DISSERTATION

MODELING PLANT HOTSPOTS IN NEW GUINEA AND VILLAGE-SCALE LAND CHANGE DYNAMICS IN PAPUA NEW GUINEA

Submitted by

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ABSTRACT

MODELING PLANT HOTSPOTS IN NEW GUINEA AND VILLAGE-SCALE LAND CHANGE DYNAMICS IN PAPUA NEW GUINEA

The island of New Guinea harbors the third largest tropical forest in the world, after Amazonia and the Congo. Forest cover changes in New Guinea are occurring at a fast rate and it is vital to improve our understanding of the drivers of forest change and identify how these changes impact human livelihoods and biotic diversity. New Guinea is politically split into two countries; the western half is Indonesia and the eastern half is Papua New Guinea. The first part of this dissertation focuses on Papua New Guinea, where logging and subsistence agriculture account for 92% of forest cover changes. Since a large majority of the population is dependent on subsistence agriculture (swidden), understanding how subsistence strategies evolve over time can be used to inform land-use and land-cover (LULC) changes. To assess how subsistence strategies relate to LULC changes, I compare remote sensing analyses alone to a mixed methods approach or participatory remote sensing (PRS) that combines land-use mapping exercises, household surveys, remote sensing classifications, and the validation of image analyses. The remote sensing analyses alone were two and a half times larger than what land managers and the PRS methods identified. The inclusion of participatory data showed that the increase in food production to support the growing population was achieved by implementing a variety of strategies rather than continual expansion of the swidden area. Participatory data also better described that swidden LULC changes were based more on social, climatic, and environmental conditions than population growth pressures. To further my investigation of subsistence strategies and swidden

LULC changes I conducted a long-term swidden LULC study using 40 Landsat scenes between 1972 and 2015. We found that swidden trends were not significant over the time period and therefore there was not a causal relationship between population growth and swidden trends. This result is different than national and provincial scale observations. Overall, the inclusion of participatory information via PRS methods should be used to understand swidden system LULC complexities and land-management strategies. Such information can improve LULC trend assessments at wider extents and be more informative for national forest cover change assessments.

The other part of this dissertation has a wider extent and looks at New Guinea as a whole. Although it is known for high rates of biodiversity, there are few quantitative studies that have assessed plant diversity on the island. Here, I model vascular and non-vascular terrestrial plants at the genus taxonomic level to predict the biodiversity hotspots. To do this, I used an ecological niche model called MaxEnt and occurrence data from online, herbarium, and museum databases are paired with environmental variables. The results from this study identify sampling efforts, sampling biases, and predict plant distributions and biodiversity hotspots (richness). I found that richness increases west to east along the central mountain range and increases from south to north across the island. Even though MaxEnt is capable of minimizing sampling biases, I speculate that sampling biases may influence the richness pattern observed south to north because the southern third of the island is under sampled and the geologic history is markedly different. At higher elevations in regions with complex topography the predicted genera richness are smaller in area but more numerous. Comparatively, larger areas of higher predicted richness occur at lower elevations and where the topography is more homogeneous. While modeling with genus level data supplies baseline information about plant distributions, some genera are more speciose than others, so this effort may not capture the full scope of richness or endemism in New Guinea. However, these results can be used to prioritize future sampling needs, support conservation strategies, compare genus diversity to other regions of the world, and discuss principles and drivers of biogeography.

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It takes a community to raise a scientist

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I am thankful to my parents, Becky and Jesse, for their love and supporting my decision to be an environmentalist and study what I am passionate about even if it didn’t quite make sense to them. I am also indebted to them as they instilled in me that with a good work ethic that anything is possible. I would like to thank my Uncle Jim for recognizing that education is

liberating and providing much needed conversations and perspectives. I want to inform my brothers that I am now a doctor and you must address me as such!

I am thankful for stats 501, this class was challenging but due to my study buddy I made it through, kind of! That study buddy is now my best friend and husband, so I think it was worth it. Dave has been my springboard and second-string advisor throughout grad school and especially when me moved to Moab and left the university setting. He has inspired confidence in me and has been there to motivate me in so many ways. Calvin, you showed me that the need to understand the world empirically is an innate human trait. Watching you navigate and organize the world around you gave me renewed confidence in the scientific process. I finished this dissertation to show you that determination and perseverance are learned traits, I think. I held you sleeping in my arms while I attempt to type with one hand, you unintentionally deleted paragraphs and added special characters to my manuscripts, and I listened to Elmo talk about jumping while making final edits to my dissertation. Most people finish their PhD without such distractions or special moments, but I wouldn't change a thing. Last, a special thank you those who watched Calvin and providing him with love, comfort, and park adventures while I locked myself in my room to work on this dang dissertation.

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CHAPTER 1

INTRODUCTION

Land use and land cover change assessments are of global interest in the tropics because forest ecosystems greatly influence climate, maintain high rates of biodiversity, and support subsistence based livelihoods for millions of people. Understanding the ecological impacts of land change and how subsistence-based communities are dependent on these forest ecosystems is paramount. Such efforts have presented many challenges due to the complexity and heterogeneity of socio-ecological systems and lack of data in many underdeveloped regions. Therefore to assess land-changes methods from many disciplines have been fused, and some include physical, natural, social, and spatial sciences (Turner et al. 2007; Rindfuss et al. 2004).

Satellite imagery has improved spatial and temporal estimates of land change, but even high-resolution imagery are innately limited by temporal resolution, spatial resolution, and cloud cover, all of which influence the ability to capture and assess land-use and land-cover (LULC) (IPCC Core Writing Team 2001, Ziegler et al. 2011, Hett et al. 2012). The union of spatial and social sciences has established a way to more comprehensively explore the socio-ecological interface and identify the driving forces between livelihood decisions and LULC changes. The inclusion of participatory data is one way to provide essential information to link observed patterns and trends from local, ground-level activities to remotely sensed data (Fox et al. 2003, Herrmann et al. 2014). Participatory methods have produced intriguing changes in the representation and validation of LULC and changes therein (McCall 2003, Dunn 2007, Lynam et al. 2007, Matthews et al. 2007, Voinov and Bousquet 2010, Fritz et al. 2012). This interdisciplinary framework has also improved results (Lynam et al. 2007, Voinov and Bousquet 2010) and shows that detailed land-use knowledge can refine remote sensing LULC classifications and change detection (Schmidt-Vogt et al. 2009a, Leisz and Rasmussen 2012). There are many examples of participatory research being used in LULC analyses, and some of recent include sea grass changes in the Solomon Islands (Lauer and Aswani 2010), coastal management in Hawaii (Levine and Feinholz 2015), invasive species management in Ethiopia (Wakie et al. 2016), vegetation changes in the Sahel (Herrmann et al. 2014), and swidden agricultural changes (Leisz and Rasmussen 2012).

Across the globe around 450 million people employ some form of subsistence agriculture (Mertz et al. 2009; Morton 2007). Subistence agriculture is defined as farming 3 ha of land or less and the yields are consumed directly with few supplemental needs purchased (Morton 2007). Subsistence agriculture is a highly diverse and this stems from the heterogeneity of climatic and environmental variables (e.g. precipitation, temperature, topography, hill slope, and soil nutrients), cultures, and techniques used (e.g. crop-fallow cycle lengths, plot sizes, terracing, and crop selection; Fox et al. 2009) across the globe. Land-use decisions are in response to different biophysical conditions, social and economic underpinnings, and cultural values (Lambin et al. 2003). Biophysical conditions that influence a change in subsistence strategy and land-use include weather and climate variability (e.g. flood, drought, and severe storm), environmental changes (e.g. fire, landslide, and insect or disease outbreaks) and species composition shifts (e.g. increased weeds). Social mechanisms influenced by infrastructure, social, and political changes result in a change of economic opportunities (Aphangthong and Yasuyuki 2009).

In Papua New Guinea, subsistence agricultural changes have receive little to no attention and such analyses are vital in a country where approximately 85% of the population depends on such means to fulfill subsistence and livelihood needs. An analysis of forest cover change at the national level cited swidden agriculture as one of the leading causes of forest degradation and loss, after timber extraction (Shearman et al. 2009). While national and regional land-use and land-cover studies provide a wealth of information and identify general trends, local level studies are also of great importance. Local level studies show how similar or opposing trends can occur at different scales and understanding these phenomenon can help link local level processes to wider extents (Wilbanks and Kates 1999, Wu 2004).

The forest cover loss and degradation is also associated with the loss of biodiversity. The forests on the island of New Guinea (PNG and Indonesian Papua and West Papua) are estimated to harbor 5-10% of the world's biodiversity and 60-90% of the species are thought to be endemic. For plants, New Guinea ranks second to Amazonia in plant biodiversity and this equates to approximately 17,000 different species, and 10,200 of these species are thought to be endemic (Mittermeier et al. 2003). Yet, the evidence to support the high rates of diversity and endemism are not based on comprehensive taxonomic collections and instead on expert opinions.

This dissertation looks at the impacts of land-change at two different scales, first, at the local scale, for a village in Papua New Guinea, and second, at the regional scale, for the island of New Guinea. I apply spatial concepts and tools to ask research questions and analyze landscape level phenomena. These topics are conducted at disparate spatial scales with the goal to contribute to the ecological research for this region, as it is vastly understudied in many scientific fields. Within the land change context, one focus of this dissertation is to improve our understanding of how land change occurs in subsistence agricultural systems and to what extent remote sensing tools and participatory methods assist in defining and delineating changes. The other focus of this research is to advance our understanding of plant distributions and predict regions of high biodiversity. We aim to objectively and quantitatively show collection density, biases, and predict genus richness to inform sampling needs, support conservation strategies, compare genus diversity to other regions of the world, and discuss principles and drivers of biogeography. With a greater understanding of plant richness and subsistence agricultural land-use the trends and impacts of land change can be used to better inform policies and conservation strategies in PNG.

1.1. Research questions and objectives

This dissertation is structured as three manuscripts and each is composed of an introduction, objectives, methods, results, discussion, and conclusion. The manuscripts are in the process of being published in peer reviewed academic journals.

1.1.1. Manuscript 1: Comparing and combining Landsat satellite imagery and participatory data to assess land-use and land-cover changes in a coastal village in Papua New Guinea

This manuscript uses Landsat satellite imagery and participatory research to examine differences between land-cover maps made by using remote sensing analysis alone and land-cover maps made using a multidisciplinary approach that combines land manager participatory information and remote sensing data. The goals of this study are to:

1) Examine differences between these two datasets; and
2) Identify how the addition of participatory information and feedback amends the image analyses.

1.1.2. Manuscript 2: Using high temporal resolution Landsat imagery to assess land-cover and relating trends to land-use and subsistence strategies in a coastal village in Papua New Guinea.

There are very few village level studies that assess swidden trends and we aim to understand if trends at wider scales are similar to those at the village scale. The goals of this study are to:

1) Use Landsat imagery to identify swidden land-use and associated land-cover trends between 1972 and 2015 at the village scale;
2) Use participatory land-use information to discuss how land-use decisions by land managers influence land-cover changes and trends; and
3) Discuss how the trends we found in this village are similar to or differ from trends at wider extents.

1.1.3. Manuscript 3: Modeling hotspots of plant diversity in New Guinea

This manuscript explores vascular and non-vascular terrestrial plant distributions for the island of New Guinea at the genus taxonomic level. To predict regions of potentially high richness occurrence points from online, herbarium, and museum databases are paired with environmental variables (elevation, temperature) and an ecological niche model, MaxEnt, is used to predict distributions and richness. The goals of the study are to:

1) Identify sampling intensity and bias;
2) List the abiotic drivers that are most influential to plant distributions;
3) Identify the regions of New Guinea that harbor high genus richness; and
4) Discuss the implications of land-use and land-cover changes.

CHAPTER 2

COMPARING AND COMBINING LANDSAT SATELLITE IMAGERY AND PARTICIPATORY DATA TO ASSESS LAND-USE AND LAND-COVER CHANGES IN A COASTAL VILLAGE IN PAPUA NEW GUINEA[1]

2.1. Introduction

Satellite imagery has improved spatial and temporal estimates of land changes, yet even high-resolution imagery can result in poor enumeration and an oversimplification of land changes (Hett et al., 2012; IPCC Core Writing Team, 2001; Ziegler et al., 2011). To better understand the drivers of land change ancillary data have been paired with satellite imagery to support observations. For example, logging exports in board lengths are used to estimate the amount of forest cleared (Mather 2005, Kohl et al. 2015). However, compiling and incorporating ancillary data for all types of land change remains a challenge, as the drivers of change are often complex. Recognizing this, it is important to utilize ancillary data to create the most accurate land-use and land-cover (LULC) analysis possible if land change data are to be used to inform policy, develop conservation strategies, and create the best management plans.

Participatory information derived from local knowledge is an important type of ancillary data that provides essential information to link observed patterns and trends of land-cover from remotely sensed data to ground-level land-use activities (Rindfuss et al. 2003; Herrmann et al. 2005; Leisz & Rasmussen 2012). Integrating spatial and social sciences is a way to comprehensively explore the human-environment interface and identify the driving forces

[1] This chapter is co-authored by Stephen J. Leisz and Melinda Laituri and has been accepted in *Human Ecology.*

causing changes in livelihood decisions and LULC (Rindfuss et al. 2003, Herrmann et al. 2014). Recent research demonstrates that more comprehensive understanding of local environmental and livelihood dynamics is achieved when stakeholders are included in research efforts (Ostrom 2009, McCall and Dunn 2012, Wakie et al. 2016). Stakeholders are those who have social or economic interests in the research results as it can influence their livelihoods or objectives (Estrella et al. 2000; Ramanath & Gilbert 2004). Stakeholders can include indigenous people, land-managers, community and development organizations, and policy makers.

In LULC change studies participatory research is conducted in collaboration with local land-managers and provides the means to assemble and quantify local peoples' environmental perspectives, knowledge, and resource use through discussions, interviews, and various activities (e.g. resource mapping, resource use ranking). This type of integrated research provides an opportunity to discuss past trends and future perspectives of change that may not be available in other empirical datasets. Participatory information and local knowledge can be made spatially explicit by using remote sensing imagery and geographical information systems (GIS) to provide further conceptualization of linear and non-linear connections between resource decisions and LULC changes (An 2012). These methods are broadly categorized as participatory GIS (PGIS). However, when the focus is to improve LULC classifications from satellite imagery we believe that a more accurate description is participatory remote sensing (PRS) because the participatory contributions are focused on the validation of LULC analyses and pairing satellite image analysis with resource maps. The advantage of PRS is that local land managers' spatial knowledge of the LULC can be recorded and explored in greater detail with the use of spatially explicit imagery and participatory maps (PPM). Also, the local land managers are included in and contribute to data analysis.

Participatory methods have produced intriguing changes in the representation and validation of LULC and changes therein (McCall 2003, Dunn 2007, Lynam et al. 2007, Matthews et al. 2007, Voinov and Bousquet 2010, Fritz et al. 2012). This interdisciplinary framework has also improved results (Lynam et al. 2007, Voinov and Bousquet 2010) and shows that detailed land-use knowledge can refine remote sensing LULC classifications and change detection (Schmidt-Vogt et al. 2009a, Leisz and Rasmussen 2012). There are many examples of participatory research being used in LULC analyses, and some of the more recent include sea grass changes in the Solomon Islands (Lauer and Aswani 2010), coastal management in Hawaii (Levine and Feinholz 2015), vegetation changes in the Sahel (Herrmann et al. 2014), invasive species management strategies in Kenya (Wakie et al. 2016) and swidden agricultural changes in Vietnam (Leisz and Rasmussen 2012, Laney and Turner 2015).

Swidden agriculture systems, the focus of this paper, have land-cover that is dynamic and heterogeneous and poses many challenges in developing land-cover maps based on satellite image analyses alone. Swidden agriculture is also referred to as slash-and-burn agriculture and shifting cultivation (from here on we will use the term swidden). Swidden is usually part of a subsistence livelihood system. Swidden shifts between cultivated and fallow periods, where tree cover is cut, dried, burned, crops planted and harvested, and fields fallowed for a length of time so that natural vegetation regenerates until it is bush or tree cover again, at which point it is cleared for agriculture. Across the globe over 300 million people employ some form of swidden (Mertz et al. 2009). As a result, land-cover associated with swidden systems is highly diverse. The diversity stems from the heterogeneity of climatic and environmental variables (e.g. precipitation, temperature, topography, hill slope, and soil nutrients), cultures, and techniques used (e.g. amount of time under crop or fallow, plot sizes, terracing, and crop selection; Fox et al. 2009). Also, swidden plots often follow natural contours, have swaths of natural vegetation between and within plots, and avoid unfavorable areas (e.g. low points with standing water).

The variation found in swidden systems challenges our capabilities to accurately map it. Within a 100-meter radius a large number of swidden land-uses can exist at one time (e.g. newly cleared land, cultivated land with young crops, recent fallow used for pasture, older fallow used for collecting non-timber forest products, etc.) and each could have a different land-cover. In this small area, swidden multiple land-covers exist as well and can include a recently cleared plot with new sprouts, an early fallow plot that is dominated by young grass and herb growth, a cultivated plot with a mix of fruit trees, ground cover crops, and bush-like crops (i.e. cassava), and areas of woody growth that include mature trees. In addition to spatial variability, swidden land-covers are also temporally variable, meaning land-covers are not permanent and can change over relatively short time scales (e.g. after a few months, annually). The spatial and temporal dynamics of swidden land-covers are influenced by local conditions and management decisions. Another aspect that makes swidden difficult to assess is that tree cover on older fallow land and tree cover of natural forest areas are nearly indistinguishable in satellite imagery due to spectral similarities.

In response to such challenges, numerous remote sensing methods have been developed to classify the diversity of swidden land-covers. Worldwide there are numerous remote sensing techniques that have been used to identify swidden. A review by Li et al. (2014) describes techniques used in Southeast Asia and these include integrating spectral classification (optical and radar), phonological (morphological and physiological responses), statistical (binomial logistical regressions, machine learning), and landscape ecology (land-cover composition patterns).

In Papua New Guinea (PNG) identifying and classifying swidden LULC changes have received little to no attention. However, such analyses are vital in a country where approximately 85% of the population depends on swidden to fulfill subsistence and livelihood needs. An analysis of forest cover change at the national level cited swidden as one of the leading causes of forest degradation and loss, after timber extraction (Shearman et al. 2009). Based on the assessment that 85% of the population relies on swidden, their analysis uses population growth to extrapolate the expansion of swidden and therefore, population growth equals growth in swidden area. Using population growth estimates, they speculate that swidden expansion will continue to be a major cause of forest degradation and losses. However, since 2000 the land-cover change literature has conclusively shown that such simplistic use of population as a driver of land-cover change is not valid (Geist and Lambin 2002). Recent reviews of swidden and forest interactions worldwide, further show that LULC dynamics are not so simple (Fox et al. 2000, Mather and Needle 2000, Lambin et al. 2001, Schmidt-Vogt et al. 2009a, van Vliet et al. 2012). The Shearman et al. (2009) study does not account for these recent studies and falls short in describing the multifaceted and complex drivers of land change by citing population growth alone (Bourke 2001, Filer et al. 2009).

The Shearman et al. (2009) study is at the national level and LULC change assessments that focus on swidden at the national or regional level are challenging due to the extensive data collection required and the necessity to aggregate the data at this coarse scale (Li et al. 2014). Rindfuss et al. (2004) show that a relationship between population growth and deforestation found at a national level is an artifact of scale and when data are disaggregated to sub-national or local levels the relationship can be lost. To accurately understand drivers of deforestation and the role that population growth does or does not play, it is necessary to link remote sensing land-cover observations to ground level activities at the local or village level. In PNG, this means that a large sample of village level case studies is vital to identify the true drivers of land-cover change in the country. Such case studies should incorporate livelihood and swidden system management decisions and the associated influences on LULC trends. A literature search of peer reviewed articles at the village scale resulted in three LULC studies in PNG and these were conducted in a single region, the highlands (Ohtsuka, 1994; Umezaki et al., 2000; Umezaki et al., 2002). Other articles found assess livelihood changes in response to major resource extraction from oil palm (Koczberski and Curry 2005, Koczberski et al. 2009, 2012) and mining (West, 2006).

2.2. Goals and objectives

As noted above, remote sensing methods alone are not sufficient to assess the dynamic nature of swidden. Therefore, the goal of this paper is to examine the difference between LULC assessment results obtained from using remote sensing data analysis alone and those obtained from using a multidisciplinary approach that integrates participatory data into remote sensing analysis. This study is conducted at the village scale and uses participatory and Landsat satellite data for 1999 and 2011. Using the results we aim to discuss and compare land-cover changes at the village and national levels (Shearman et al. 2009) and demonstrate the implications of the scale of analysis on the results.

2.3. Methods

2.3.1. Study area

The study village is a coastal community approximately 60 km south-southeast from Lae, the second largest city in PNG (Fig. 2.1). The customary territory contains diverse flora and fauna in both the terrestrial (330 km^2) and marine (170 km^2) habitats (Bein et al., 2007; Longenecker, et. al. 2011). Customary land tenure governs how land is used in the livelihood system, which is subsistence based and includes land-use activities (swidden, forest, animal husbandry, and hunting) and marine resources (ocean and reef). Swidden is the primary means of subsistence production. The main swidden area is located 5 km north of the village in a river delta. Some smaller swidden plots are scattered around the village. Seasonal deposits of rich fluvial sediments from rainy season floods replenish soil fertility and allow for shorter fallow periods. As a result, the fallow periods are typically five to seven years and have not been longer than 10 to 12 years throughout the village history. Because of the fertile soils and the large expanse of the delta, cultivation has remained contained in the flat land of the delta area. The crops include sago palm, root crops (cassava, taro, sweet potato, yam), fruit trees (betel nut, mango, coconut, banana, papaya), melons, cucumbers (which are actually a type of melon), pineapple, sugar cane, pit-pit (local variety of sweet cane), and leafy greens.

