIO5–BIO6) = bio_7	0.01	0.08	0.12	0.05	0.03	0.03	0
Annual Precipitation = bio_12	**0.77**	**0.99**	**0.81**	**0.57**	**0.6**	**0.89**	**6**
Precipitation of Wettest Month	0.01	0.41	0.36	0.05	0.07	0.32	1
Precipitation Seasonality (Coefficient of Variation) = bio_15	0.07	0.23	0.49	0.06	0.41	0.24	2
Precipitation of Driest Quarter = bio_17	0.18	0.66	0.38	0.09	0.09	0.68	3
Precipitation of Warmest Quarter = bio_18	0.04	0.05	0.2	0.03	0.01	0.05	0

Supplementary Table 3. Relative importance (TSS score) of BIOCLIM variables west of the Rift Valley. Major contributing BIOCLIM[1] variables highlighted in grey, for each of the six niche modelling methods.

BIOCLIM Layer	Description
BIO1	Annual Mean Temperature
BIO3	Isothermality (BIO2/BIO7) (* 100)
BIO4	Temperature Seasonality (standard deviation *100)
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter

Supplementary Table 4. The nine BIOCLIMS used for SDMs. Derived from the full BIOCLIM dataset[1] of 19 variables.

References (also cited in the main paper)

1 Hijmans RJ, Cameron SE, Parra JL, Jones PG & Jarvis A. Very high resolution interpolated climate surfaces for global land areas. *Int. J. Climatol.* **25**, 1965–1978 (2005).

2 Knutti R & Sedláček J. Robustness and uncertainties in the new CMIP5 climate model projections. . *Nat. Clim. Chang.* **3**, 369–373, doi:doi:10.1038/nclimate1716 (2013).

3. Appendix II:

Poster: The view from Kew: Remotely sensed solutions for plant sciences and conservation

Poster presented at the symposium: “Remote Sensing for Conservation: uses, prospects and challenges” at the Zoological Society of London.

THE VIEW FROM KEW

Remotely sensed solutions for plant sciences and conservation

Authors: Susana Baena (s.baena@kew.org), Justin Moat (j.moat@kew.org), Steve Bachman (s.bachman@kew.org), Amanda Cooper (a.cooper@kew.org), Jenny Williams (jenny.williams@kew.org), Tim Wilkinson (t.wilkinson@kew.org), Robert O'Sullivan (r.o'sullivan@kew.org)

Abstract: All life on Earth depends on plants. They are the basis of ecosystems in which all animals, including humans, live, survive and grow. Kew is furthering plant science and conservation through the use of Remote Sensing to help understand plant diversity and to guide better conservation practices. We will present our latest research using case studies covering the application of satellite-based information and remote sensing techniques to the science and conservation of plant diversity at multiple scales: from mapping individual tree species to assess the impact of local land-use to analysing global extinction risk from deforestation.

Locally in Peru, we are using the latest techniques through the application of object-oriented image analysis applied to very high resolution satellite and unmanned aerial vehicles (UAV's) images to map five common tree species of the coastal dry forest of northern Peru. Regionally, we are unravelling the full potential of the Landsat continuity mission in combination with spatial distribution models and future climate projections to map and predict the distribution of wild coffee forests in Ethiopia. Globally, through the Sampled Red List Index for Plants project we will show how outputs from remote sensing such as deforestation maps can be applied directly to Red List assessments linked to global policy targets. We continue to drive Kew's science and conservation outputs through the application and development of these Remote Sensing techniques which contribute widely to support global conservation and decision making.

Local:

"Forest reserves for the community"

The coastal plain of northern Peru is recognised for its unique dry forest with high endemism and diversity. The forest and associated arid land vegetation are also highly threatened ecosystems. The local community of San Francisco de Asís is experiencing over 60% die-back of its Algarrobo (*Prosopis spp.*) forests upon which livelihoods depend.

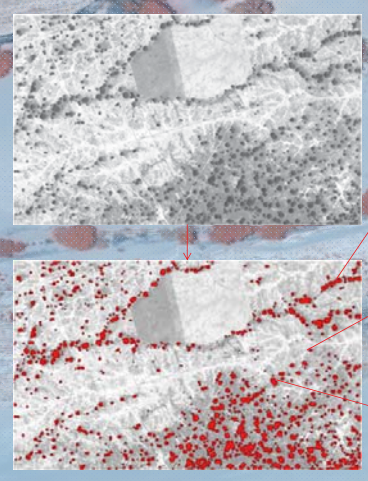


"Mapping and identifying species from the air: The very high resolution challenge"

Object-oriented image analysis applied to very high resolution satellite images form the basis for mapping common tree species. The analysis reveals the structure and health of the vegetation and to identify the impacts and solutions for local people. UAV imaging using both colour and near infrared cameras provides the means to obtain images meeting specific requirements of spatial and temporal resolutions. This along with the capability to produce three dimensional models provides an invaluable tool for species identification.

This remotely sensed information is complemented by measurements on the ground. Permanent plots provide fundamental baseline data for ongoing monitoring of the ecosystem. By using terrestrial LiDAR we can capture the superfine structure and composition of the plot and monitor changes throughout time.





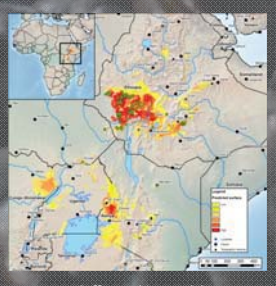


Regional:

"Building a climate resilient coffee economy for Ethiopia"

Coffee is the backbone of the Ethiopian economy, providing more than 30% of its export earnings and 25% of the population depends directly or indirectly on coffee for its livelihood. Climate modelling indicates a distinctly negative impact on coffee forests and coffee production in Ethiopia.





Coffee arabica model

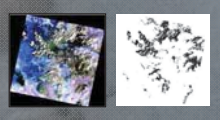


At present there are few resources for understanding and managing the risks associated with climate change and land-use change In Ethiopia. This project aims to fill this major gap, by producing a detailed mapping tool for coffee production and indigenous coffee genetic resources (the Coffee Atlas), and a series of scaled scenario-based responses according to how climate change tracks over this century and beyond.

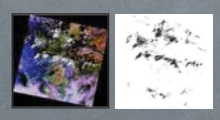
"The Coffee Atlas: a Remote Sensing based resource for conservation planning"

Coffee producing areas and coffee forest habitat in Ethiopia are the focus of our research, these areas have persistent cloud cover even in the dry season. A set of Landsat 8 images have been collated to produce a 3-month surface reflectance composite making use of the new quality assessment band. Areas subject to cloud contamination are easily identified and masked out from each individual image to produce a near cloud-free final composite.

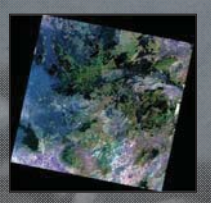
Based on this surface reflectance composite "coffee areas" are identified using Kew's extensive coffee database with over 700 georeferenced occurrence data for "*coffee arabica*" and the physiological/environmental niche of the species giving its potential distribution. Results from a preliminary analysis show that coffee growing areas can be highlighted and mapped using multispectral images at 30 meter resolution.



L8 and Cloud Mask. November 2013



L8 and Cloud Mask. December 2013



L8 2-Month reflectance composite



Preliminary results

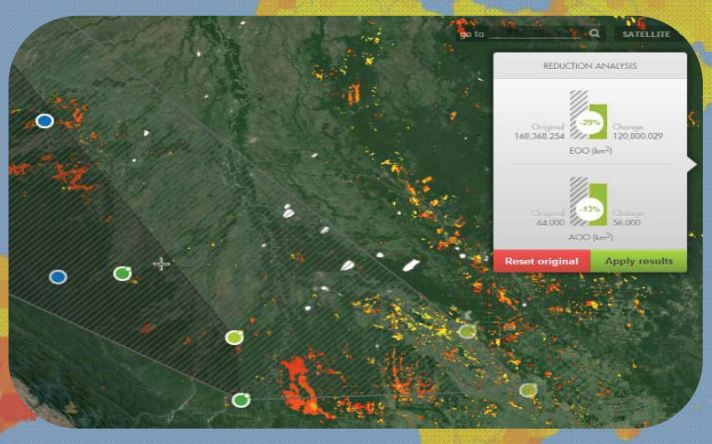
Global:

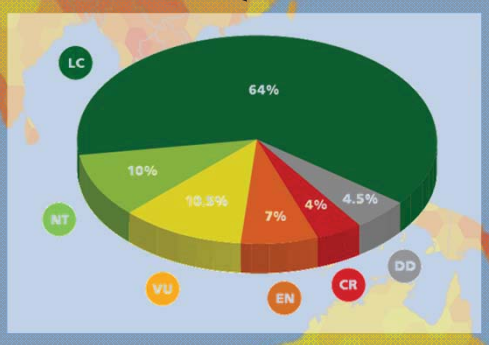
"Rapid Red List assessment"

Global products derived from remote sensing are vital for conservation efforts. For example when taking a look at extinction threat to plants to inform policy targets such as the Convention on Biological Diversity or the Global Strategy for Plant Conservation we can harness the power of maps showing forest change. For each species we can use tools like GeoCAT to assess how much of the distribution range has been impacted by deforestation and that leads to global Red List conservation assessments. Using these techniques we assessed a random sample of plants that revealed as much as one in five plants are at risk of extinction.

"Harnessing global remotely sensed products for conservation"

As more global products such as Global Forest Watch and Terra- i become available, the process of producing Red List assessments will become easier and more rapid. Enabling us to effectively monitor thousands of species and identify areas in most need of conservation interventions





One in five plants at risk of extinction

Find out more:

www.kew.org/gis @KewGIS storify.com/KewGIS geocat.kew.org/

Acknowledgements: Many scientists from around the world are involved in these projects and we are thankful for all their support. Specially we would like to thank the Peru, plant SRLI and Rubaicace team at Kew and abroad. Oliver Whaley and Aaron Davis have been instrumental in heading up the Coffee and Peru work.

Kew
ROYAL BOTANIC GARDENS