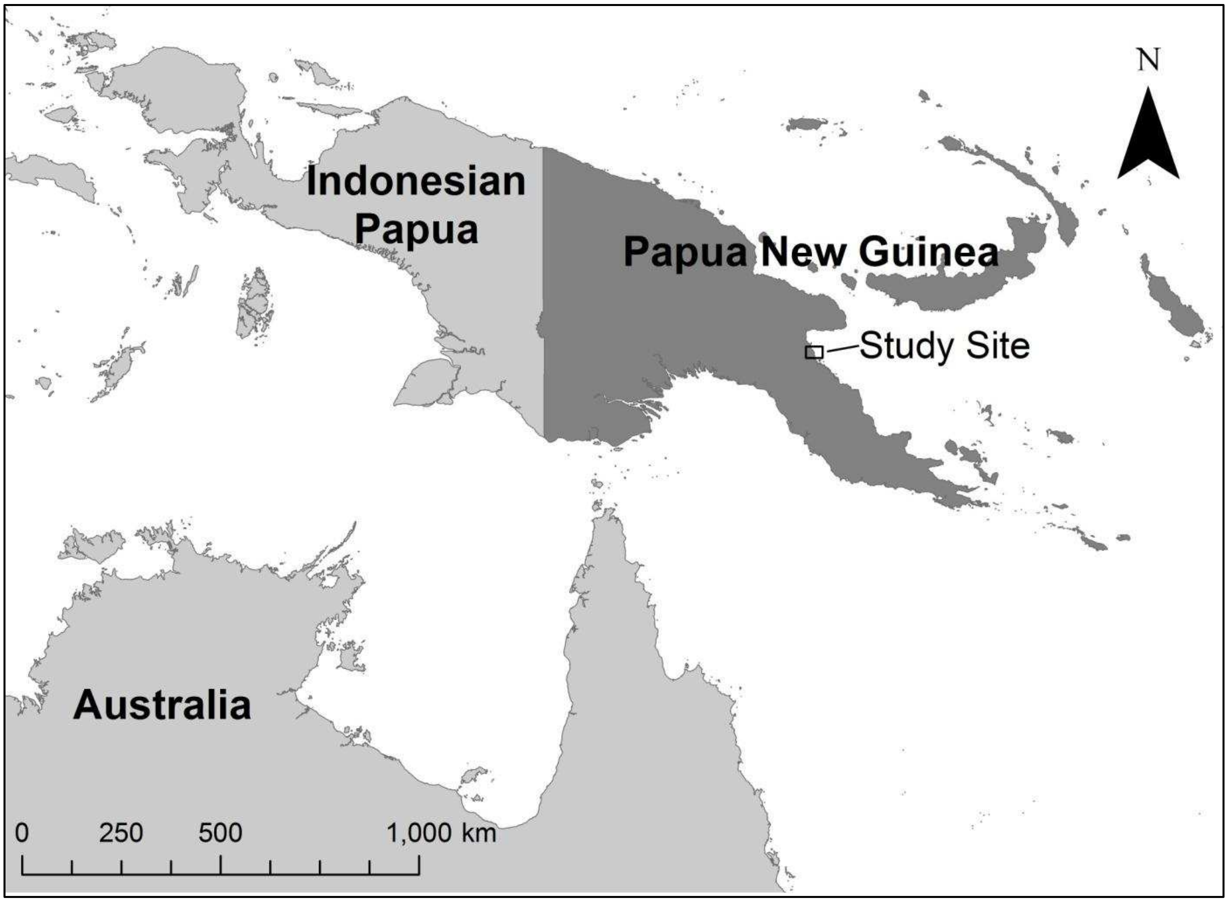

Figure 2.1. Papua New Guinea, the surrounding countries, and the approximate location of the village study site.

There are many reasons that this village is an ideal site to assess land-cover changes within a swidden system. First, swidden in this village is located atop a fertile delta and, while this is locally unique, McAlpine & Freyne (2001) report that 4% of the PNG land surface are littoral and alluvial fans and support approximately 19% of the population. Therefore, it is representative of areas where a fifth of PNG's population lives. Second, the village's land has not experienced any major logging or other resource extraction to date, which limits village resource degradation and losses. The lack of such resource extraction also eliminates the possibility of confounding land-cover classifications between logging and swidden, which is common in tropical regions. Third, there is no road access to the village (access is by boat only) so additional pressure on resources from an influx of migrants are limited. Last, the population growth rate between 1980 and 2011 in the village is 6% per year, higher than the national average of 4.5% per year, allowing us to test the view that population increase can be used to forecast swidden land expansion.

2.3.2. Satellite image processing and analysis

Landsat scenes from 1999 and 2011, corresponding to interview data, were selected. The 1999 image is a Landsat 5 TM image and 2011 is a Landsat 7 ETM+ image. Both scenes were captured during the dry season (September – December) when the differences between land-covers are more spectrally distinguishable and land is more intensively cultivated. A single scene covers the entire village area. Image preprocessing included atmospheric corrections, georectification, and cloud masking. The classification process includes tasseled cap transformation, wetness –brightness difference index (Helmer et al., 2009), and K-means unsupervised classification. A binary classification of swidden and non-swidden land-covers was created (Table 2.1). A detailed description of image classification methods and accuracy assessments can be found in Appendix 2, 9.2.

Table 2.1. Land classification categories for swidden and other cover types.

Swidden-fallow	**Other**
▪ Cleared of vegetation ▪ Burned plots ▪ Sparse crop cover (wide spacing or early growth) ▪ Denser crop cover ▪ Early fallow (weeds and grass) ▪ Moderate fallow (grass, bushes and small trees (2-3 meters in height)) ▪ Late fallow (Small and medium trees (5-6 m in	▪ Built structures ▪ Forest ▪ Riparian ▪ Wetland ▪ Water bodies ▪ Sandy beach ▪ Clouds ▪ Shadows

height))	

Independent, high resolution imagery (satellite imagery or aerial photos) is not available for the period of time when the 1999 Landsat scene was obtained for an accuracy assessment and therefore, visual interpretation of the raw imagery was used in combination with GPS ground-truth points from the Bein et al. (2007) paper to assess the accuracy of the 1999 land-cover results. To conduct classification accuracy assessments for the 2011 Landsat image analysis, an independent image from the GeoEye satellite is available for 2010. The GeoEye image has a finer resolution (2 m) than the Landsat image (30 m) and is useful for visually interpreting land-cover accuracy for the 2011 classification results.

2.3.3. Participatory data

We gathered information about land management and land-use from the local land-managers using participatory methods including semi-structured surveys, structured interviews (Chambers 1994), and participatory resource and land-use mapping (King 2002, Dunn 2007). The semi-structured surveys and discussions were conducted with knowledgeable community members to gain a comprehensive understanding of the framework of the customary land tenure system and swidden practices. Fieldwork was done in 2011 and 2014. Similar structured interviews conducted in 1999 by Bein et al. (2007) and Wagner (2002) to assess swidden land-use were referenced to add a temporal aspect to the study.

2.3.4. Surveys and interviews

Through structured interviews we obtained information about household resource use. There were 32 randomly selected households and informants were divided equally between male and female. The interviews followed a list of questions that were consistent across informants and focused on swidden resources. Each informant described household swidden plots as the area currently cultivated. We observed that fallowed land is not reported by village land-managers as part of their swidden area. This is due either to the phrasing of interview questions or to how land-managers perceive swidden land. Numerical values obtained from the interviews (e.g. plot area) were averaged across the 32 households and scaled up to represent the village population. Qualitative information, such as opinions about the drivers of resource use changes, typically fell into 3-4 categories and was generalized. To account for the total area utilized in the swidden cycle (cultivated swidden and fallowed swidden land), the cultivated swidden area is multiplied by the total time of the swidden cycle for 1999 (7 years; Bein et al. 2007) and 2011 (5.75 years).

2.3.5. Participatory mapping of the swidden area

A hand-drawn participatory map (PPM) map of the village and swidden area was created. Ground-truthing of swidden plots was done with a GPS and tape measure to confirm plot location, size, orientation, and the phase (newly cleared, cultivated, or fallow). The PPM was digitized and georeferenced to the 2011 Landsat image. Reference points were added to a GeoEye image captured in 2010, as the finer resolution assists in comparing land-cover and the PPM in greater detail.

2.3.6. Participatory remote sensing and data validation

A critical component of participatory data collection, which is often skipped, is for researchers to incorporate and seek feedback from stakeholders before results are published (McCall 2003, Laituri 2011). The data validation process has been shown to facilitate additional discussions, information sharing, and collective learning among collaborators, and also improve resource and management negotiation and decision-making (Ruankaew et al. 2010, Laituri 2011). To validate our results we returned to the village in 2014. The results of PRS data analysis were presented to a 20-person group and the community as a whole. Posters were created and translated into Pidgin (national language) and each poster was presented orally and hung in the community center so that anyone could review and comment on the results. Everyone was encouraged to ask questions, discuss the results, and make edits to the posters. In the smaller 20-person group specific questions were posed, detailed notes taken, and map edits made to assure the accuracy of LULC classifications. Edits and corrections to the data and analyses were recorded and incorporated into final products. The remote sensing and participatory methods are processed independently and then paired for comparison and the summarization of results (Fig. 2.2).

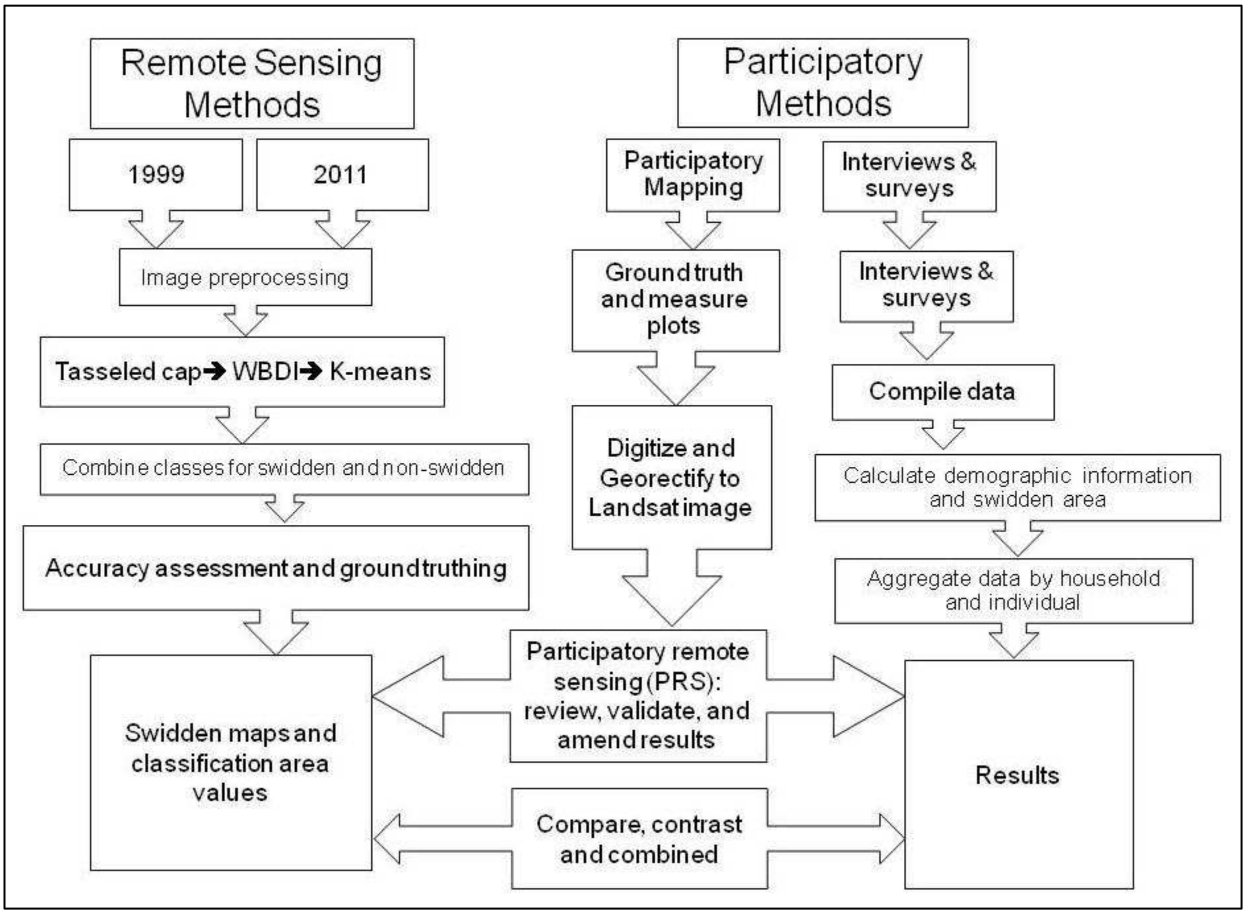

Figure 2.2. Remote sensing and participatory methods are shown side by side to illustrate how data were merged for analyses and results.

2.4 Results

2.4.1. Satellite image analyses

The maps in Figure 2.3 show swidden and village land-cover for 1999 and 2011. The village area is composed of smaller swidden plots, fruit trees, and the village settlement (e.g. houses, schools). The northern arm of delta and land boundary changes over time, as it is influenced by the meandering river. Evidence of the river changing course can be observed between the scenes. Most of the non-swidden area between the two arms of the delta remains naturally vegetated because the soil is too moist to be successfully cultivated. This causes the swidden area to maintain a similar shape over time. There are two areas with notable increases in swidden area in the 2011 classification. First, swidden associated land-cover is wider along both arms of the delta. Second, swidden associated land-cover is more extensive in the area between the delta and the village.

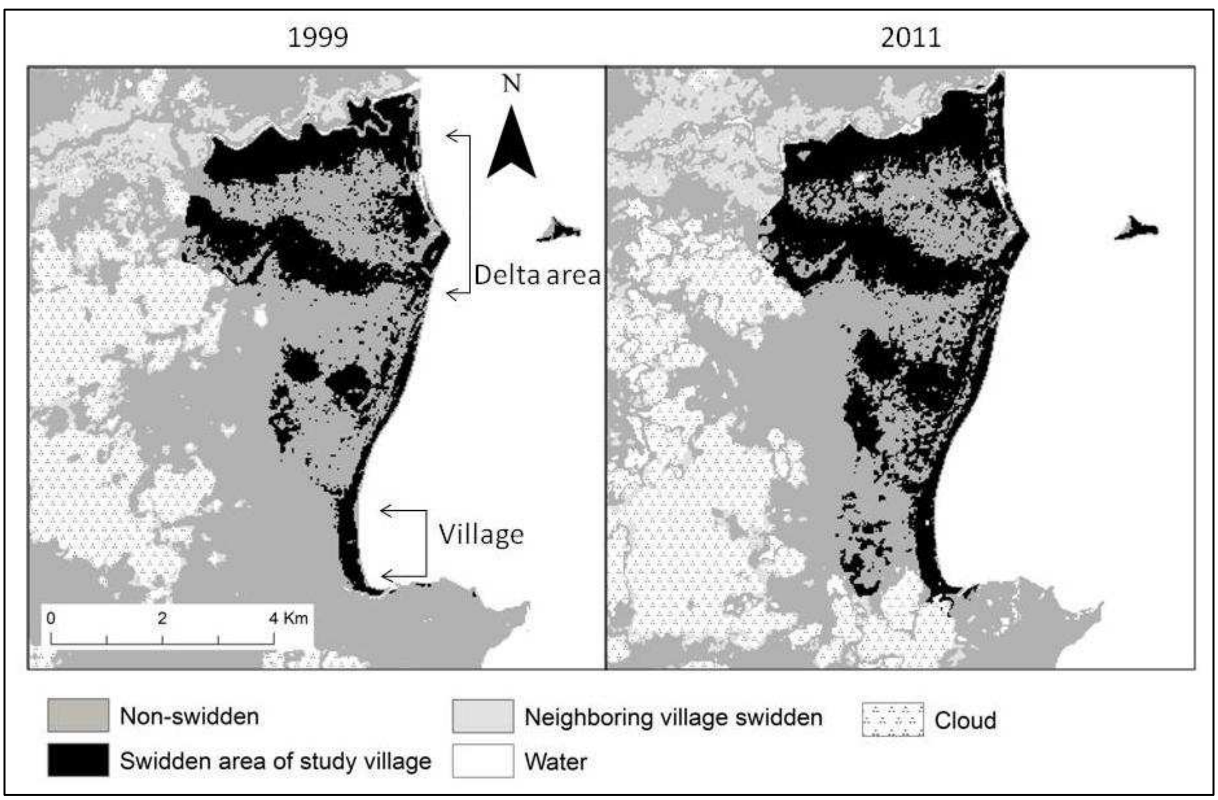

Figure 2.3. Swidden land-cover using remote sensing data alone for 1999 and 2011.

2.4.2. Participatory data

2.4.2.1. Structured interviews

Data compiled from our 2011 interviews and the 1999 data from the Bein et al. (2007) and Wagner (2002) studies are presented in Table 2. Between 1999 and 2011 the population grew by 371 people and the number of households in the village increased from 80 to 128. The length of the swidden cycle (cultivated and fallowed) was 7 years in 1999 and 5.75 years in 2011. To accommodate these changes the duration of the cultivated swidden lengthened from 1.2 to 2.75 years and the fallowed area shortened from 5.8 to 3 years. The average cultivated swidden area per household decreased from 0.404 ha (64 m^2) in 1999 to 0.323 ha (57 m^2) in 2011. While the number of cultivated swidden plots per household increased from 3.1 in 1999 to 3.8 in 2011, the average swidden area of a single plot decreased from 0.13 (36 m^2) to 0.095 (30 m^2) ha, respectively. Households maintained a greater number of smaller plots with the total area per plot decreasing over time.

2.4.2.2. Combining participatory and remote sensing datasets

Figure 2.4 shows the hand-drawn land-use map or PPM overlaid on the 2011 classified Landsat image. The subsets compare the output from remote sensing analysis alone and from the integrated PRS method for two locations, the main swidden (4a and 4b) and swamp (4c and 4d) areas. The swidden area in Subsets 4a and swamp land in Subset 4c show the land-cover classification using remote sensing analysis alone. Land managers reviewed these results during the PRS review and analyses decided that the swidden area in subsets 4a and 4c (remote sensing classifications alone) includes too much swidden land-cover. Therefore, Subsets 4b (swidden) and 4d (swamp) show the swidden land-cover area (dark grey) that should be merged with the non-swidden class. The dark grey land-cover will be referred to as the adjacent- non-swidden area. Land managers described that the adjacent- non-swidden area (Subset 4b) is made up of forest land-cover and is not used for swidden (cultivated or fallow). The PPM overlay further supports the land managers' perspectives, as the swidden plots in the PPM have a tighter fit within the swidden land-cover class in Subset 4b than in Subset 4a. Also, when the adjacent-swidden area is allocated to the non-swidden class, the blocks of natural vegetation that are scattered within the swidden area are identified. Land managers explain that these blocks of natural vegetation are common and can include fallow vegetation, groups of large trees (fruit trees, shade trees), natural fences, or vegetation on land not suitable for cultivation.

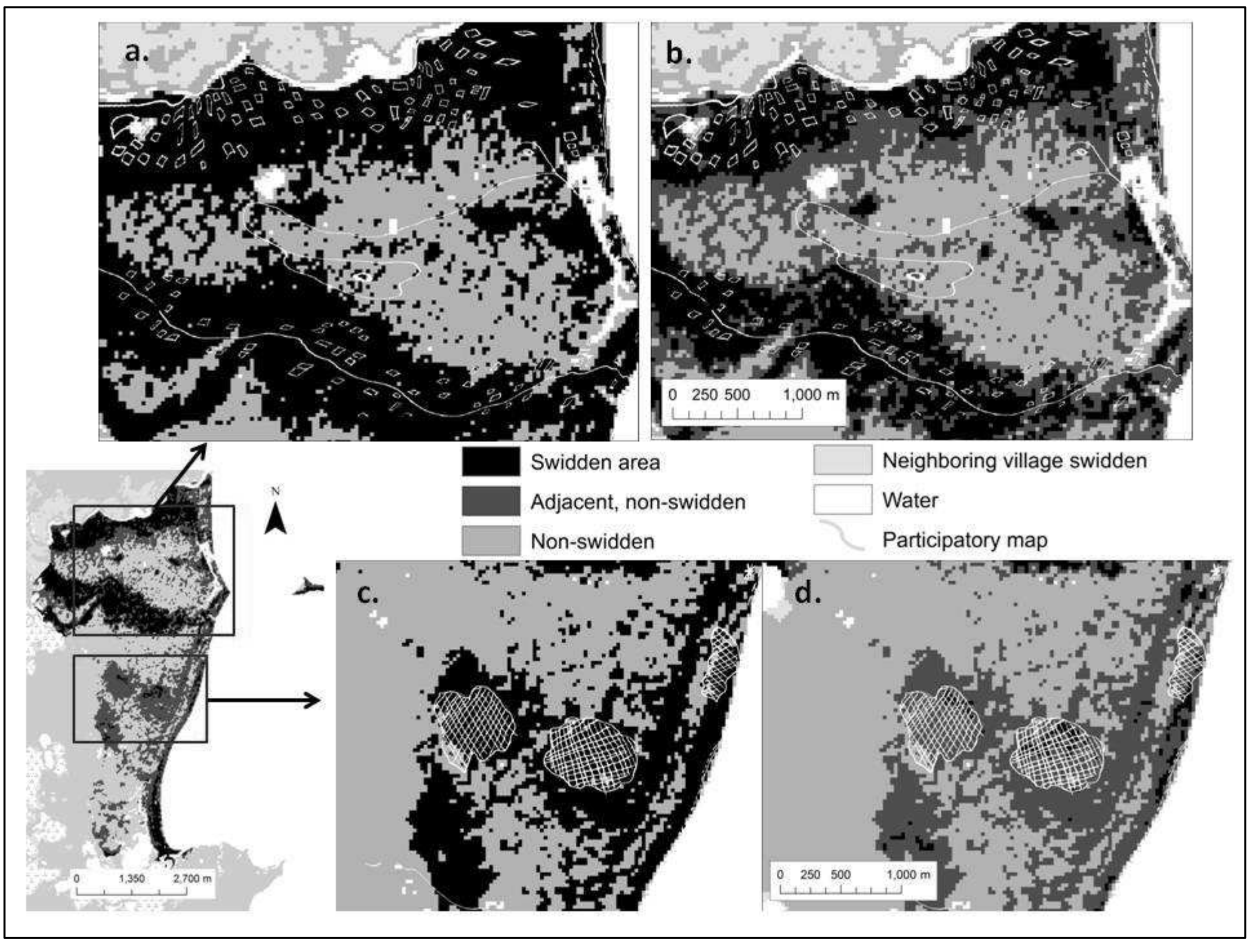

Figure 2.4. The participatory map (PPM) of village and swidden LU is overlaid with the 2011 Landsat classified image. Subsets a and b show the delta swidden area and subsets c and d show a swamp area. Subsets a and c are land-cover classifications using remote sensing analysis alone. Subsets b and d are the classifications after the land managers delineated misclassified swidden LC, shown in dark grey, and these areas should be merged with the non-swidden class.

Subset 4c is dominated by swamp vegetation and land managers explained that this area is too wet for swidden, and any land-cover classified as swidden is incorrect. Therefore, nearly all of the land in this region is misclassified as swidden when only remote sensing analytical methods are used and should be non-swidden. The adjacent- non-swidden area in Subset 4d greatly reduces the amount of swamp land included in the swidden class. Both subset groups b and d show the portion of the swidden land-cover class that should be merged with the non-swidden class and this change reduces areas of misclassified swidden land-cover.

Figure 2.5 shows georeferenced swidden plots atop the classified Landsat (30 m) and raw GeoEye (2 m) images. The pixilated structure and different spatial resolution of these images shows how scale influences the interpretation of swidden LULC. Due to the difference in the fieldwork and capture dates of the GeoEye image, some of the listed LULCs have changed. In general, this figure better shows the complex and fragmented nature of swidden land-cover and why it is difficult to assess using remote sensing methods alone. First, swidden plots differ in orientation, size, and shape. Regardless of size, a swidden plot can be contained within a single Landsat cell or cross into multiple cells. Also, even though the georeferenced plots are rectangular, plots were often irregular in shape and often follow natural contours or features. Second, the land-covers do not always match the land-use and plots can have multiple uses and be classified as a single land-cover. Third, the newly cleared plots are easier to identify compared to plots with crop or fallow land-covers and can influence reflectance qualities disproportionally as bare soil has higher reflective qualities in some wavelengths.

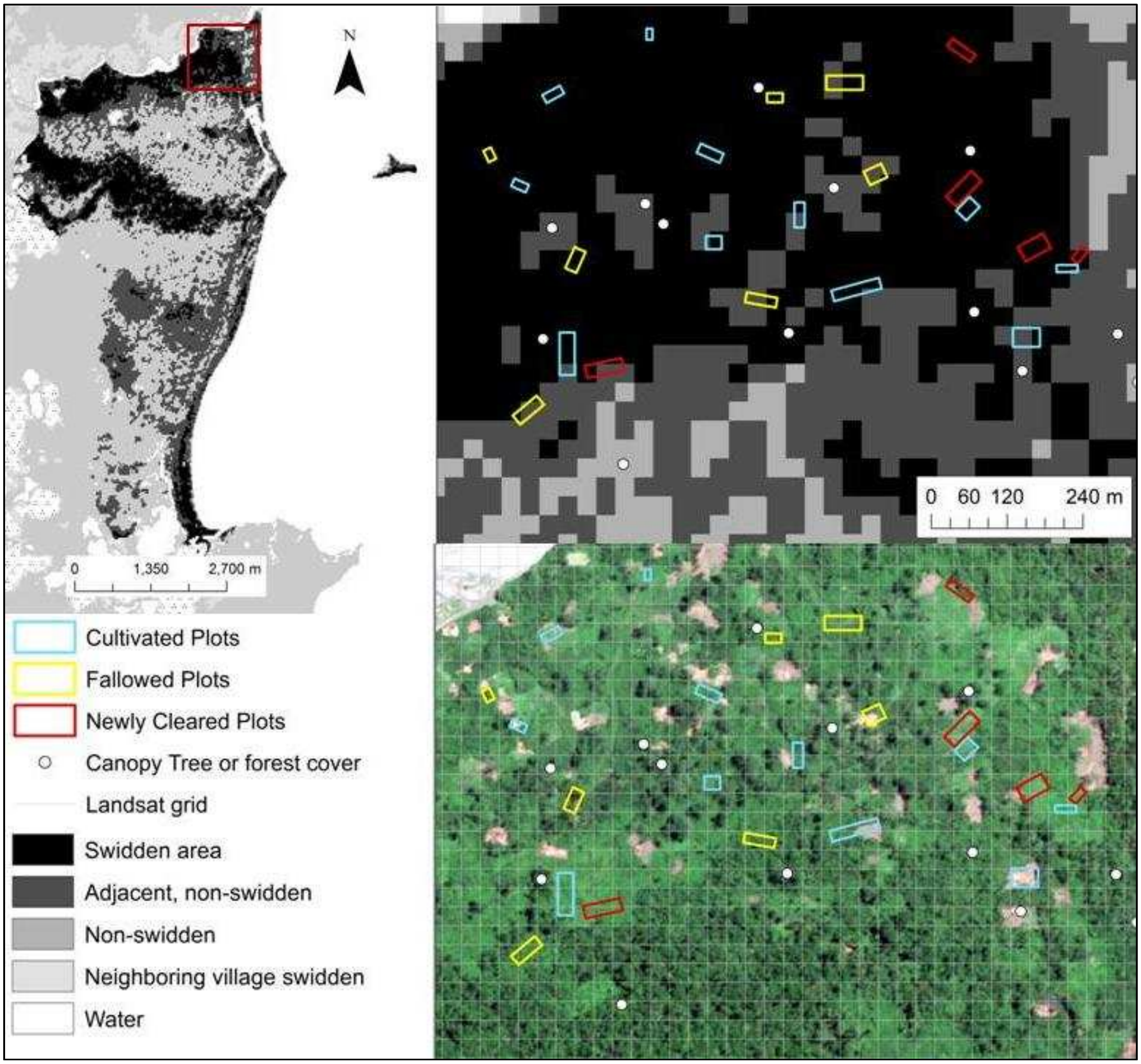

Figure 2.5. The ground-truthed points and swidden plots shown are accurate area, location, orientation, and LU and land-cover type. The GeoEye image resolution is 2 m pixels and shows the swidden landscape in greater detail than the Landsat image which has a resolution of 30 m. A grid is overlaid on the GeoEye image for resolution comparison.

Figure 2.6 compares the swidden area in hectares classified using remote sensing analysis alone and the PRS methods for 1999 and 2011. The remote sensing classifications without land manager inputs are 993 ha in 1999 and 1395 ha in 2011. The PRS method results in an output that includes two land-cover classes, swidden and adjacent-non-swidden. These two classes are combined for the 1999 and 2011 PRS methods to illustrate how much of the land-cover from remote sensing analysis alone is classified as adjacent-non-swidden by land managers. The amount of swidden area is 455 ha and 491 ha and the adjacent-non-swidden area is 537 ha and 905 ha for 1999 and 2011, respectively. The adjacent-non-swidden area accounts for 35% and 45% of the swidden land classified by remote sensing analysis alone.

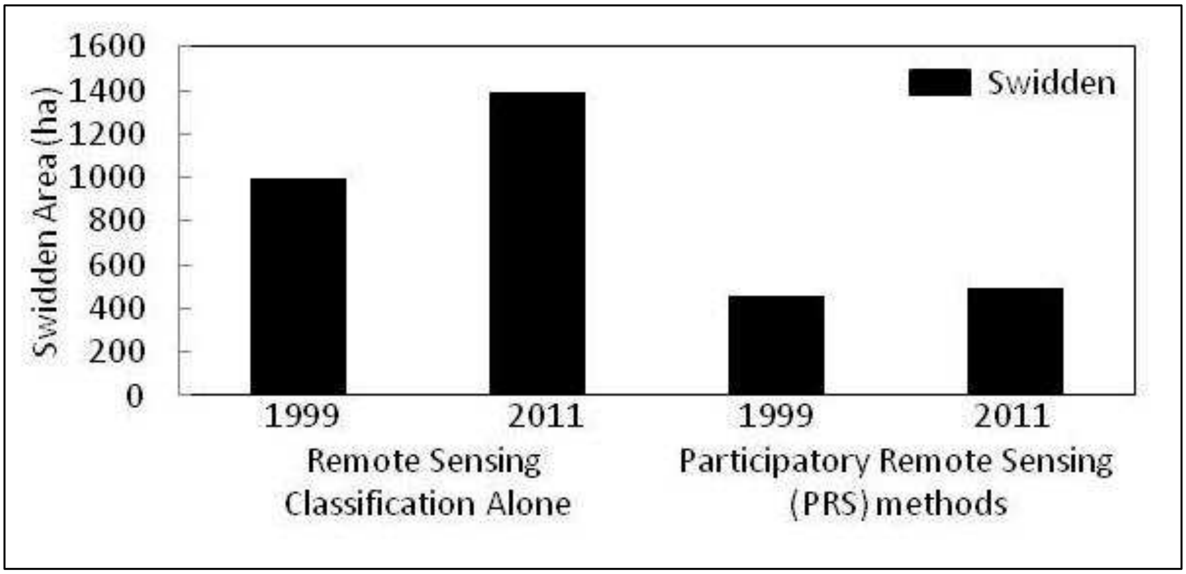

Figure 2.6. Total swidden area classified using remote sensing analysis alone and PRS methods for 1999 and 2011.

Each dataset in Figure 2.6 shows an increase in swidden area over time. The larger increase in swidden area is for remote sensing analysis alone at 402 ha. The PRS swidden area increased (without the adjacent-non-swidden class) by 35 ha between 1999 and 2011. The percent increase over time for the remote sensing analysis alone is 40% and PRS is 8%.

2.5. Discussion

The land-cover datasets for PRS and remote sensing analysis alone present different information about swidden area and changes at the village scale. The PRS methods results show that when these data are paired a more in depth and comprehensive understanding of swidden area LULCs are achieved than when either data set are used alone. The integration of land-manager perspectives and knowledge via PRS methods offers a unique insight into local land-use.

The classification of swidden area land-cover using remote sensing analysis alone is over two and a half times larger than the results using PRS methods. In part, the differences in area are a result of transforming a continuous landscape into the discrete and categorical format of the imagery and analysis, respectively. Some land-cover categories are classified correctly, but swidden areas are made up of highly complex land-covers and it proves more difficult to accurately classify swidden using Landsat data alone. The overlay of the PPM shows areas that are actively cultivated swidden plots. Land managers identified in the PPM that the area between the swidden plots is a combination of fallow and non-swidden (natural vegetation) land. As recommended by the land-managers during PRS methods, an additional adjacent-non-swidden class (dark grey; Fig. 2.4) is added to the land-cover classification to show how much land was misclassified. The area classified as swidden is consequently reduced and land managers agreed that merging the adjacent- non-swidden area with the non-swidden class is more representative of the land-covers found in the swidden areas and that fallowed and non-swidden natural vegetation are better identified.

The increase in swidden LULC area seen between 1999 and 2011 on maps produced using PRS methods is minimal compared to the increases observed using remote sensing analysis alone (Fig. 2.6). Remote sensing analysis alone does not differentiate between these two land-covers, whereas the inclusion of PRS methods allows the classifications to be more accurately allocated.

At the national extent, Shearman et al. (2009) classified land-covers that were adjacent to swidden areas and villages as land deforested by swidden activities because these areas could not be attributed to other causes of forest loss. This contrasts with information supplied by land managers at the village level, as the land-cover adjacent to the swidden area was reassigned to the non-swidden class. For large areas with a coarse resolution data, land-cover classifications that rely on remote sensing analysis alone are likely to allocate more forest loss to swidden in regions where resource extraction and villages and swidden areas border one another. To improve the delineation of land-cover associated with swidden land-use systems at wider extents, a finer spatial resolution may help. However, if such data are not available for the time series desired, the inclusion of PRS methods would assist in refining land-cover classifications to more accurately distinguish among the different land-covers found in swidden landscapes.

For our study village LULC assessments and changes are not confounded by logging yet classifying swidden with remote sensing analysis alone still over classified swidden LULC. However, collaborative PRS methods allow us to refine the land-cover classification and we identify multiple areas that were misclassified as swidden in the output of the remote sensing analysis alone. Although Shearman et al. (2009) preformed ground-truthing and accuracy assessments for land-cover classifications, none of their methods included land manager participation. It is highly likely that many swidden areas are over classified because, as we find, the land-cover adjacent to swidden proves difficult to categorize at a 30 m resolution without knowledgeable land manager input. We argue that in regions where swidden is a major land-use, additional LULC classification strategies should be incorporated into land-cover classification processes, such as PRS. Also, swidden should be allocated as a separate LULC category at national and wider extents because there are a range of different LULC types and the ecological impacts among these differ (Rerkasem et al. 2009, Ziegler et al. 2011, Kremen and Miles 2012, Delang and Li 2013).

The georeferenced plots and finer resolution of the GeoEye image (Fig. 2.5) demonstrate and confirm that the swidden area is a patchwork of land-covers that has countless different combinations in one Landsat (30 m) pixel. We find that the size and orientation of swidden plots in the PPM do not align with Landsat pixels and plots often cross into multiple pixels or only occupy a portion of a pixel. We posit that the over estimation of swidden area using remote sensing analysis alone is a artifact of mixed pixels that include different proportions of swidden, fallow, and natural vegetation land-covers and have a spectral signature that is different than natural and forested land-cover. Regardless of a finer resolution, the pixilated nature of satellite imagery does not match how swidden plots are organized, since plots are created in response to the topographic and vegetation characteristics of the landscape in order to maximize crop yields.

2.5.1. Potential sources of error

A potential source of error from participatory data collection is that swidden plots could have been misestimated during the data collection phase when land-managers were asked to describe their plots in approximate length and width measurements. Although ground-truthing efforts measured plots and assured that estimates were accurate in area, all of the plots in the swidden area were not measured. Also, length and width area measurements do not account for natural and irregularly shaped plots, which are widespread in this swidden area (Fig. 2.4). While these methods capture the approximate area of a plot, it is likely that the true area slightly differs, which would affect cultivated and total swidden area calculations. As land-use results show, a large majority of the total swidden area is under fallow or natural vegetation, yet not much information was collected about the fallow periods aside from the duration. Simply multiplying the cultivated swidden area by the swidden cycle length may not be a good representative of total swidden area because land may be used and rotated in a different manner. In general, more information is needed about fallow and naturally vegetated areas and this is another area where land-cover information could be usefully paired with land-use information from local land managers to estimate how much land is devoted to the complete swidden-fallow cycle.

The second aspect that influences land-cover assessment is the resolution of the satellite imagery in relation to the mean swidden plot area. Land-managers described single swidden plots ranging from 12 m^2 to 105 m^2, with a mean of approximately 30 m2. The average plot size is equivalent to the area of one Landsat pixel but this does not account for the smallest identifiable object in an image (spatial resolution). To visually identify individual swidden plots multiple Landsat pixels are needed and we found that approximately 100 m^2 or just over a 3x3 pixel area is needed to identify a plot. Such a large area only accounts for larger plots and we surmise that the spatial resolution of Landsat data is too coarse to identify swidden plots on an individual basis. The finer resolution (2 m) of the GeoEye imagery allowed for smaller swidden plots to be identified, but deciphering the different land-uses and associated land-covers is still a challenge due to the fragmented and varied landscape created by swidden land-use. While the GeoEye data have a finer resolution, it does not have the temporal or spatial coverage available from the Landsat archives, and thus Landsat data will continue to be used for time series analysis of swidden LULC changes in the future. This reality makes it imperative to find methods for using Landsat data to accurately classify land-uses and their associated land-covers, such as swidden, that many rural populations worldwide continue to make use of and rely upon for their livelihoods.

2.6. Conclusion

Overall, swidden landscapes are difficult to classify and more prone to mixed pixels than other agricultural land-uses and their associated land-covers. Although finer resolution satellite data may be better suited for swidden LULC detection and change analyses, these data are often costly and do not have the same historical extent as the Landsat archives. Therefore refining Landsat classifications of swidden LULC is vital as many people in the world continue to rely upon swidden for their livelihoods.

Participatory data from local land-managers may be just as important as satellite data for understanding observed LULC trends. Therefore, in regions where swidden is the mainstay of subsistence livelihoods, the inclusion of participatory data is essential for accurate LULC assessments. We demonstrate that although the information derived from the participatory and Landsat datasets differ, the data can be used together to improve LULC assessments and understand temporal dynamics. Importantly, the assessment of swidden area from PRS methods is more accurate than that from a single disciplinary remote sensing analysis.

PRS methods reveal the differences between Landsat analyses and land manager information. Landsat smoothes the fragmented landscape into pixels representing single land-covers and overestimates the swidden area by two and a half times compared to land manager land-cover descriptions. One reason these datasets differ is that land managers described swidden area as only actively cultivated land, whereas Landsat analyses include cultivated swidden, fallowed, and natural vegetation indiscriminately. When both datasets are used in tandem, the distinctions among actively cultivated swidden, fallow, and natural vegetation can be extracted. We suggest that the cultivated swidden area, as described by the land managers, could be subtracted from the total swidden area classified using Landsat to distinguish how much land is cultivated, fallowed, or under non-fallow natural vegetation.

In conclusion, if only LULC classifications from remote sensing analysis methods alone are used when assessing swidden LULC then people's swidden livelihood systems will continue to be misclassified and mischaracterized. This has arguably happened for land-cover change analysis in PNG at the national extent. We show at the village level how PRS methods, combination of the remote sensing and participatory data, is one avenue of refining swidden LULC assessments to more accurately reflect the reality of swidden land-use and the associated land-covers.

CHAPTER 3

ASSESSING SWIDDEN LAND-USE IN A COASTAL VILLAGE IN PAPUA NEW GUINEA[2]

3.1. Introduction

Subsistence agriculture is a dominant land-use in Papua New Guinea and over 85% of the population depend on it for livelihood needs (Ramakrishna and Bang 2015), yet very few studies specifically focus on this type of land-use and land-cover (LULC) change. In PNG subsistence agriculture takes the form of a swidden-fallow system, where individual plots are cycled between cultivation and fallow periods. The swidden-fallow system follows a pattern where first tree cover is cut, dried, and burned, crops planted and harvested, and then fields are abandoned or fallowed so that natural vegetation regenerates. The swidden-fallow cycle, or sum of cultivation and fallow periods, can range from less than 5 years to over 25 years depending on local environmental conditions and management. Swidden-fallow agriculture is also referred to as shifting cultivation and slash-and-burn. Across PNG the heterogeneity of climatic and environmental characteristics (e.g. precipitation, temperature, topography, hill slope, and soil nutrients) influences diverse swidden techniques and cycles (e.g. swidden-fallow cycle lengths, plot sizes, terracing, and crop selection; Fox et al., 2009).

Although remote sensing analyses provide a wealth of information, assessments and change detection are challenging in swidden-fallow landscapes (Fox et al., 2003; Leisz & Rasmussen, 2012; Rindfuss et al., 2004; Schmidt-Vogt et al., 2009). Unlike plantations, mono-cropping, or industrial agriculture where growing seasons and fields are highly structured, swidden-fallow systems are more difficult to detect and differentiate because the land-use is

[2] This chapter is co-authored by Stephen J. Leisz and Melinda Laituri and is in review at *Human Ecology.*

highly mosaicked (Schmidt-Vogt et al. 2009). This mosaic is created because cultivated plots are selected for local conditions, can be any shape or size, and the swidden-fallow cycle has multiple phases, each of which has a unique land-use and associated land-cover. For example, the land-cover of a single plot can range from cleared forest to burned forest to cultivated crops to different stages of fallow regrowth (weeds and grass, grass and bushes, bush, bush and small trees, and small and medium size trees). Fallows can often be nearly indistinguishable from neighboring forest in satellite imagery. Therefore, the remote sensing methods used to assess and track the location and changes in a swidden-fallow system are numerous and have included spectral (optical and radar), phenological (morphological and physiological responses), statistical (binomial logistical regressions, machine learning), and landscape ecology (land-cover composition patterns) see Li et al. (2014) for a review of Southeast Asia. Such diverse methods stem from attempts to optimize the detection of swidden-fallow and other forms of subsistence agriculture for nearly a billion people, across 64 countries in Latin America, Central Africa, and South and Southeast Asia (Li et al. 2014; Mertz et al. 2009).

The inclusion of participatory data is one way to minimize remote sensing classification challenges and provide essential information to link observed patterns and trends from local, ground-level activities to remotely sensed data (Rindfuss et al. 2003, Herrmann et al. 2014). The union of spatial and social sciences has begun to more comprehensively explore human-environment interactions and identify the driving forces between livelihood decisions and land changes. Participatory methods have produced changes in the representation and validation of LULC and changes therein (McCall 2003, Dunn 2007, Lynam et al. 2007, Matthews et al. 2007, Voinov and Bousquet 2010, Fritz et al. 2012), and are valuable in data-poor regions where ancillary data lack. This interdisciplinary framework also has improved results (Lynam et al.

2007, Voinov and Bousquet 2010) and showed that detailed land-use knowledge can refine remote sensing land-cover classifications and change detection (Schmidt-Vogt et al. 2009; Leisz & Rasmussen 2012). The inclusion of participatory data at wide geographical extents, e.g. national, is too laborious. Therefore local-level studies are vital and provide a wealth of information to link local-level processes to wider geographical extents (Wilbanks and Kates 1999, Wu 2004). There are many examples of participatory research being used in recent LULC analyses (Lauer and Aswani 2010, Leisz and Rasmussen 2012, Herrmann et al. 2014, Laney and Turner 2015, Levine and Feinholz 2015, Wakie et al. 2016).

In PNG, very few LULC change studies exist. Those at the national scale have confounding perspectives on the degree to which swidden-fallow land-use has influenced changes. Shearman et al. (2009) cites swidden-fallow as a major driver of LULC change between 1972 and 2002 and associates population growth as the cause of change. Whereas, Filer et al. (2009) and Bourke et al. (2000) identify that swidden-fallow intensification strategies were more common than expansion, and therefore the amount of land change caused by swidden-fallow is much less. In a follow up study, Bryan & Shearman (2015) assess the drivers of forest cover change and identify that land classified as swidden-fallow did not change between 2002 and 2015. They suggest that for a majority of the population swidden-fallow intensification has been used to accommodate the larger population, whereas the remainder of the population has become more dependent on a cash-based economy due to resource extraction operations (oil palm, mining, and logging). Although the national level studies break down analyses into provinces, there is only one study that focuses on a single province (Ningal et al. 2008) and village level studies are limited in spatial distribution and number. Village scale studies include two studies in the Highlands (Umezaki et al. 2000, Bailey et al. 2008), one in southwest PNG (Eden 1993), and one along the northern coast (Bein et al. 2007; Chapter 3). Across four of these studies intensification strategies are cited as the primary means to increase yields whereas expansion of swidden-fallow areas is only identified in one village (Umezaki et al. 2000).

Subsistence strategies and land-use decisions are influenced by a large and complex set of factors and draw from dynamics that are situation-specific and occur at different spatial and temporal scales (Lambin et al. 2001; Schmidt-Vogt et al. 2009; Fox et al. 2000; Mather & Needle 2000; Sirén 2007; Lambin et al. 2003). Therefore, to explain LULC phenomenon and trends in adequate detail, participatory data are needed. This study uses 40 dry-season satellite images and participatory information from local land-managers to assess swidden-fallow land-use over time. The goals of this study are to:

1) use Landsat imagery to identify swidden LULC trends between 1972 and 2015 at a village scale;
2) use participatory information from land-managers to determine how land-use and subsistence decisions influence swidden-fallow land-cover trends; and
3) analyze how the trends we found in this village are similar to or differ from trends at wider geographic extents.

3.2. Study area

The study village is a coastal community 65 km south-southeast from Lae, which is the second largest city in PNG (Figure 3.1). To preserve the anonymity of this community, we will not refer to it by name. The customary territory is approximately 500 km^2 and includes terrestrial (330 km^2) and marine (170 km^2) habitats that contain diverse flora and fauna (Bein et al. 2007, Longenecker et al. 2011). Over 90% of the customary land is made up of primary, lowland forest. In PNG lowland forests constitute 65% of forest cover, and have experienced the highest rates of change, show the greatest likelihood for future change, and have the least amount of conservation area (Shearman and Bryan 2011, Bryan and Shearman 2015). To date, no commercial logging or other major resource extraction has occurred in the village.

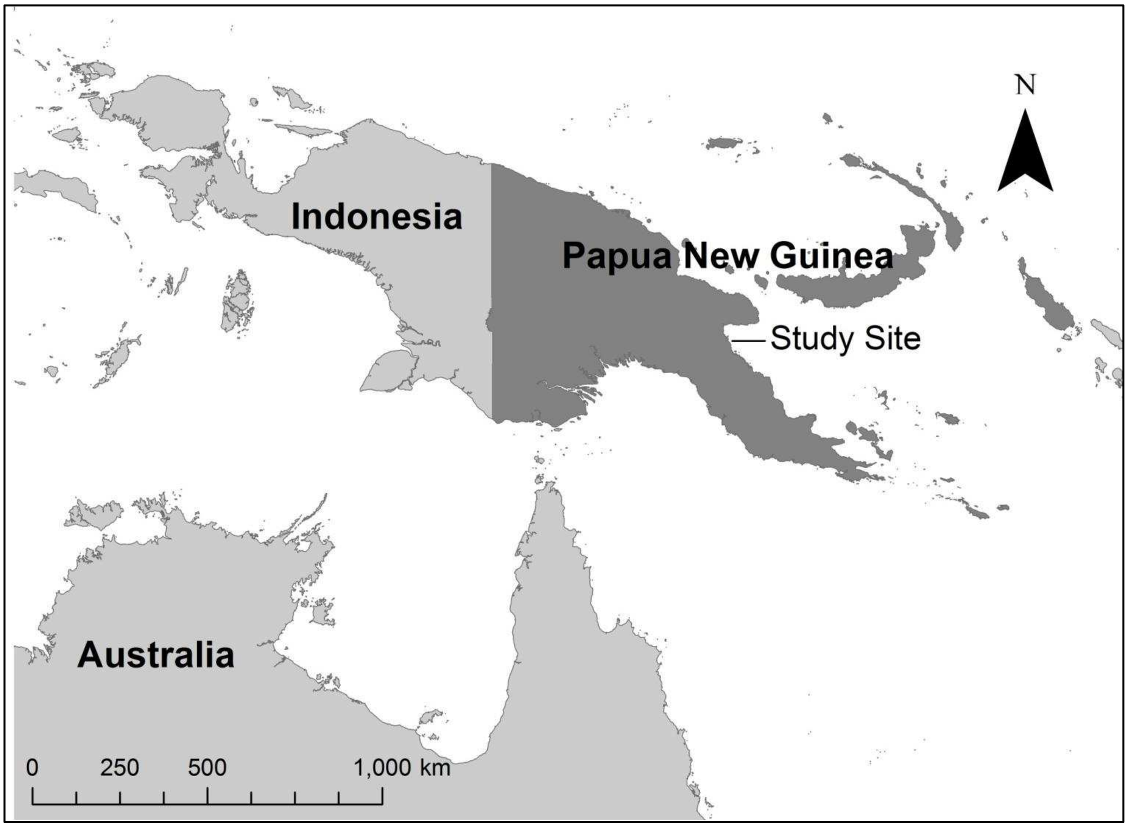

Figure 3.1. Papua New Guinea, the surrounding countries, and the approximate location of the village study site.

The village livelihood system is subsistence based and includes land-use activities (swidden-fallow, forestry, animal husbandry, and hunting) and marine resources (ocean and reef). Swidden-fallow agriculture is the primary means of subsistence. The main swidden-fallow area is located 5 km north of the village in a river delta and smaller swidden-fallow plots scattered around the village. Seasonal deposits of rich fluvial sediments from rainy season floods replenish soil fertility and allow for shorter fallow periods. The population of the village has grown from approximately 300 people in 1972 to 950 people in 2015 (village elders and landmanger estimates; Wagner 2002). This is an increase of 5% per year and is slightly less than the national average of 6% per year (Kenneth 2012, World Bank 2016).

3.3. Methods

3.3.1. Satellite data, classifications, and statistics

This study spans 1972 to 2015. Forty images are used from multiple Landsat platforms (Table 1). We limited our scene collection to Landsat platforms to maintain data consistencies and together these images form a comparatively densely spaced time series for a tropical location. The images selected are captured during the dry season (October 1 – December 31), when agricultural areas are more intensively cultivated and spectrally defined. A single Landsat scene is sufficient to achieve total coverage of the village and all of the customary land, and eliminates the need for mosaicking. Landsat 7 scenes with scan-line correction (SLC) errors are used because the center of each path coincides with the agricultural area and is gap free so all spectral data has been maintained. However, the full extent of the village has data gaps from the SLC error, most of which overlap with cloud cover and were masked in latter processes. Because there are very few cloud-free scenes available for the entire geographical extent, an image is selected if it was cloud-free over the village and swidden-fallow areas. To assess forest cover changes for the entire customary land area an additional analysis is preformed using scenes with minimal cloud cover and these include 1987, 1992, 2003, and 2015 (details in Appendix 2, 9.1.2.). Cloud cover, on average, accounted for 4% of the extent for the scenes in the forest cover change analyses.

All satellite scenes between 1987 and 2015 have a spatial resolution of 30 m^2 and were processed using the same methods. The 1972-282 MSS scene has a resolution of 60 m^2 and was processed slightly different because it has 4 reflectance bands compared to 7 or more bands of the other satellites. Because this is such a small geographical extent, visual methods for classifying the land-uses and associated land-covers could have been used, but we wanted to process the scenes to be more similar to automated processes conducted at wider geographical extents. In this paper we focus on the participatory component of the study and therefore the details of the image analyses are provided in Appendix 2, 9.1.

The study area was classified into two categories, swidden-fallow and non-swidden (Table 3.1). The swidden-fallow class for each scene was used in the trend analyses. A linear model was fit to the 40-scene dataset to assess swidden-fallow area trends over time. The 1972 data have a larger pixel resolution, a different spectral range, and different processing methods, which may influence classifications. While such disparities could influence analyses and skew trends, we did not want to exclude potentially informative data. Thus, the model was run with and without land-cover data from 1972.

Table 3.1. Land classification categories for swidden and other cover types

Swidden-fallow	**Other**
▪ Cleared of vegetation	▪ Built structures
▪ Burned plots	▪ Forest
▪ Sparse crop cover (wide spacing or early growth)	▪ Riparian
▪ Denser crop cover	▪ Wetland
▪ Early fallow (weeds and grass)	▪ Water bodies
▪ Moderate fallow (grass, bushes and small trees (2-3 meters in height))	▪ Sandy beach ▪ Clouds
▪ Late fallow (small and medium trees (5-6 m in height))	▪ Shadows

3.3.2. Participatory data

Local land-managers or informants contributed swidden-fallow and livelihood information. Detailed livelihood and land-use information was collected in 2011 to understand LULC changes in the village. Our participatory methods included semi-structured surveys, a ranking exercise, structured interviews (questions in Appendix 1), and resource mapping. The semi-structured surveys or discussions were conducted with various knowledgeable community members to gain a more comprehensive understanding of the framework of the customary land tenure system, swidden-fallow practices, fishing methods, and the socioeconomic structure. The semi-structured surveys were conducted as a free-form discussion that was guided by a list of questions and included the specific events, general trends, observed changes over time, and speculation of future changes of the topics. A ranking exercise was conducted to understand how the different resources changed in importance, quality, and dependence over time.

3.3.3. Accuracy assessments

To assess the accuracy of the classifications, multiple methods were used and included ground-truth points collected using a Global Positioning System (GPS), accuracy assessments and Kappa statistic analysis, and participatory information. First, GPS points were collected in 2011 and 2013 to ground truth land classes. Independent, high resolution imagery from NASA displayed on Google Earth (GE: 2010, 2014) was available for two Landsat scenes. Google Earth is increasingly being used in accuracy assessments due to the ease of access, enormous database of global coverage, and high spatial resolution (1 m; Yu & Gong 2012). The GE images captured on 2010-289 and 2014-054 were used to assess the classification accuracy for the Landsat classifications for 2010-295 and 2014-042, respectively. For each GE image 100 random points were generated and accuracy assessments preformed. For the remaining scenes, independent imagery was not available and accuracy assessments and the Kappa statistic were derived from the raw, unprocessed satellite images. For each of the 40 images, we generated 100 random points and visually interpreted the land-use at each point. The average accuracy and kappa statistic are provided in the results, for more detailed information see the Appendix 2, 9.2. Last, in 2013 the results of our analysis were described to land-managers who were then asked to systematically review, discuss, and edit 13 of the 40 scenes. Any changes or issues identified were incorporated into the analysis prior to final results.

3.4. Results

3.4.1. Accuracy assessments

Informants from participatory focus groups in the village reviewed the classified swidden-fallow maps and any changes identified were incorporated into the analysis prior to final results (see Chapter 2). For the independent GE images the overall accuracy and Kappa statistic for the GE 2010 image is 92% and 84%, respectively. The GE 2013 image achieved 95% for overall accuracy and 90% for the Kappa statistic. For the 40-scene dataset, the mean overall accuracy is 93% and Kappa statistic is 83% (Appendix 2, 9.2).

3.4.2. Forest cover changes

Local land-managers indicated that no major forest cover changes had occurred during their tenure which began circa 1900. They also indicated that no community members access the forests further than 5 to7 km from the village for subsistence needs (e.g. firewood, house materials) and swidden-fallow areas are confined to areas around the village and in the river delta. Across all images cloud cover hinders approximately 4% of the customary extent. Image analyses showed that on average 95% of the customary extent experienced reflectivity and land-cover changes that were less than 4% and this percentage of change was not identified as land-cover change, but likely attributed to seasonal or yearly variation among the scenes. One percent of extent experienced changes greater than 4% and these areas were identified in the swidden area, riparian areas, coast line, and some locations near the village. Manual assessments of each image further supported a lack of major or patterned forest cover changes that would suggest large tracts of forest removal, aside from changes in the swidden-fallow and village areas.

3.4.3. Swidden land-cover and land-use

The swidden-fallow area trends derived from all scenes is presented in Figure 3.2. The mean swidden-fallow area inclusive of all years is 680 ±101 ha and shows a significant trend over time with a p=value < 0.001 and an r^2 of 0.2421. However, the 1972-282 and 1988-322 swidden-fallow areas are identified as outliers. Because both scenes are early in the time series, they have a greater influence on the slope of the regression and trend significance. When the 1972-282 and 1988-322 swidden-fallow areas are excluded from the linear model, swidden-fallow area changes overtime are non-significant with a p=value of 0.1681 and an r^2 = 0.0258. The mean of the swidden-fallow area when the outliers are excluded is 695 ±78 ha. The inclusion of the 1972-282 and 1988-322 data strengthens the r^2 value more than when theses data are excluded, yet much of the variability is still unaccounted for as the r^2 values are low in both cases. The percentage that swidden-fallow area increases over time is 143% between 1972 and 2015. However, when 1972 data are excluded, the sw idden-fallow area increased by 18% and equates to 123 ha.

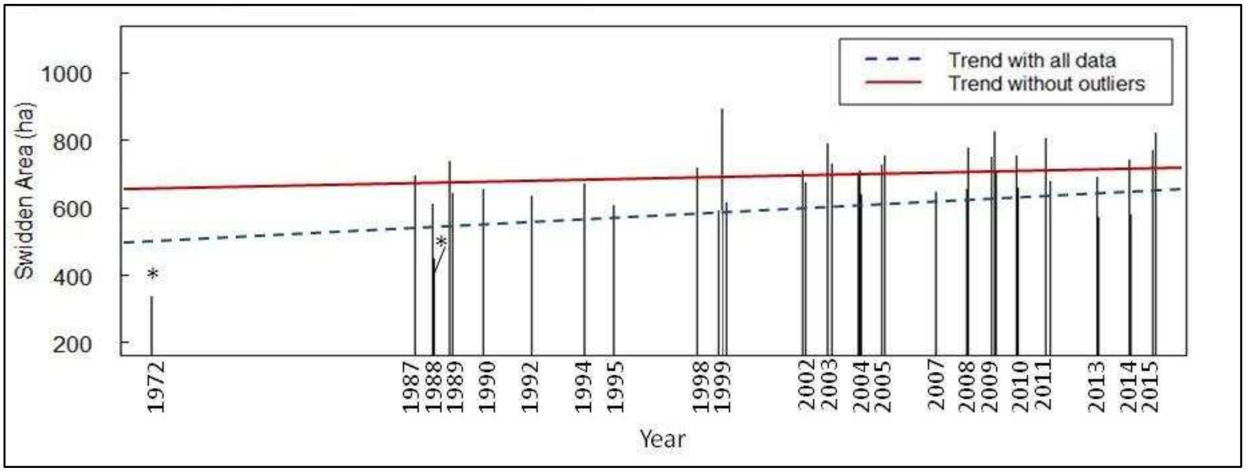

Figure 3.2. Swidden-fallow area in hectares (ha) according to each year. The trend line of the linear regression is shown with all data (dashed) and without outlier scenes (solid). The outlier scenes are indicated with the * symbol.

There is variability in swidden-fallow areas from scene to scene and over time. There are some scenes that were captured relatively close in time, e.g. a week apart, but show different swidden-fallow areas. For example 1999-304, 1999-313, and 1999-361 are all captured in the same season and year, but the 1999-313 has the largest area (~900ha) of the entire time series. The 1999-304 and 1999-361 scenes sandwich the 1999-313 scene and have slightly below average areas at 550 ha and 615 ha, respectively. For pairs and triplet date sets during the same year swidden-fallow area can differ by 100 ha or more (e.g. 2008) or by less than 30 ha (e.g. 2005). For the years that have only one scene (e.g. 1990-1998) the swidden-fallow areas are more similar to the mean area.

Land-cover maps were selected to show the spatial distribution of swidden-fallow changes in relation to specific participatory information (Figure 3.3). In general, the northern arm of the delta fluctuates in area without major increases or decreases over time. Swidden-fallow plots near the southern arm and surrounding the village increase in density over time. The 1972 data do not show swidden-fallow area along the southern arm of the river delta, whereas the remaining scenes have swidden-fallow along both north and south arms of the delta. Participants explain that all households have become more and more dependent on swidden-fallow resources over time and this, in part, supports why the 1972 scene has the smallest swidden-fallow area. Since there are no images available between 1972 and 1987 identifying when swidden plots were established is not possible and reliance on participatory information is necessary. The shift in resource dependence was described to begin during the late 1970's, when the marine resources began to decline. Fish populations are perceived as undependable due to a continued decline in quantity and quality, even though fishing equipment has improved catch success, e.g. bone hooks to barbed metal hooks. Therefore, land-managers have placed more dependence on swidden-fallow agriculture as the primary and most important resource. This resulted, first, in the development of additional swidden plots along the northern arm of the delta. Second, in 1986 new swidden plots were developed along the southern arm of the delta when greater demands for land and changes in swidden productivity occurred. This development is visible in 1987-287 (Figure 3.3).

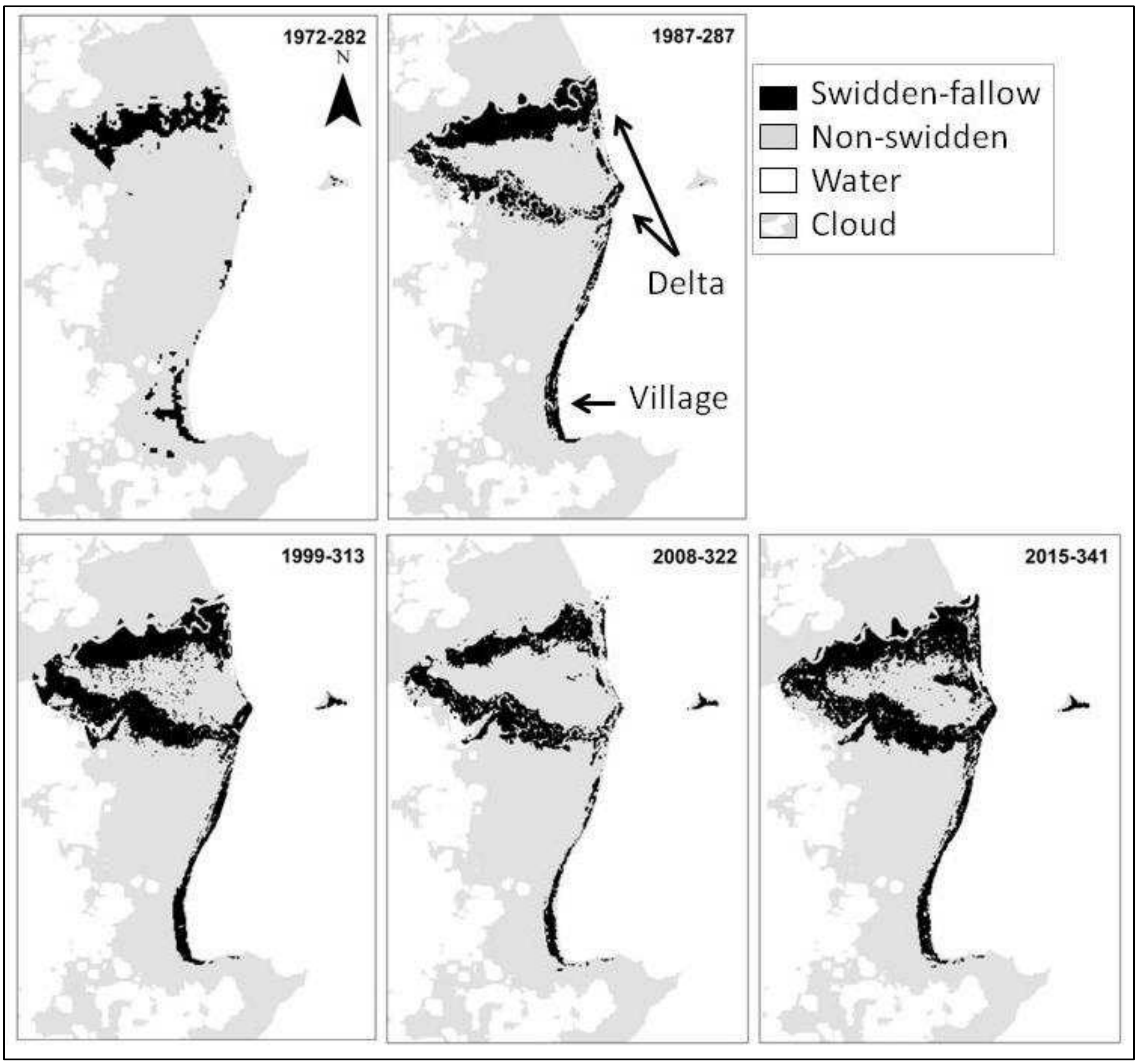

Figure 3.3. Land-cover maps showing swidden-fallow area for 1972, 1987, 1999, 2008, and 2015 during the dry season (October-December).

Swidden productivity began to decline during the early 1980's due to beetle infestations in taro and an extreme weather event. Taro is a staple crop and while growing taro was not necessary to fulfill subsistence needs, it is culturally important. Although unsuccessful, different strategies were used to improve taro cultivation such as lengthening fallow periods, rotating crops, developing new swidden plots along the southern arm of the delta, and introducing a new variety of taro referred to locally as Singapore taro (sp. *Xanthosoma).* However, none of these strategies were successful for long and eventually taro was not a viable crop. This resulted in a greater reliance on other crops such as sweet potato and cassava. The second change in swidden productivity was caused by the 1982-1983 El Nino events, which was recorded in climate records as 'very strong'. Strong and very strong El Nino events cause major ocean surges and river flooding and, because the swidden-fallow area is located in a river delta, fresh and salt water inundate the crops and cause crop losses.

Informants describe that there is an initial response after such extreme weather events to increase the number of swidden plots and the hardships of the food shortages influences swidden-fallow strategies for multiple years after a severe event. A second 'very strong' El Nino event occurred during 1997-1998 and drought plagued most of the nation. This El Nino event was considered one of the most severe El Nino events in the past 100 years (Barr 1999). Serious food and drinking water shortages were widespread and led to food ration distributions from the government and international organizations (Barr 1999, Minnegal and Dwyer 2000). Many informants believe that the slightly larger swidden-fallow areas observed between 1999 and 2004 were in response to food shortages experienced during the 1997-1998 droughts. The 1999-313 scene shows the largest swidden-fallow area in the time series and when participants reviewed the 1999-313 scene they described that, first, the expansion was in response to recent droughts and food shortages. Also, they describe that December is a month of celebration and there are times when they harvest yields and start new plantings so that they don't have to work as much over the holidays. They said that it was likely that they just harvested a lot of the crops to prepare for festivities. This was also detailed in an annual calendar of swidden-fallow and community activities (Appendix 1). The larger swaths of freshly cleared plots have a higher reflectance due to soil exposure and therefore more area is identified as swidden-fallow in the imagery. Because there are 48 days until the next scene is captured, there is ample time for vegetation to grow and reach a stage where vegetated ground cover is dense. When crops are near maturity, deciphering swidden-fallow from natural vegetation becomes more difficult due to spectral similarities and classifying a smaller swidden-fallow area is more likely.

The three 2008 scenes are an example of swidden-fallow area differences over a short period of time, and the smallest swidden-fallow area 2008-322 is selected for Figure 3.3. For 2008 the capture dates are closer in time and the swidden-fallow area successively increases. The first two scenes, 2008-322 and 2008-330, are 8 days apart and the swidden-fallow area increases by 86 ha, whereas the second two scenes, 2008-330 and 2008-354, are 14 days apart and the swidden-fallow area increases by 125 ha. In total, the first and third scenes are separated by 32 days and the difference in swidden-fallow area by 211 ha. This observation follows the seasonal participatory data that indicated more plots were harvested and cleared as the Christmas holiday approached.

The 2015-341 image has the third largest swidden-fallow area in the time series and of the last six scenes, four show above average swidden-fallow area. In 2012 pesticides were applied to the swidden-fallow area to eradicate the taro beetle and the increase in taro cultivation influences land-use classifications in these scenes. At first, taro was planted in small areas to test its success and after successful harvests more and more taro was planted. Land managers described that they decreased the number of sweet potatoes and increased taro. Sweet potatoes are planted in mounds and grow outward as an untamed ground cover, whereas taro are planted individually in rows and grows vertically. Spectrally, the change from a vegetated groundcover to organized rows results in higher proportions of bare soil exposed. Bare soils reflect more light and make cultivated swidden-fallow areas more distinct, thus more swidden-fallow area is observed.

An El Nino event that has been classified as 'very strong' has been listed for 2015-2016. The response to this El Nino event is yet to be apparent in the swidden-fallow area. However, informants described that they have begun to prepare for such events by planting more sago palm, a native and staple crop that can feed a family for one to two months. Sago palm is planted and grows wildly in this region and is very resilient to flooding and drought conditions. Each informant described having 50 to 500 sago palms in different stages of growth. From a remote sensing perspective, it is also nearly impossible to identify or enumerate the palms using satellite imagery, because they are in natural vegetation areas, along rivers and streams, and there are many other varieties of palms.

Land-managers described changes in swidden-fallow strategies to increase crop yields that cannot be accounted for in the satellite analyses such as 1) shortening fallow periods, 2) increasing crop density, 3) introducing new crop varieties, and 4) selling more fish to purchase goods. The money gained from fish sales is usually used to purchase items such as clothes, kerosene, fishing equipment, axes, machetes, and nails. Supplemental food (e.g. canned meat and rice) was rarer because it is more of a treat than a necessity. From the interview information, data show between 1999 (Bein et al. 2007) and 2011 fallow periods were shortened and cropping periods lengthened (Table 3.2). Even though all informants acknowledged that shortening the fallow period results in reduced soil fertility, more pests, and more weeds compared to longer fallow periods, such methods are still used to increase crop production. The changes in crop density and the introduction of new crop varieties were also a way to increase harvests without expanding overall area.

Swidden-fallow changes were also influenced by a change in household structure. Traditionally in PNG, men and women live in separate, gender-specific houses. A shift towards nuclear family houses is challenging this norm and creates a change in household needs and the division of labor. This gendered to nuclear-family house shift began in the early 1990's and has impacted how individual swidden plots are shared and divided among family members. Individual swidden plots were larger when gender-specific houses were common and the plots were maintained and harvests shared by multiple generations and the extended family. While crops are still shared among extended families, plots are more commonly split up so that each nuclear family has a portion. Similarly, when a couple weds, they are given their own swidden plot, and this is usually a subdivision of a larger family plot. The decrease in the area of a single plot and area of all household plots is observed between 1999 and 2011 and can be reviewed in Table 3.2.

Table 3.2. The 2011 data were collected during household structured surveys. Data in the 1999 column were derived from (Bein et al. 2007)and some values in this column were calculated using the available data.

	1999	2011
Total population	479	850
Number of households interviewed	26	32
Approximate number of households in the village	80	128
Average people per household	6.1	6.4
Average cultivated & fallow length (yr)	1.2 & 5.8	2.75 & 3
Total swidden-fallow cycle (yr)	7	5.75
Average swidden area of a single plot (ha)	0.13	0.095
Average area of all plots per household (ha)	0.40	0.36
Average number of plots per household	3.1	3.8

3.5. Discussion

This village presents a unique opportunity to identify agricultural changes over time because we combine land-use and agricultural strategy information from participatory data with 38 Landsat scenes across a 28-year period. The inclusion of participatory information is vital, as it explains general swidden-fallow trends, land-use during imagery gaps, scenes with swidden-fallow area anomalies, and resource use changes that would otherwise be excluded. Understanding changes in land-use are a key component to identifying how and why the associated land-cover changes occur in areas where swidden-fallow systems are found. From a remote sensing perspective, the study area is free of large-scale logging, scenes were not mosaicked, and the high-temporal resolution of the data presents a clear assessment of swidden-fallow land-use changes.

Our results are in agreement with McAlpine & Freyne (2001) at the provincial level and by Bourke (2001; 2012) at national level and show that swidden-fallow areas were not expanded to accommodate the growing population but land most favorable for swidden-fallow agriculture was intensified. These results are also similar to the few village level studies that exist (Eden 1993, Umezaki et al. 2000, Bailey et al. 2008). Our participatory data support that the increase in food production is achieved by implementing a variety of strategies (e.g. intensification, cultivar selection, subdividing large plots), rather than continual expansion of the swidden-fallow area. Also, due to the high fertility of the delta area, intensification has been the most common way to increase production. Land-managers describe that environmental impacts and extreme weather events that are associated with climate change play more of a role in subsistence strategy changes and influence decisions to expand or contract the swidden-fallow area on a seasonal and annual basis. For example, cleared swidden-fallow areas often increase in response to prolonged pest infestations, drought, and frequent ocean surges and flooding. Conversely, when environmental and weather patterns are more predictable the yearly clearing of swidden-fallow areas tend to remain constant.

Information from land-managers also helps inform some of the general fluctuations across the time series. Two severe El Nino years (1982-83 and 1997-98) were mentioned as one reason for subsistence strategy changes. Although we lack imagery for the first El Nino event, the 1997-98 event shows slight increases in swidden-fallow area for years afterward. We posit that the impacts felt from these events will only continue to influence swidden-fallow strategies as extreme events strengthen and become more frequent in the years to come. Because landmangers described planting more sago palm, it is unknown if swidden-fallow area changes will occur in a predictable fashion. An increase in taro plantings may also confound future assessments because taro fields are reflectively more distinct. However, pesticide resistance may influence crop selections to revert back to sweet potato cultivation. Identifying these changes is not possible with satellite imagery alone and more participatory involvement is required.

Acquiring a spatial dataset that has multiple dates is also essential to capture the long-term change trends as swidden-fallow is a highly adaptable land-use system that constantly changes to accommodate subsistence needs (Mertz et al. 2009; Padoch et al. 2007). Thus, the inclusion of all possible dry-season scenes between October and December allows us to observe the swidden-fallow area over multiple scenes during the same period and assess how slight differences in spectral qualities and classifications influence changes in swidden-fallow area. We identify that the stage of growth of the swidden crops influence classifications when multiple dates for the same year and season are available, e.g. 1999 and 2008 scenes. Even when scenes are relatively close in time, there can be large differences in the swidden-fallow area assessed. These differences often relate to the reflectance qualities of the swidden-fallow cycle phase (cleared, newly planted, mature crops, fallow) or type of crops (taro, sweet potato, etc) in the cultivated plot. Understanding the nuances of swidden-fallow agriculture is a key component to identifying slight differences among scenes and for overall trends. Without local land-use information, such nuances may go unnoticed and influence trends in an erroneous way.

The high number of scenes also gives us a high confidence in the legitimacy of the swidden-fallow trends identified at the village level. If only a handful of scenes were used to assess swidden-fallow area, then the outliers in those trends could influence the analyses. While the longest time series is typically favorable to observe trends, careful consideration of these data and results is necessary. Swidden-fallow area significantly increased over time (p-value<0.001) when all 40 scenes (1972-2015) are analyzed. However, when the outlier scenes, 1972-282 and 1988-322, are excluded from the linear model, the swidden-fallow area change over time is not significant. Even though this dataset has an ample number of scenes to assess temporal trends, outliers can still influence trends. Identifying outliers is not common in LULC analyses because acquiring a large number of scenes is challenging, especially for wide geographic extents and in regions with nearly continuous cloud cover. One possibility that may cause the 1972-282 scene to be an outlier is that it was captured with a Landsat MSS sensor, which differs in radiometric and spatial resolution than the remaining scenes and as a result slightly different methods were used to classify the swidden-fallow area. Participatory data supports that the 1972 swidden-fallow area was smaller due to a greater dependence on marine resources and fewer issues with swidden cultivation. However, without additional scenes for comparison, we still do not have confidence that including this scene better informs the trends in swidden-fallow land-use changes. Comparatively, the 1988-322 scene is not affected by sensor or classification differences but still is an outlier. Because there are two scenes for 1988, 322 and 290, a comparison of the swidden-fallow areas is possible. These two dates are separated by 32 days, yet the decrease in swidden-fallow area by 160 ha. This suggests that the 1988-290 scene has larger swaths of bare soil and new vegetation whereas the land-cover in the 1988-322 scene had more established crop cover, the latter of which made spectral similarities between crop cover and natural vegetation less distinguishable. Participatory information confirmed this observation.

Our results differ from the Shearman et al. (2009) and Ningal et al. (2008) studies that draw strong and causal relationships between population and swidden-fallow land-use trends. These two studies fail to incorporate reasons other than those influenced by population growth and population density for LULC changes and rely on a perceived relationship between population growth and land-use change to explain swidden-fallow expansion and subsequent forest cover changes. At the village level, we neither found a significant temporal trend for swidden-fallow area expansion, nor do we believe that population growth and swidden-fallow expansion are causally related. Also, in this study, the 1972-282 data have a large influence on temporal trends. Even when nearly identical methods are used to analyze the Landsat scenes, there is a substantial difference in swidden-fallow area in 1972-282 scene compared to the remaining 39 scenes and, as a result, the trend significance differs. Another factor to consider is that land-cover changes the Shearman et al. (2009) and Ningal et al. (2008) studies used two (1972 and 2002) and three (1972, 1990, and 2002)scenes to analyze trends over time, respectively. When additional dates are added to the analyses and fill in some of the temporal gaps, the relationship between population and swidden-fallow area is likely to change. In our time series 1972-282 is the smallest and 2002-305 is about average in area, and a trend line between these two scenes does not fully or accurately portray swidden-fallow area trends over the whole time period. With the inclusion of 13 additional scenes between 1972-282 and 2002-305, a different pattern of swidden-fallow agricultural area emerges. The pattern of slightly expanding and contracting swidden-fallow area is further supported with 38 scenes. Thus, the swidden-fallow expansion observed at the national and provincial scale may be an artifact of the 1972 data used and the limited number of Landsat scenes in the time series.

3.6. Conclusion

Understanding changes in land-use and subsistence strategies is a key component to identifying how and why land-cover changes occur in areas where swidden-fallow systems are found, especially when population growth is an overly simplistic explanation. The inclusion of participatory information and noted changes in swidden-fallow strategies, land-use, and land allocation better links land-use to land-cover trends. The coastal village studied here is unique because no commercial logging has occurred. Additionally, a single Landsat image covers the village extent and all scenes that are used in the analysis are captured during the same season. This allows the identification of swidden-fallow land-use changes by minimizing confounding land-covers and data inconsistencies, and allows us to form a clearer relationship between land-use trends and subsistence strategies.

The 38 scenes used to assess swidden-fallow area do not show a significant temporal change trend. Instead, our results show that as the population grew, swidden-fallow area fluctuated over time. We find that such dynamics are based on swidden-fallow land-use characteristics and the land-cover reflective properties associated with different phases of crop growth and harvest schedules. Land-use decisions are influenced more by local social, climatic, and environmental conditions than by population growth pressures. This finding is different from findings of studies at the provincial and national extents, which draw a strong relationship between population and swidden-fallow LULC changes. Across PNG, approximately 19% population practice swidden-fallow on littoral and alluvial fans, similar to those found in the study village. However, it is unknown what swidden-fallow trends exist in other villages because there are few village scale studies.

Overall, assessing swidden-fallow land-use and the associated land-cover change patterns at multiple scales is important to assure that critical information is not skewed when spatial scales change. As more data become available, it is essential to increase the number of scenes used to assess LULC change in areas where swidden-fallow systems are found and such land-use patterns dominate. To better inform policy and land management planning, additional research should be conducted at the village level to assess whether the change patterns we have identified occur elsewhere in PNG. This type of high temporal resolution analysis should also be done in other locations throughout the world where people still rely on subsistence agriculture systems.

CHAPTER 4

MODELING HOTSPOTS OF PLANT DIVERSITY IN NEW GUINEA[3]

4.1. Introduction

New Guinea is estimated to harbor 5-10% of the world's biodiversity in only 0.5% of earth's land area (Supriatna et al. 1999, Mittermeier et al. 2003). For plant biodiversity, New Guinea ranks second to Amazonia and this equates roughly to 17,000 unique species, 10,200 of which are thought to be endemic (Mittermeier et al. 2003). While it is difficult to deny the diversity of the biota in New Guinea, the evidence to support the high rates of diversity and endemism are not based on comprehensive taxonomically vouchered collections. This is especially the case for embryophyta or vascular and non-vascular terrestrial plants, the focus of this study (hereafter referred to as terrestrial plants). Estimates of diversity have been based on expert opinion (Vollering et al. 2015), and endemism rates for terrestrial plants have been estimated using the richness of taxonomic groups, such as orchids and ferns (Supriatna et al. 1999). However, in Ecuador, Mandl et al. (2010) showed that epiphytic plant diversity differs from other terrestrial plant diversity due to differing environmental requirements. Other more systematic approaches have used topographic and climatic data to identify unique biogeographical environments where high diversity is likely to occur (Heads 2006, Vollering et al. 2015). Phylogenetic molecular techniques for identifying dispersal and speciation for the tropical South Pacific have been conducted but are limited to a handful of species and higher level taxa and likewise, New Guinea is poorly represented (Keppel et al. 2009).

[3] This chapter is co-authored by all committee members and is currently in review at *Tropical Ecology*

There are two widely accepted explanations for the high biological diversity in New Guinea. First, island biogeography theory states that islands larger in areas with higher elevation and closer in proximity to source areas have the richest species diversity (Heads 2001, Roos et al. 2004, Cronk et al. 2005, Brooks et al. 2006, Neall and Trewick 2008, Keppel et al. 2009, Vollering et al. 2015). The island of New Guinea fits all of these characteristics as it is the largest in the Pacific, has the highest mean elevation (highest point at 4884 m in Southeast Asia and Oceania), and is proximal to many source areas, such as Southeast Asia, Australia, and multiple island archipelagos across Malesia, Micronesia, and Polynesia. Second, the tectonic history of New Guinea along the northern coast was formed by the accretion of 32 distinct terrains, each with unique origins, histories, and biota (Heads 2001, 2006, Hill and Hall 2003), whereas the southern portion of New Guinea is the northern reach of the Australian Craton (Hill and Hall 2003, Baldwin et al. 2012). Therefore, the processes of dispersal and vicariance are believed to largely influence patterns of plant distributions (Cronk et al. 2005, Heads 2009, Keppel et al. 2009).

New Guinea is comparatively understudied compared to other tropical areas (Heads 2001, 2006, Keppel et al. 2009, Vollering et al. 2015) and even the more systematic approaches and sound theories lack adequate taxonomic catalogues to verify or comprehensively assess the distribution of biota and richness therein (Roos et al. 2004). Tropical forests rarely have complete catalogues of biota because these ecosystems have high species richness and surveying efforts are laborious, expensive, and spatially biased. In New Guinea, survey efforts are spatially biased in multiple ways. First, there are more specimens collected in areas that are easier to access (near towns, rivers and roads). This is exacerbated in New Guinea as travel on the island is greatly limited due to the lack of infrastructure. Second, collection densities in New Guinea increase from west to east and from south to north (Takeuchi 2007). Even though Indonesia is known for high rates of biodiversity, the full scope of diversity is unknown because the Indonesian territories in New Guinea are severely under sampled. Although collections are still low, the number of specimens collected in Papua New Guinea (PNG) is over 30 times greater than Indonesia's collections in New Guinea. This can be easily visualized online at biodiversity data websites such as Global Biodiversity Information Facility (GBIF; http://www.gbif.org/) and iDigBio (https://www.idigbio.org/). Third, survey efforts increase with elevation, and this is especially the case in the highland areas of Papua New Guinea (PNG) (Takeuchi 2007). Fourth, it is a challenge to gain land access to study biodiversity or collect specimens because land is under customary land tenure and foreigners are viewed as untrustworthy. Even though researchers approach land managers with transparent intentions, government agencies and resource extraction companies have had a long history of corruption and illegal operations and this history has caused distrust of all types of surveying (PNG specific, A. Allison, personal comm.). Last, the biological surveys that have occurred in recent decades are rapid biological assessments (RAP surveys), which are conducted over a short period of time, cover small areas, are often in response to pending resource extraction or development (e.g., dams and mining; Katovai et al. 2015), and are published in grey literature (Leisz et al. 2000, Mack and Alonso 2000, McGavin 2009, Richards and Gamui 2011).

The ability to identify distribution patterns is interesting theoretically to the scientific community but also can be used for land-use planning and management and conservation strategies (Heads 2001, de Barros Ferraz et al. 2012, Anderson 2013). Information on the spatial patterns of terrestrial plant species richness in New Guinea is not available, and it is urgently needed to address threats to biodiversity due to habitat losses via resource extraction and development (logging, mining, fiber, and oil palm), which have cleared or degraded approximately 30% of forests across New Guinea and the surrounding islands (Shearman et al. 2009, Abood et al. 2015, Bryan and Shearman 2015). Higher rates of forest losses are observed in areas that are more easily accessed such as coastal lowlands and islands and in PNG over 43% of forests cleared at least once between 1972 and 2014. Regulations are violated often across New Guinea with repeat harvests occurring on too short of a time scale (e.g., 15 years instead of 35 years), illegal logging, and industries expanding outside set boundaries (Bryan and Shearman 2015). Across the whole of Indonesia, around 55% of resource extractions occurred outside of set boundaries (Abood et al. 2015).

Although the biological knowledge of the island is far from complete, recent interest in understanding the spatial distribution of biota has been ignited with efforts that have amalgamated and digitized specimen data from herbaria, museums, and private collections into online databases. These databases along with ecological niche models (ENM; also called species distribution models (SDMs)) have become a valuable tool in biogeographic research. ENMs are based on the fundamental and realized niche concepts and approximate a species' distribution using occurrence data and environmental conditions (e.g., climate, topographic; Peterson et al. 2011).

To date there have been few attempts that systematically and objectively assessed terrestrial plant distribution (Heads 2001; Vollering et al. 2015; Roos et al. 2004) and none to date have used all available occurrence data. In this study our aim was to map the distribution of terrestrial plants at the genus taxonomic level using maximum entropy model or MaxEnt (Phillips et al. 2006). The specific goals of this study were to: 1) identify sampling intensity and sampling bias; 2) identify the most influential abiotic drivers associated with terrestrial plant distributions; 3) identify the regions of New Guinea that are likely to harbor high terrestrial plant richness; and 4) discuss the implications of threatened habitat and biodiversity losses due to resource development and land use changes.

4.2. Materials and methods

4.2.1. Study area

This study was conducted on the island of New Guinea, which is politically divided into the Republic of Indonesia to the west and the Independent Nation of Papua New Guinea (PNG) to the east. Many of the surrounding islands were also included in this study and some of the major island groups are the Bismarck Archipelago and Admiralty Islands of PNG, Biak and Yapen of Indonesia, and the autonomous island nation Bougainville, which is part of the Solomon Archipelago (Figure 4.1).

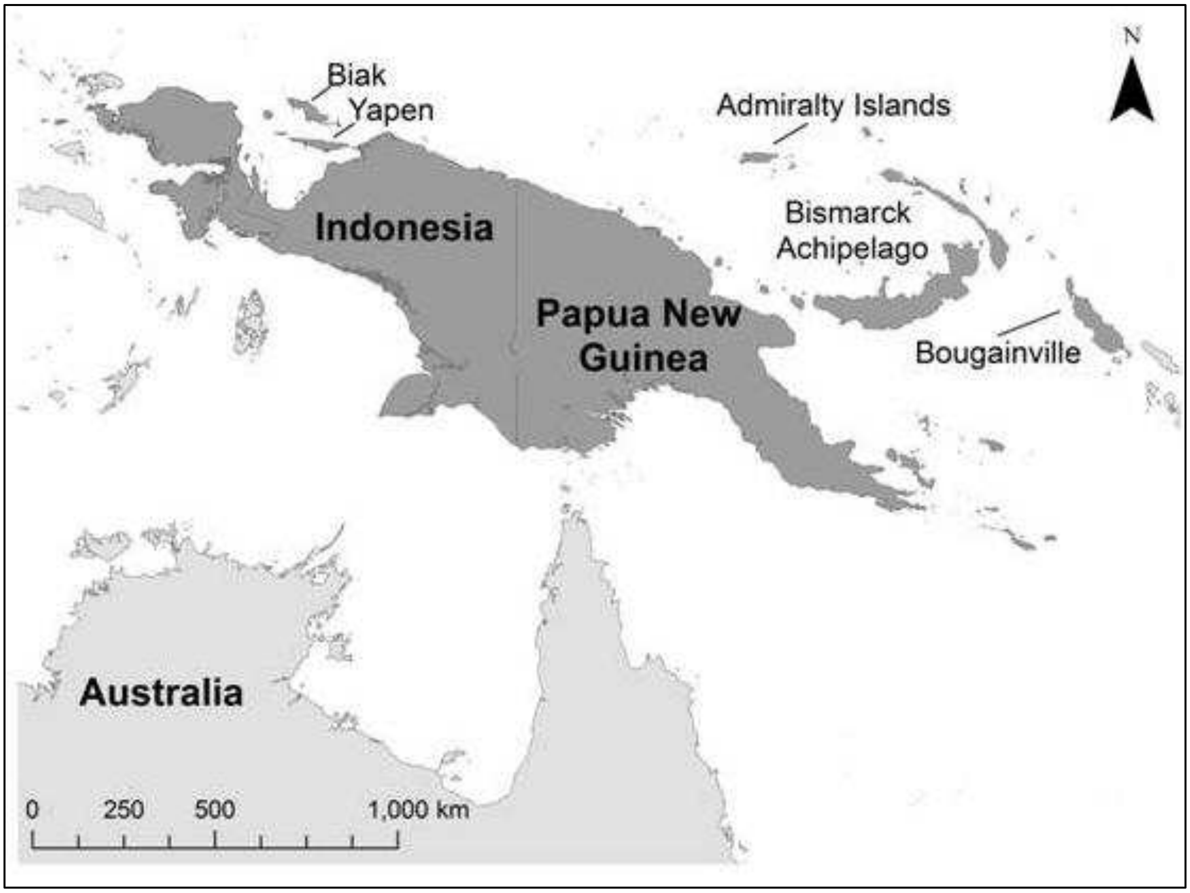

Figure 4.1. The island of New Guinea is occupied by two countries, Indonesia to the west and Papua New Guinea to the east. Included in this study are the Indonesian islands Biak and Yapen, and Papua New Guinea's Admiralty Islands and Bismarck Archipelago. Also part of the study is the autonomous island of Bougainville, which is part of the Solomon Archipelago. The projection is Albers Equal Area projection, WGS84.

The total landmass of New Guinea is 786,000 km^2, excluding the surrounding island archipelagos. New Guinea is the second largest island in the world and tallest landmass in the south Pacific, which includes Southeast Asia, Australia, and New Zealand. Elevation ranges from sea level to 4884 m and is typically divided into coastal lowlands (0-1000m), lower montane (1000-2800m), and upper montane (2800-4900) (Bryan and Shearman 2008). On average temperatures are 28°C at sea level, 26°C for inland and mountain areas, and 23°C for higher elevations. The temperature variability ranges between 6.8 and 14.6°C, with the greatest degree changes in the lower and upper montane zones. Precipitation varies greatly across the island from 970 mm to 7500 mm per year. Peaks in the upper montane zone still retain glaciers, but the snowlines have been rapidly retreating in the past century (Hope 2014).

New Guinea is composed of three distinct geologic formations, the Stable Platform, Fold Belt, and Mobile Belt. The Stable Platform is a continuation of the Australian Craton and the Fold belt is the northern edge of this Craton (Hill and Hall 2003, Heads 2006). The Fold Belt or central mountain range spans east-west across New Guinea was the result of fold and thrust deformations from arc-continent collisions (Polhemus and Polhemus 1998, Hill and Hall 2003, Baldwin et al. 2012). The Mobile belt was created over the past 40 million years from a series of 32 island arcs, some composite, that accreted to the Fold Belt (Heads 2001, 2006, Hill and Hall 2003). The Bismarck Archipelago is in route to collide with New Guinea in the next 10 million years (Polhemus and Polhemus 1998).

4.2.2. Occurrence data

All georeferenced specimen occurrence records were combined from the PNGPlant database (Conn et al. 2004), Herbarium Pacificum, Bernice P. Bishop Museum (www.bishopmuseum.org, 2015), and Global Biodiversity Information Facility (GBIF) data portal (GBIF 2015). Generic taxonomy was updated based on Angiosperm Phylogeny Group (APG) IV classification (Chase et al. 2016). To maximize the number of unique occurrences and ensure data quality the genus taxonomic level was used, as the species level data had many inconsistencies and too few occurrences per species. The original dataset contained around 3,000 unique genera with over 100,000 specimens. All occurrences with incomplete location information, missing or incorrect taxon names were removed from the dataset. Any occurrence records of cultivated or introduced taxa in New Guinea were removed from the dataset. Of the remaining occurrences, 36% of the genera were not used in the study because there were fewer than 10 specimens.

Duplicates were removed using occurrence identification numbers and location information. If multiple records of the same genus were found in the same 1 km^2 grid cell, only a single record was included. To account for spatially auto-correlated occurrence points and avoid model overfitting, all points were spatially filtered at 5 km. Spatial filtering also ensured that the test and training data were independent when cross-validation evaluation techniques were used (Veloz 2009, Boria et al. 2014, de Oliveira et al. 2014, Radosavljevic and Anderson 2014, Sidder et al. 2016). After spatial filtering, genera with fewer than 10 occurrences constituted 7% of the dataset and were not included because there were too few occurrences for a general model (Austin 2002, Bell and Schlaepfer 2016). The final dataset contained 1,354 genera with 85,481 occurrence points. There were around 5,000 occurrence points in Indonesia and 80,000 points in PNG. Appendix 3A provides a table of the genera used in this study and the number of occurrences. The genera that lacked adequate occurrences are also in the Appendix 3B, so that future surveys can focus on data deficient genera.

4.2.3. Sampling intensity and biases

To identify the spatial distribution of collection efforts across New Guinea and surrounding archipelagos a 50 km grid was created. The occurrence data were counted per grid cell in two ways. First, all occurrences were counted to show overall sampling efforts per 50 km grid cell. The second method counted the number of unique genera or genus richness per grid cell. The spatial biases for sampling efforts was created using Gaussian kernel density estimate tool from the SDMToolbox (Brown 2014).

4.2.4. Environmental data

Environmental data from three different sources were used and these included 19 bioclimatic and elevation variables from the WorldClim dataset (Hijmans et al. 2005), global habitat heterogeneity (GHH; Tuanmu & Jetz 2015), and soil data from the ISRIC (ISRIC 2015; Table 4.1). Multiple variables were generated from the altitude data including slope (in degrees), aspect, and topographic exposure. The GHH data were all based on texture features of the enhanced vegetation index (EVI) and aimed to quantify spatial heterogeneity (Tuanmu and Jetz 2015). The northness and eastness variables were derived from the cosine and sine transformation of the aspect, respectively. Topographic exposure was calculated using the difference between the altitude layer and a transformed altitude raster where a 3x3 neighborhood mean was applied. All environmental data were continuous variables and had a spatial resolution of 1 km^2.

Table 4.1. Environmental variables used in the model. The * indicates the variables used when occurrence points are between 10 and 25.

Predictor	Description	Source
ALT*	Altitude from digital elevation model	BioClim http://www.worldclim.org/
BIO4*	Temperature seasonality (standard deviation *100)	
BIO7*	Temperature annual range (Max T. of warmest month - Min T. of coldest month)	
BIO12*	Annual precipitation	
BIO15	Precipitation seasonality (Coefficient of variation)	
BIO18	Precipitation of warmest quarter	
pH	Ph of water in soil at 10 cm depth	ISRIC World Soil http://www.isric.org/
BD	Bulk Density: ratio of soil mass to soil volume at 10 cm depth	
CEC	Cation exchange capacity at 10 cm depth	
Clay*	Fraction of clay by weight at 10 cm depth	
CF	Coarse fragments >2mm in volumetric percent at 10 cm depth	
OC	Organic carbon at 10 cm depth	
Silt	Fraction of silt by weight at 10cm depth	
Exposure*	Topographic exposure	A 3x3 cell mean was calculated on the ALT layer; the difference between the ALT and 3x3 mean layers is calculated.
Slope*	Slope in degrees	Calculated using the ALT layer
Eastness*	Sine of aspect	Aspect calculated using the ALT layer; sine or cosine is calculated
Northness*	Cosine of aspect	
Correlation	Linear dependency of EVI on adjacent pixels	Global habitat heterogeneity http://www.earthenv.org/texture.html
evenness	Evenness of EVI	
Uniform	Orderliness of EVI	
Variance*	Dispersion of EVI combinations between adjacent pixels	

For this study, the Pearson correlation coefficient (r) among environmental variables was used to account for multicollinearity (Dormann et al. 2013). If two variables were highly collinear ($|r| > 0.75$) one was removed and the variable retained was the one that was perceived to be more ecologically influential to terrestrial plants. The number of environmental predictor variables used in the modeling was reduced to 21 (Table 4.1). All 21 variables were considered when the occurrence counts were greater than 25. For the group of genera with occurrences between 10 and 25 the number of environmental variables was reduced to 10 so to not over or under predict the distribution based on limited collections. The 10 environmental variables selected were the ones that were directly measured (e.g., altitude and temperature) and were least correlated (Table 4.1). All environmental and occurrence data were projected to an equal area projection (Cylindrical Equal Area Conic, Datum WGS84).

4.2.5. Model calibration and validation

The maximum entropy model or MaxEnt (version 3.3.3; Phillips et al. 2006) was used to map the distribution of terrestrial plants in New Guinea. Of the current models available, MaxEnt was the top choice for this study for multiple reasons. First, MaxEnt uses presences-only data. Second, it generally outperforms other niche models (Evangelista et al. 2008). Third, it has performed well with small sample sizes (Wisz et al. 2008) and found to be suitable for our dataset as some of the genera have a minimum of 10 occurrence records. Last, MaxEnt can be used to run models for thousands of species at a time.

In general, default settings were used, and when this is not the case we describe changes below. The dataset was split into two groups of occurrences, between 10 and 25 (group1) and greater than 25 (group2), so that different set of variables could be considered in the MaxEnt model; fewer number of variables for group 1 and higher number for group 2. This was done specifically for Feature selection and the number of iterations. Auto Features was selected for all genera unless the genera had too few occurrences and in such case the Linear (L) and Quadratic (Q) to L, Q and Product (P), L to L, Q, and hinge threshold defaults were retained in the experimental tab. The number of iterations was set to 10 for 10-fold cross-validation to test model accuracy. The number of background points was left at the default value of 10,000 because this relates to the overall extent of the study area and is appropriate for New Guinea. The background points were not randomly assigned but adjusted to account for to the sampling bias (Elith et al. 2011, Syfert et al. 2013). Although there may be datasets collected in New Guinea with non-bias sampling strategies, the data are from multiple different sources and all were treated as biased. The bias surface was created using a kernel density estimate in the SDMToolbox (Brown 2014), and it was used to constrain background samples so that there was similar bias between the occurrence and background points. This essentially canceled out the bias within the model (Phillips et al. 2009). Fade-by-clamping was selected as predictions were not be made where clamping occurred, resulting in more accurate predictions(Owens et al. 2013).

4.2.6. Binary map creation

To minimize an overfit model a 5^{th} percentile sensitivity threshold was calculated for each genus and was applied to the average occurrence probability outputs from MaxEnt. The occurrence data points were used to identify the 5^{th} percentile value. If the 5^{th} percentile value landed between two points, the value was rounded to the nearest integer or point and this point value was used as the 5^{th} percentile sensitivity threshold. This value was then used to create binary maps of presence-absence. For each occurrence probability map, the cell values lower than the 5^{th} percentile value were converted to 0 (species absence) and those higher were converted to 1 (species presence). All of the binary maps were summed to create a map that showed genus richness.

4.2.7. Analyzing model results

To evaluate model performance, the area under the receiver operating characteristic (ROC) curve (AUC) and test sensitivity was used. The AUC is the probability that a randomly selected presence site is ranked above a randomly selected absence site and is a quantitative assessment of performance because it is independent of a chosen threshold. AUC values greater than 0.75 indicate that the model is able to accurately predict test points (Phillips and Dudık 2008) and values greater than 0.9 are considered very good (La Manna et al. 2011). By contrast, AUC scores lower than 0.5 indicate a worse than random predicted distribution. We reviewed each genus with a low AUC score (<0.5) and the genera with greater than 50 occurrences were retained in the model. We felt that occurrences greater than 50 were representative distributions of each of the genera and that the lower AUC scores more likely corresponded to a more widely distributed genus (Elith et al. 2006, Raes and ter Steege 2007) than a poorly fit model. We report the mean AUC in our results; AUC scores for all individual genera are provided in Appendix 3A.

We acknowledge that some of the genus distributions may not be accurate as the occurrence data may not represent the realized niche (e.g. sink-source populations, biased, low number of occurrences, time since collection). Likewise, the generalized model parameters may miss unique environments where a genus could occur. To improve our distribution modeling efforts and test the assumption that the distributions are driven by environmental parameters, we used Raes & ter Steege (2007) null-model approach. While running MaxEnt 999 times for each taxa is valid when the number of different taxa is reasonable low, it is computationally exhaustive for over 1300 genera. Also, statistically comparing null-model AUC scores to our test

AUC scores did not improve model performance or predictive power and we did not want to exclude additional taxa from the study due to significant differences in AUC scores. However, we did compare null-model results to four genera with narrow to wide ranging distributions (*Nothofagus, Rhododendron, Alstonia, and Acaena*). We found that the AUC scores were higher than the Null AUC scores for all except *Alstonia*, which had nearly equal scores. These comparisons are available in the Appendix 3A. We hope that other researchers collect more occurrence data in different locations in New Guinea to validate or refute this baseline information in the future.

4.3. Results

The sampling intensity (Figure 4.2) shows the number of genera collected per 50 km cell. Much of the Indonesian side has not been sampled, or at the very least, voucher specimen collections have yet to be digitized and data mobilized. Also, many cells that contain occurrences had five or fewer specimens (yellow). Sampling efforts on the Eastern half of New Guinea showed that a majority of the cells contained less than 500 collections per 50 km cell, and although this is substantially higher than the western half of New Guinea, it is still quite low.

Figure 4.3 shows genus richness or the number of different genera accounted for in each 50 km cell. The retention of a single genus for each cell does not account for the number of different species that were present but it provided a relative idea of the diversity of genera collected in each area. In Indonesia, the majority of cells had five or fewer genera collected and only seven cells had more than 100 genera. PNG had a larger number of collected samples overall and therefore the number of genera represented is greater.

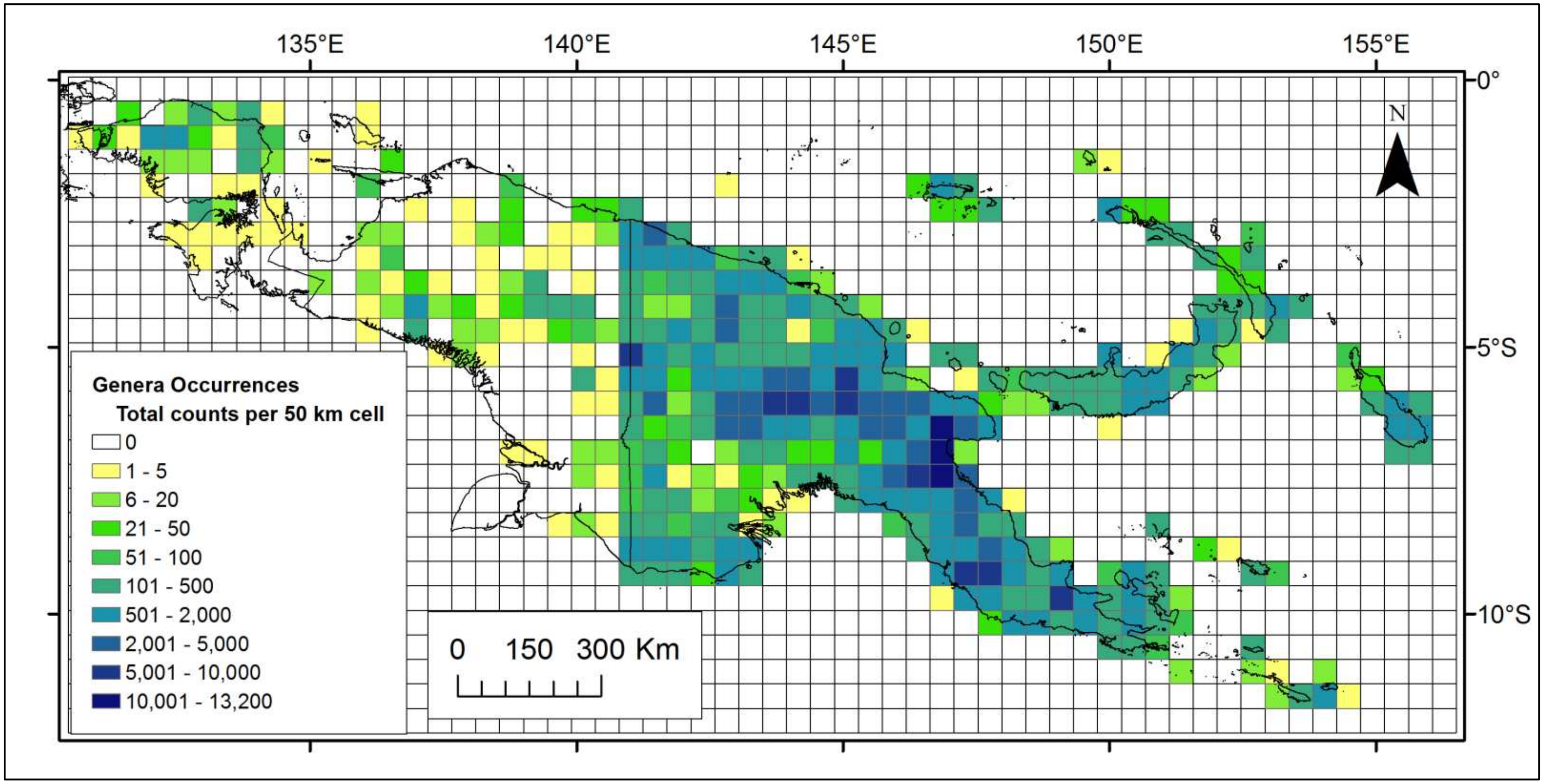

Figure 4.2. The total number of specimens collected per 50 km grid cell shows collection efforts. A single cell can have one or more of the same genus. The projection is Albers Equal Area projection, WGS84.

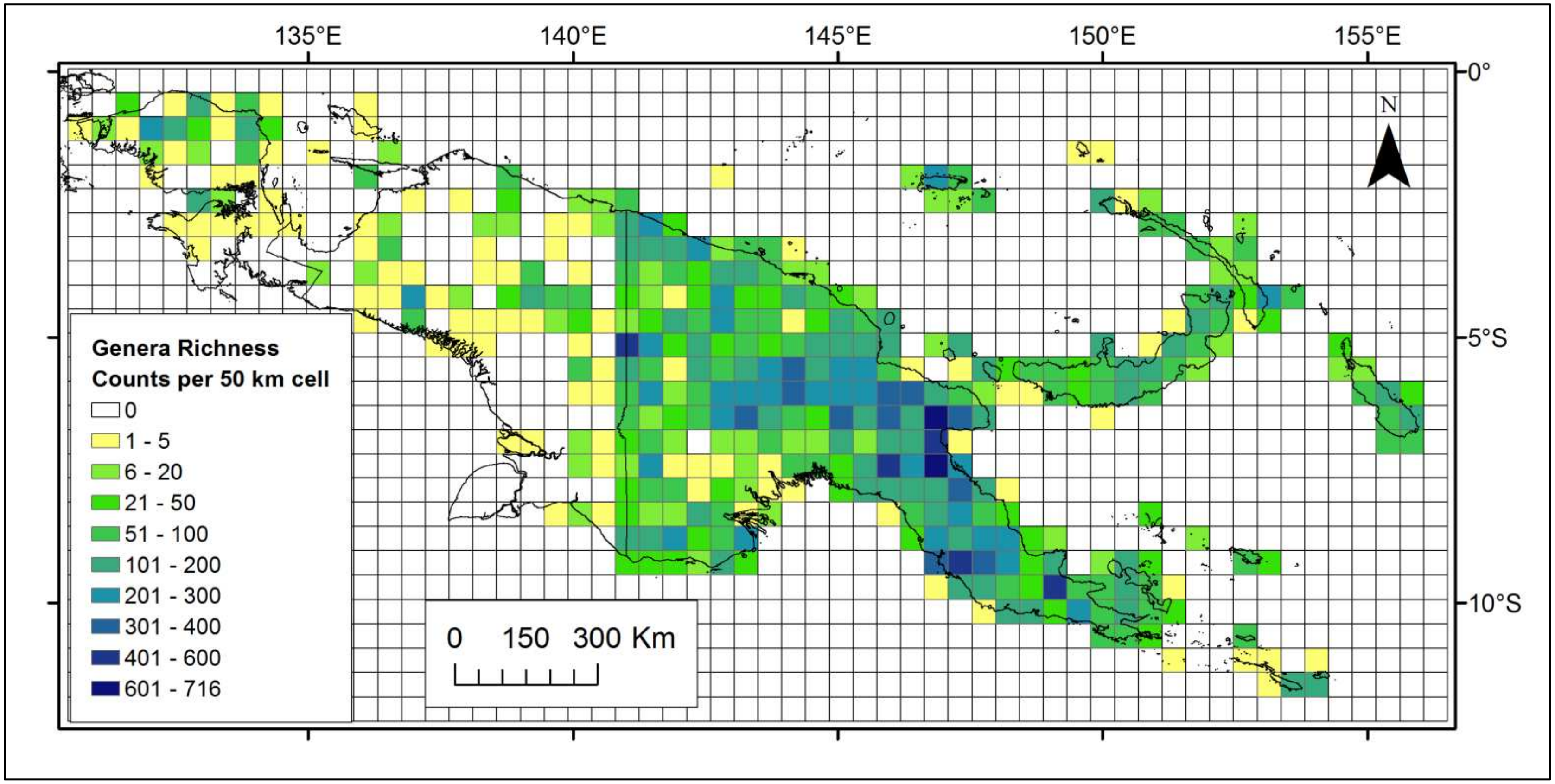

Figure 4.3. Genus richness shows the number of unique genera collected per 50 km grid cell. The projection is Albers Equal Area projection, WGS84.

While the total number of collected specimens alluded to a more comprehensive sampling effort, many of the 50 km cells with higher genus counts in Figures 4.2 and 4.3 were subject to sampling bias (Figure 4.4). Due to the very low sampling effort across all of Indonesia, biases were virtually nonexistent. In PNG sampling biases were higher along the roads and near areas with larger populations (towns and the Highlands region), but these areas are relative to the areas around them, that are very low. Because sampling efforts along the coast, along rivers, and near airports have occurred, low sampling biases were observed (maroon). However, these show up only because the areas around these locations had fewer, if any occurrences.

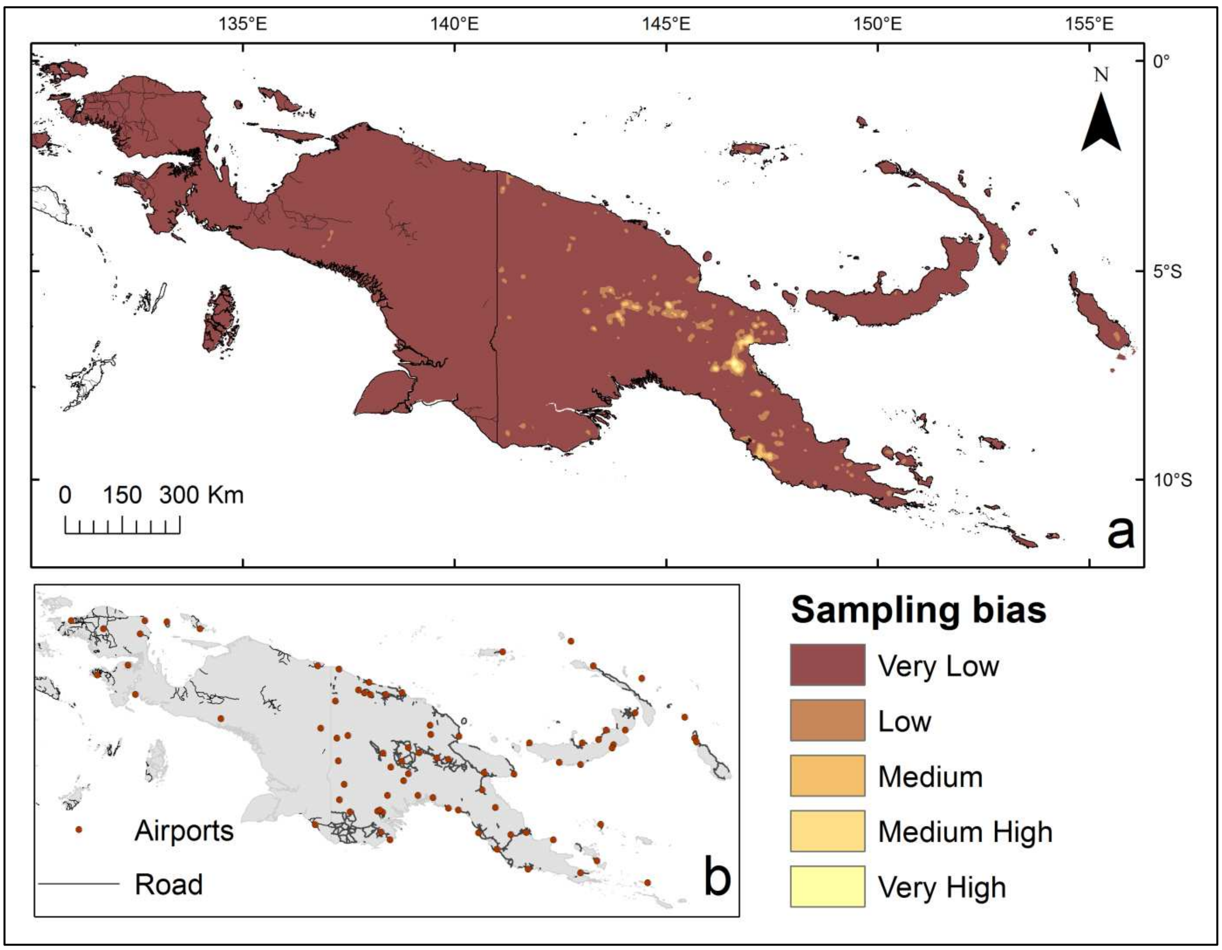

Figure 4.4. (a) Sampling bias created using kernel density estimate at a 10 km resolution with some locations identified. (b) Roads and airports show the influence of infrastructure on sampling bias. The projection is Albers Equal Area projection, WGS84.

4.3.1. Model performance

The 10-fold cross-validation test AUC (AUC_{cv}) scores ranged between 0.42 and 0.99 with a mean of 0.7. There were 83 genera with AUC_{cv} scores lower than the 0.50 threshold. The genera with an AUC_{cv} lower than 0.50 and greater than 50 occurrences totaled 21 and achieved a mean AUC_{cv} of 0.48. The number of occurrences was not correlated to the AUC_{cv} score (Appendix 3A). A list of the genera with low AUC_{cv} scores that were not included in the analysis is provided in Appendix 3B. Elevation, slope, and temperature annual range (BIO7) ranked, in order, as the most influential environmental and climate variables in the model. The average contribution of each environmental variable is provided in the Appendix 3A. Figure 4.5 shows genus richness in relation to elevation. Genus richness was greatest at elevations between 100 and 600 m and slightly decreased as elevation increased. Elevations between 0-100m had the largest area comparatively, but the lowest generic richness.

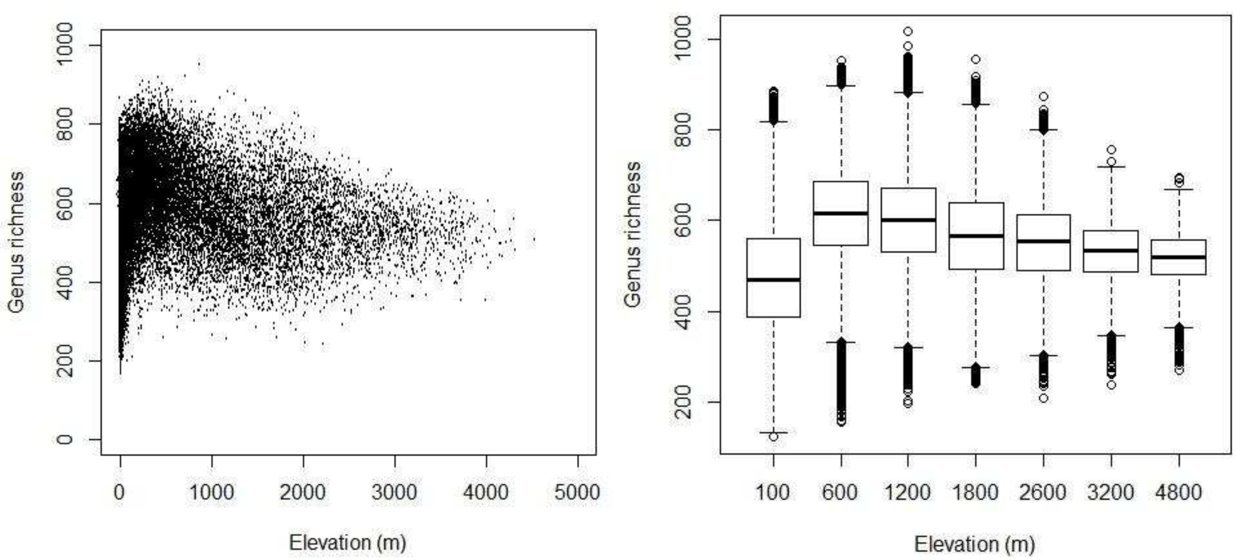

Figure 4.5. Generic richness in relation to elevation.

The relative, predicted genus richness for New Guinea and the surrounding islands is shown in Figure 4.6. Across the study, the predicted number of genera per 1 km cell ranged between 120 and 1020, where the total number of genera possible was 1354. Warmer colors show regions with higher predicted genus richness, whereas cooler colors show lower predicted richness. Across New Guinea there was higher variation in predicted richness, yet in general, the northern two-thirds of New Guinea showed higher predicted richness than the southern third.

Regardless of area, the generic richness across the different geologic land forms was similar (Figure 4.7). The Islands achieved the highest predicted richness with a mean of 594 and were smallest in area (8% of land area). Accreted Arcs closely followed the Islands for predicted genus richness with a mean of 587, but covered 19% of the land area. The Mobile Belt and Fold Belt were similar in (563 and 564, respectively) predicted genus richness but the Mobile Belt had slightly more land area at 25% compared to 19%. The Stable Belt had the lowest predicted richness with a mean of 454 and was largest in area at 28% of the study area.

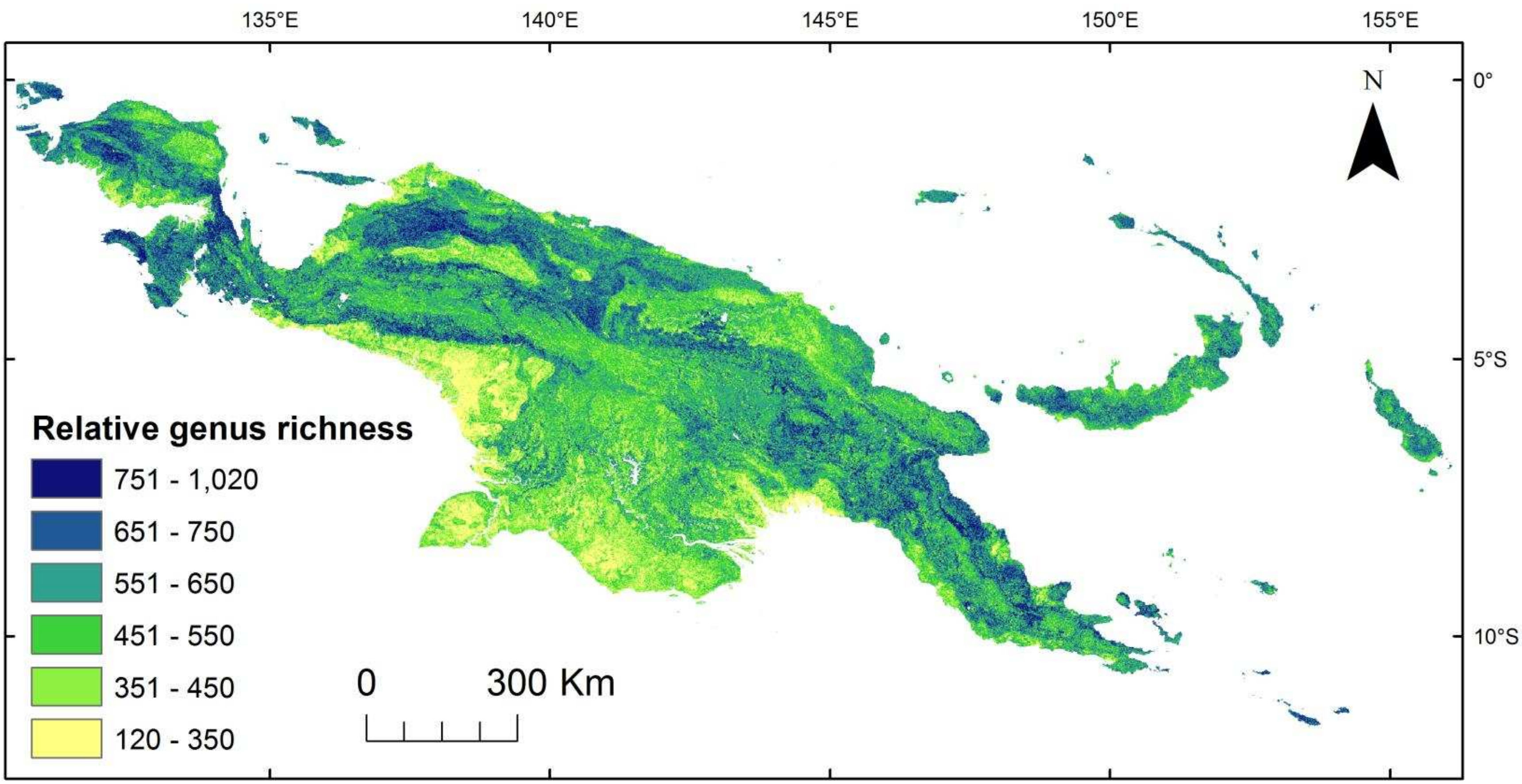

Figure 4.6. The number of genera predicted to occur across New Guinea and the surrounding islands. This map is the sum of binary occurrence maps using the 5th percentile sensitivity threshold for 1354 genera. Darker colors indicate areas with higher predicted richness (1 km spatial resolution). The projection is Albers Equal Area projection, WGS84.

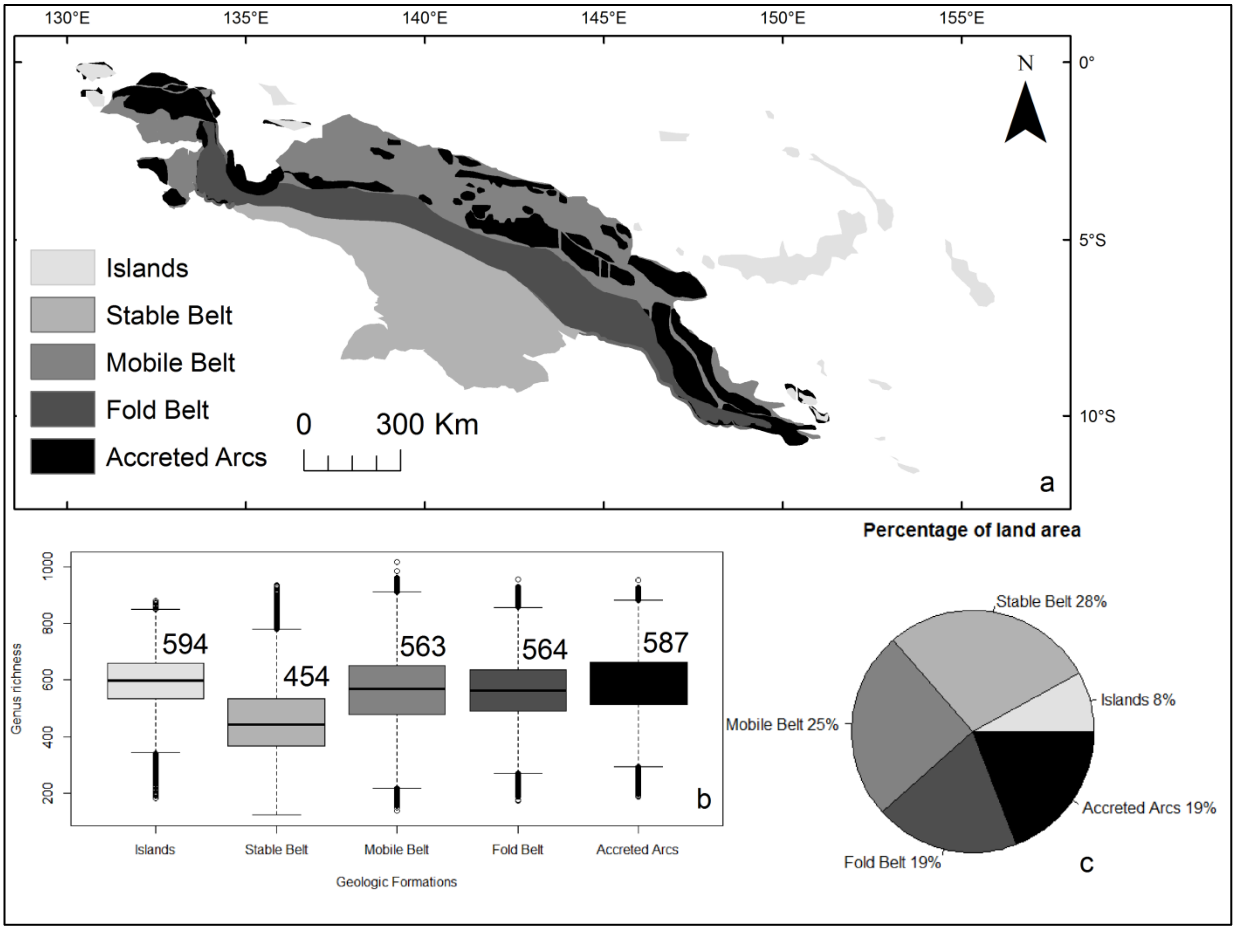

Figure 4.7. (a) Major Geologic formations, (b) the predicted genus richness per geologic formation, and (c) percentage of land area each formation covers in the study area. The predicted richness box plot shows the mean number of genera per formation with outliers. The projection of the map (a) is Albers Equal Area projection, WGS84.

4.3.2. Conservation implications

Our results show predicted genus richness without consideration to land-use and land-cover (LULC) changes which would influence plant distribution and community composition. The five major contributors to deforestation and land degradation were logging, subsistence agriculture, fiber, mining, and oil palm development (Shearman et al. 2009, Abood et al. 2015, Bryan and Shearman 2015). In PNG Special Agricultural and Business Leases (SABL) are designated for industrial agricultural activities, such as oil palm development (Nelson et al. 2014). We provided

C

a conservation areas and resource extraction map with data from multiple sources (Figure 4.8a) and population density in people per km^2 (Figure 4.8b). Conservation areas are loosely defined as land under a type of protection or conservation, and ranges from community-based Wildlife Management Area (PNG specific), marine reserve, hunting reserves, national parks, and internationally recognized conservation areas (IUCN and UNEP-WCMC 2016).

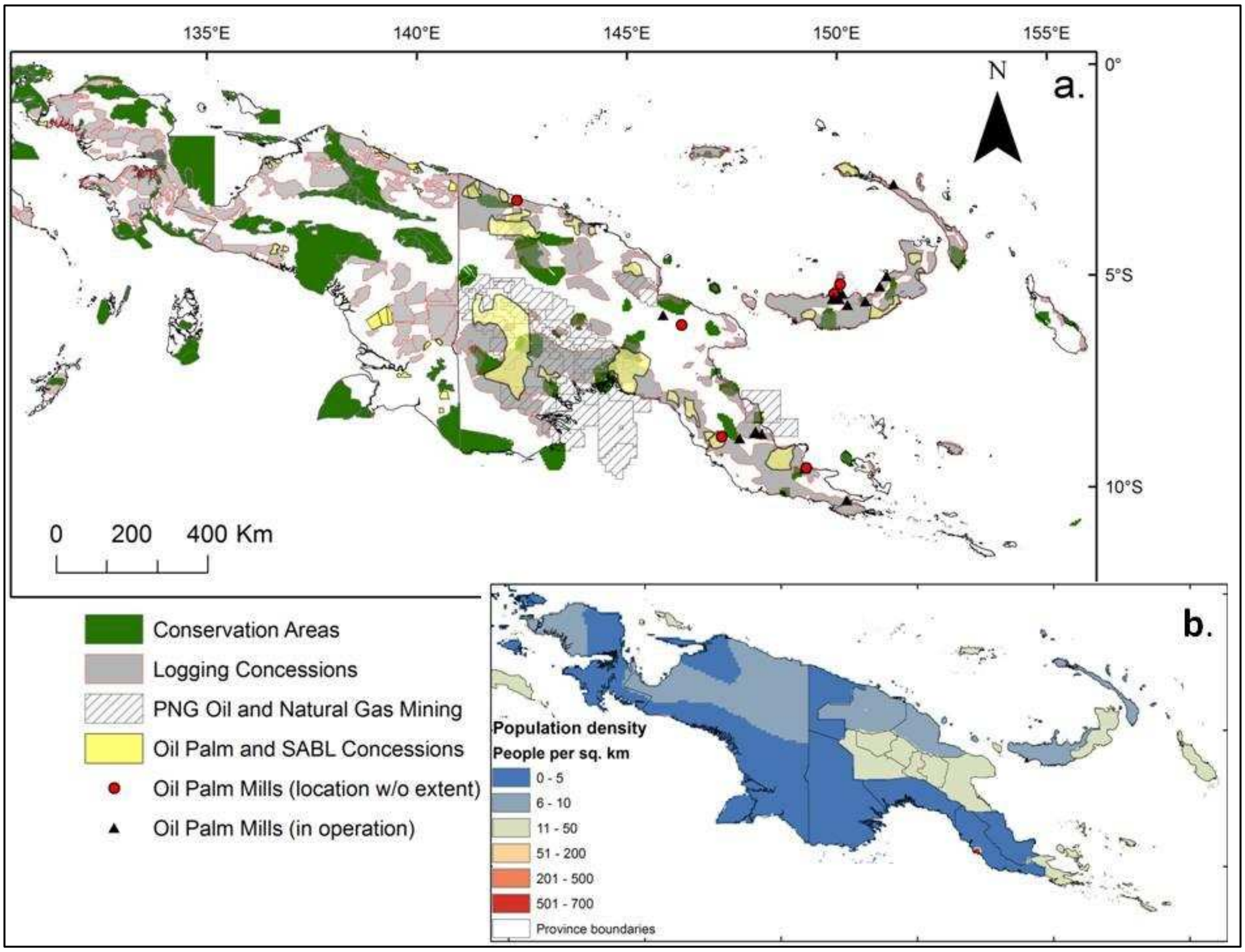

Figure 4.8. New Guinea conservation areas and resource extraction (a) and population density (b). For PNG, oil palm area data were derived from Nelson et al. (2014) and Bryan and Shearman (2015) and most areas were simplified into composites; logging concessions (Shearman et al. 2009); conservation areas (IUCN and UNEP-WCMC 2016), and oil and natural gas (World Resources Institute 2016). For Indonesia spatial data were derived for oil palm, logging, (Ministry of Forestry 2010, ESRI ArcGIS online data 2016), and conservation areas (IUCN and UNEP-WCMC 2016). The projection is Albers Equal Area projection, WGS84.

4.4. Discussion

Our study provides a foundation for terrestrial plant distributions at the genera taxonomic level across New Guinea and for the surrounding islands. These results objectively and quantitatively show collection density and spatial sampling biases and predict patterns of genus richness at the finest spatial resolution (1 km). The collection density and sampling bias maps provide guidance for future sampling strategies. However, there may be areas that have been sampled that are yet to be digitized and georeferenced, and these data may fill some gaps. Likewise, there are collections data that have not been released to the public and could also be informative to a wide audience and for other efforts such as this. Biogeography in this region of the world is complex and is a result of a combination of abiotic and biotic drivers that influence terrestrial plant distributions and richness. The predicted patterns of genus richness conform to and differ from previous observations and theories, and we acknowledge that there is much work to be done to confirm or refute our analyses and observations.

4.4.1. Influence of sampling bias and density

After spatial biases and filtering, around 1083 genera had to be excluded from the analyses due to fewer than 10 occurrences. Approximately 23% or 252 of these are genera with only a single available specimen record. Specimen occurrence data eliminated from studies due the lack of presence points is not limited to New Guinea as similarities are observed for the African continent. Africa has one of the longest sampling histories, yet Stropp et al. (2010) identified that 31% of species in their dataset contained only one specimen. The lack of numerous collections for single taxon greatly inhibits using the modeling framework to predict distributions and inhibits our understanding of the ecology and community structure of the region.

The number of genera found in the highest sampled areas of New Guinea (Figure 4.3) show that over 1000 different genera are present. Although collection biases are typically a negative aspect of distribution modeling, we can use the cells with the highest genera richness and ecological principles of the tropics to posit that the potential genera abundance across the study area may be similar. While we cannot assume that all regions in New Guinea have 1000 different genera, tropical areas typically harbor high taxonomic abundance compared to other biomes, such as grasslands. Grasslands have hundreds of different plant species but are dominated by only a few, and the abundance of the non-dominant species is quite low.

In general, tropical forests lack dominant species and instead have a larger number of different taxa. ENMs are unable to predict abundance, yet they can identify environments that are more suitable for a larger number of genera according to occurrence data. Because the regions that are more comprehensively sampled are not predicted to have particularly high generic richness, it is unknown if under sampled regions would have a similar amount of generic richness or even similar communities. For locations that are progressively distant from well sampled areas we lack the data to assess beta-diversity and question if the principle of distance-decay is applicable (Tobler 1970, Nekola and White 1999, Condit et al. 2016). As found in the first law of geography and in island biogeography, the species assemblages in communities that are closer in proximity have more similarities than those more distant and this is influenced by environmental gradients and dispersal limitations (Nekola and White 1999, Stropp et al. 2016). This was shown by Condit et al. (2016) in Panama and Amazonia (Peru and Ecuador), where specie similarities declined rapidly with distance. In Panama, only 1-15% of the species were similar for plots separated by 50 km and in Amazonia only 30-40% of species were similar for plots separated by 100 km. There is a greater decline in species similarities found in New Guinea by Katovai et al. (2015) who found that across a 13 km transect species composition similarities ranged between 4% and 18%. From these results, Katovai et al. (2015) proposed that beta diversity may be higher than expected in New Guinea due to the diverse terrain that exits across the island. Overall, diversity in the tropics changes with distance and thus community composition in one location may not be similar across a larger extent, even if environmental variables are similar.

Vollering et al. (2015) suggested that the higher orchid richness observed in eastern New Guinea is not favored by higher collection densities because environmental conditions of occurrences are well represented and spatial biases were accounted for when modeling. We agree with this on an east-west basis for New Guinea because we also found that predicted generic richness increased west to east along the central mountain range. However, on a north-south gradient we speculate that low collection counts may influence differences in communities, as sampling intensities are very low and the environmental characteristics and geologic histories are markedly different. For instance, there is a large region of lower genus richness (genus predictions ranging between 120 and 400) which coincides with the area with the lowest sampling intensities (Figures 4.2 and 4.3). Similarly, the Stable Belt has fewer pockets of high genus richness compared to the Fold and Mobile Belts. We posit that the Stable Belt may be in, and of itself, unique or taxonomically similar to northern Australia, as both are part of the Australian Craton. Although these landmasses are separated by higher sea levels today, they have been united twice in the past 120,000 years during glacial maxima when sea levels dropped 90 m. Therefore, vicariance also may explain the lower or different genus richness in the Mobile Belt. Vicariance is when a species exists in an area and then through continental drift, sea level changes, or mountain formations the taxa are separated into two locations and over time, and speciation occurs. Biota along the mountain range of the Fold Belt may share taxonomic lineage with biota found in the Stable Belt, but many have adapted to higher elevation environments. The Fold Belt also separates the Stable Belt from the Mobile Belt, and thereby the interactions between communities are minimized. The Mobile Belt biota also may differ from the Stable Belt because it has experienced various island accretion events and with each event, different taxa are in tow. Overall, due to the low number of samples, different geologic histories and biogeographical processes, and mountain barrier splitting New Guinea, we question whether the model performs adequately for Stable Belt. More occurrence records are needed across the Stable belt to confirm this hypothesis.

4.4.2. Geologic drivers and environmental variables

The geologic history, topography, and the location of New Guinea are believed to be the main drivers of plant distribution and richness. New Guinea sits at the crossroads of Southeast Asia, Australia, and many Pacific Islands, it is both at the receiving end and acts as a source area for dispersal events. Since most of these Pacific Islands east of New Guinea (Solomon Islands, Bismarck Archipelago, Fiji, Vanuatu, Samoa, and Tonga) were formed from volcanic activity and tectonic plate shifts, colonization of taxa occurs from long and short distance dispersal events. New Guinea is believed to be a primary source of biota for many of the Pacific islands and the farther an island is from New Guinea, the fewer genera are present (Keppel et al. 2009). Dispersal events are continuous, yet much is left to chance and the resilience of the traveling disperser. The populations that make it to these islands are genetic subset of the larger population and are isolated for long periods of time so speciation often results. As in the past, these isolated islands shift towards and will eventually accrete to the northern coast of New Guinea. As these islands move closer to one another dispersal is facilitated by proximity, in a stepping stone fashion or transported by carriers such as birds, bats, or humans (Keppel et al. 2009, Boivin et al. 2016).

Areas of higher predicted richness are not consistent across all areas outlined as accreted islands. We observed that it is not the accreted land that harbors the highest richness but the margins or collision zones between these accreted terrains and the Mobile Belt. As an island moves toward the north coast of New Guinea and begins the accretion process a collision zone forms. Collision zones or successor basins overlap terrain boundaries and help to constrain the time of accretion. Successor basins can begin as submerged alluvial sediments that either dry out as ocean inlets close or are pushed above sea level from continued plate movements. Our results suggest that the interiors of nearly all basins are associated with lower richness, except the Bintuni Basin (130-135°E and 1-4°S) and have higher predicted richness. However, for the remaining basins higher predicted richness occurs outside the borders of the basins. For example, there are two large successor basins with locations centered at 137°E and 3°S (Meervlakte Basin) and 142°E and 4°S (Sepik Basin), that show genus richness to be low within the basin and higher outside the basin. We posit that this is what causes higher genus richness across the Mobile Belt (Figure 4.7). In theory, collision zones are areas where the rates of species interactions and dispersal is the greatest, yet many of these regions have yet to be identified or investigated as regions with potentially high richness.

Successor basins and the surrounding areas with high genus richness are topographically homogenous areas (see Appendix 3A) for topographic heterogeneity map). Topographic heterogeneity and unique abiotic environments are often used as proxy data to identify regions of higher diversity rates because there are more opportunities for niche partitioning. We found the opposite to be true in some regions of New Guinea, where topographic homogeneity was associated with higher genus richness. This is supported by Allouche et al. (2012) who showed that environmental heterogeneity has a unimodal response rather than a positive effect on species richness. They suggest that richness is more dependent on available area than a diverse environment. This seems to be the case in our study area, as the larger, more homogenous areas (e.g. Figure 4.6 at approximately 137°E and 2.5°S) are associated with higher richness. Comparatively, we find that areas with higher environmental heterogeneity are smaller in area and tend to occur at higher elevations and where elevation gradients rapidly change. It is this response that causes slope to be one of the second most influential environmental variables.

The other type of basin is a foreland basin, and these occur adjacent and parallel to mountain belts and are formed through mountain belt growth and lithosphere flexion and stretching. The foreland basin (Mapenduma) is located between 135°E-140°E and 5°S-5.5°S and in this case higher predicted richness occurs along the northern edge of the basin where the mountain range begins (Mapenduma anticline). This conforms to the relationship between heterogeneous environment and higher richness.

4.4.3. Land-cover changes

New Guinea remains one of the last high-biodiversity wilderness areas, meaning on average there are fewer than 5 people per km^2 (Mittermeier et al. 2003) and the loss of wilderness and forest cover is occurring at a more rapid rate than the Amazonia (Hansen et al. 2013). In PNG rates of forest loss between 2002 and 2014 to 0.49% per year and again accessible forests show higher rates of loss at 0.61% per year. While the lack of successful conservation areas is an issue (Shearman and Bryan 2011), more attention should be drawn to illegal resource extraction, the disregard for regulations and laws, and the transparency of land leases and concessions for customary land managers (Nelson et al. 2014). The rates of forest loss in Indonesia are similar to those in PNG but have increased since 2000. It is estimated that Indonesia is losing 1% of primary forests per year (Miettinen et al. 2011). Approximately 30% of Indonesian forests in New Guinea forests have been degraded or deforested via industrial concessions (oil palm, logging, fiber, mixed concessions) (Potapov et al. 2008, Abood et al. 2015). Across the whole of Indonesia, 41% of forests are under some type of preservation, however, Abood et al. (2015) identified that over 55% if Indonesian deforestation has occurred outside industrial concessions and regulations are weakly enforced. It is unknown how much of the boundary violations occur next to preserved land in the Indonesian territory in New Guinea.

Many of the logging concession data sources are outdated for both Indonesia and PNG. Although logging has been and will continue to be a major threat to forests in New Guinea, oil palm is resulting in forest changes quite rapidly and this is especially so in Southeast Asia (Dislich et al. 2016). It is estimated that oil palm accounts for 3.4% of deforestation in Indonesia and 3.0% of deforestation in PNG (Abood et al. 2015, Bryan and Shearman 2015). However, for many areas oil palm spatial data were not available and this is shown in PNG where dots and triangles in Figure 4.8a represent oil palm concessions and mills locations instead of geographic extents (Nelson et al. 2014). Likewise, Indonesian lacks adequate spatial oil palm data, as the areas devoted to it are much fewer in number and smaller in area compared to PNG.

The ecological and social impacts of oil palm were recently comprehensively addressed in a review by Dislich et al. (2016). Oil palm development in peat swamp forests, which constitutes 21% of concessions across the nation of Indonesia, result in long-term greenhouse gas emissions, flooding, salinization of freshwater, and high fire risk (Abood et al. 2015, Dislich et al. 2016). Slightly different ecological impacts influence the SABL land that is designated for oil palm in PNG because these areas are often used for unsustainable logging even though contracts are explicitly for industrial agricultural development. Twelve percent of PNG land area is designated as SABLs and concession boundaries are often disputed, overlap with customary tenured territories or other concessions, and do not inform or seek consent from landowners (Nelson et al. 2014).

The comparison of Figures 4.8a and 4.8b shows that population densities are slightly higher (11-50 people per km^2) in the mountains of PNG, but remain relatively low (0-10 people per km^2) for much of the study extent. Subsistence agriculture is the dominant land-use for the majority of the people in New Guinea, yet there are few studies to assess the land-cover changes associated with subsistence agriculture. In PNG between 1972 and 2002 Shearman et al. (2009) found that subsistence agriculture was responsible for 43% of the 36% of forests degraded or cleared. However, in a follow up study between 2002 and 2014 by Bryan and Shearman (2015) that subsistence agriculture did not claim any additional land. These slightly confounding results, suggest an opportunity to study how much population density may influence plant biodiversity and conservation measures.

4.4.4. Methodological limitations and considerations

Selecting the genus taxonomic level for occurrence data improved data quality for this study. Species level data were littered with issues that included a large number species with fewer than 10 occurrences, numerous data entry errors (e.g. misspelling, incorrect species identifications according to genus listed) and missing information (e.g. coordinates). The genus level data may not fully capture the richness or endemism because some genera are more speciose than others. It is also likely that many of the rarer genera were excluded from the model because there were either too few collection points initially or after biases were accounted for the occurrence dropped below 10.

ENMs are based on the assumption that taxa are in equilibrium with the climatic envelope in which they are present, and absent in unsuitable climates. This translates to ENMs assuming the fundamental niche, or all of the locations where the species could exist. The realized niche is where the taxa actually occur. However taxa found in the realized niche could be source or sink populations and not represent the true niche of the taxa. Due to the history of island accretion and mountain orogeny there have been relatively rapid changes in environmental gradients, which has assisted dispersal and created unique community assemblages. This violates dispersal limitations and shifts plant communities to exist in unsuitable climates for a short time periods. For example, a portion of a coastal community could be uplifted to an alpine environment over a short period of time(e.g., one million years), and while some taxa in the alpine environment will go extinct and others will persist (Heads 2006, Trigas et al. 2013).

ENMs also do not integrate taxa range limitations (biotic and environmental), traits (biotic interactions, dispersal type, pollination type, lifespan (short or long lived)), or intra-species competition and this influences the predictive performance (Hanspach et al. 2010). In part, this is an issue of scale as the predicted distributions use climatic and environmental variables that are at regional and continental scales and biotic interactions and competition are at a local scale (Austin 2002, Kumar et al. 2015).

The predictive performance (AUC scores) ranged among genera. Low predictive performance was observed for taxa that have a large range (low specialization) because there are fewer contrasts among the occurrence locations (Evangelista et al. 2008). We found this to be the case for *Ficus* and *Syzygium*, which have more than 700 occurrence points and achieved AUC scores of approximately 0.5. Similarly, highly specialized taxa do not perform well in ENM models, as the environmental conditions in which they exist are localized. A low AUC score could be caused by a narrow or wide ranging genus but due to sampling bias and the limited spatial distribution of collections, it is unknown which is the case.

Land-use and land-cover (LULC) changes are also important to understanding terrestrial plant distributions and potential changes. Much of the biased sampling across the New Guinea occurs near airports, the coast, and populated areas. The taxa in these regions have likely been influenced by human induced LULC changes where viable habitats have been limited or seed sources reduced and ultimately influence the long-term survival of certain taxa. Yet, there are large tracts of forest that rarely experience human alterations because of the relatively low population densities across the island, the lack of a water source, and the remote nature of some locales.

4.5. Conclusion

It is extraordinarily difficult to tease apart the nuances and drivers of diversity in New Guinea because it is necessary to examine the ecology and evolutionary biology throughout geographic space and geologic time. While relationships can be drawn to support or refute nearly every theory concerning the biodiversity in New Guinea, such conclusions will not be adequate until there are ample collection data in which to do so and a greater understanding of biological and environmental interactions.

As suspected, we identified many areas with high genus richness in regions of high elevation and topographically heterogeneous locations. What differs from previous expectations is that we also found areas of high genus richness at low elevations, in regions that are topographically homogeneous. The difference between these two results is the area that each covers. At higher elevations and in transition zones, where topography is more complex, there are numerous smaller areas with higher richness. Comparatively, lower elevations are associated with more homogenous topography and have larger tracts of predicted genus richness. The environmental variables that most influenced these results are elevation, slope, and temperature annual range.

The geologic history is an important driver of genus richness and accreted islands often are the focus of diversity. Our results suggest that more focus should be drawn to the regions between these accretions (successor basins) as they offer ample space for niche partitioning and show many areas of predicted high genus richness. Sampling strategies can be approached in a few ways, but any additions to the occurrence database are welcomed. Sampling efforts could focus on specific genera that have low overall occurrences or on regions that are poorly sampled. Sampling could also be focused in regions with high or low predicted richness to assess our results. Review maps and Supplemental Materials for regions and genera to focus on, as there are ample opportunities whatever avenue chosen.

The results can be used to prioritize sampling needs, support conservation strategies, compare genus diversity to other regions of the world, and discuss principles and drivers of biogeography. There are ample avenues identified for future work throughout this text, most of which cite the need for increased sampling efforts and data quality improvements. Identifying the most current LULC trends will assist in improving the success of current conservation areas and prioritizing new conservation strategies. To do this, finer resolution remote sensing data (≤30 m) should be paired with data from various sources, such as, government sanctioned concessions, small-scale resource extractions, illegal concessions and operations, Food and Agricultural Organization (FAO) data, and land-manager land-use. Collaborating with land-managers and communities to thwart resource development and incentivize preservation is also vital.

CHAPTER 5

CONCLUSION

This dissertation contributes to the body of knowledge at a regional level for New Guinea and at the village level in Papua New Guinea. The three primary research objectives I focus on are 1) comparing PRS methods to remote sensing classifications and identifying how participatory contributions influence swidden area classifications; 2) identifying long-term swidden LULC tends using 40 Landsat scenes between 1972 and 2015; and 3) assessing sampling biases and predict genus richness for the island of New Guinea and surrounding archipelagos.

In regions where swidden is the mainstay of subsistence livelihoods, participatory data are essential so that LULC assessments do not misestimate land actually in use. PRS methods complement satellite image analyses in swidden landscapes because swidden is difficult to classify, changes frequently, is a mosaicked LULC, and is prone to mixed pixels compared to other agricultural types. PRS methods reveal that Landsat data smooth the fragmented swidden landscape into homogenous land-cover categories and over estimates the swidden area by two and a half times. Land managers indicated that there were large, naturally vegetated areas that should not be counted as swidden and it is this that causes the overestimation of swidden when remote sensing analyses are used alone.

The results from the PRS methods guided land-cover classifications so that I could conduct a long-term assessment of swidden trends for the study village. Participatory research improved the level of detail for swidden strategy, land-use, and land allocation to better link land-use to land-cover for a clearer understanding of trends. I was able to identify that the 1972 and one of the 1988 image results are outliers for two reasons. First, the 1972 data are likely subject to methodological and data differences because it was captured with a different type of satellite sensor. Second, both swidden areas could be smaller due to the reflectance and classification challenges in swidden landscapes, where the similarities between swidden and natural vegetation cover are minimal. Last, during the 1970's there was equal dependence on swidden and fishing resources and this may contribute to why the swidden area is so much smaller. Since there were two scenes available in 1988 and I could verify swidden areas differences are likely due to reflectance similarities because the two images were a month apart. When the 1972 and 1988 data are included in the linear model, swidden area significantly increases over time. When these two outliers are removed from the analysis, the swidden changes over time are not significant. I have more confidence in the trends when the outlier data are excluded for two reasons. First, the large number of scenes supports that the smaller areas are outside of the norm, and second, these two dates are in the beginning of the dataset and have more of an effect on the slope of the trend. Because there is not a significant trend for swidden expansion over time, I could not link population growth as the driving cause of change. Instead, I identified that swidden changes are based on local social, climatic, and environmental conditions and food production is increased by implementing a variety of strategies (e.g. cultivar selection, subdividing large plots). These results at the village scale are important because they differ from studies in PNG at wider extents that strongly correlate population and swidden to forest cover losses.

Across New Guinea patterns of biodiversity hotspots align with and differ from theories of island biogeography theory. The areas of predicted genus richness (biodiversity hotspots) are available at a resolution of 1 km, which are the finest resolution to date and provide baseline information to inform sampling strategies, management plans, and prioritize conservation areas. Identifying the drivers of diversity for New Guinea and surrounding archipelagos requires a detailed knowledge of ecology and evolutionary biology through geographic space and geologic time. Different hypotheses suggest that accreted terrains and topographically complex areas are the most likely drivers of richness. While this may be true in theory, my results show that accreted terrains are often associated with lower richness. Instead I suggest that successor basins, the areas filling the space between accretions, have higher richness, as there is more space is available for niche partitioning and interactions. Another hypothesis within the literature is that high elevation and topographically complex areas result in greater biotic richness. While I found this to be true in the eastern half of New Guinea, I also identified that there were large regions at low elevations with homogenous topography that also have high richness in the western half of New Guinea. The difference between these two topographies is that the complex terrains had numerous smaller areas of higher richness compared to the fewer, yet larger richness areas in homogenous terrains. A caveat of the predicted richness maps is that the genus level data will not fully capture the richness or endemism that exists across New Guinea because some genera are significantly more speciose than others. In addition, niche modeling makes estimates of distributions based on environmental factors and does not include biotic interactions, competition, dispersal capabilities, or human influenced LULC changes, which may also influence taxon distributions. All areas across New Guinea should be subjected to additional sampling, or groundtruthing, to verify if the predicted genus distributions are valid.

Overall, more research in New Guinea is needed to understand basic biology and the socio-ecological dynamics of one of the world’s most culturally rich and biologically diverse tropical areas. There are many avenues of research that need attention, from my research I believe that comprehensively assessing the drivers of LULC change at multiple scales and with the assistance of local land managers is most important so that management policies are better informed. Likewise, the inclusion of land-manager information and participation can insure that conservation or land management policies are established in a way that promotes long-term success and the preservation of this unique region of the world.

CHAPTER 6

REFLECTIONS ON THE PHD EXPERIENCE

Human judgment and perspective inevitably influence the scientific process, yet science strives for objectivity and is continually subjected to critical examination and reevaluation in the light of new or different evidence.

I feel honored to receive a PhD in Ecology and contribute to the cumulative body of knowledge organized as science. Throughout graduate school, you are reminded of this quote by Isaac Newton, “if I have seen further than others, it is by standing on the shoulders of giants”. Because Newton is celebrated as making great scientific discoveries, this quote has been used to time and again to show gratitude to predecessors and justify new discoveries and ideas. I never really put much thought into this quote until I began write this reflection piece and thought about to whom I am grateful for this accomplishment. I thought about the ‘giants’ who paved the way, but the people that are typically listed as the totem giants (Copernicus, Kepler, Einstein, Galileo, etc) of scientific discovery and advances don’t really do *it* for me. Before anyone screams obscenities or throws down this dissertation with disgust, I will explain my point. During my comprehensive exams I was asked to define and discuss science in a historical context and identify how my research fits into this paradigm. I began to question how science could be objective if human perspectives and judgment are so influential in the processes. My opposition to the ‘shoulders of giants’ quote stems from an understanding of the history of science and how the selection of the noteworthy figures is highly flawed. For instance, there is a distinction between the written history of science and science as the pursuit of knowledge but both are strongly intertwined in their powers to define phenomena. The history of science is about the power to define and tell the story of science's progress (Tuhiwai Smith 2012) and it is wrought with biases, arrogance, prejudices, and the theft of ideas and recognitions. If one was to acquire a list of the people who were most influential in science, the "giants" and what their discoveries entailed, the individuals are all white European men and not all of the discoveries were original thought.

There are examples littered throughout history that Western science has been the driver of advancing science and society for millennia. However, this skewed perspective, hunt for power, and convenient *history* has ultimately resulted in the oppression and lack of recognition of science as a global, human phenomenon. It is this struggle for power that has caused many women to be neglected from ranking as notable scientific contributors, a.k.a. not 'Giants'. The women that have been recognized as important contributors were done so retroactively (e.g. Caroline Herschel, Marie Curie, Barbara McClintock, and Rosalind Franklin) and often their bios that are littered with love stories, child bearing, and how a significant male figure in their life facilitated their scientific curiosity. There is very little information about their scientific achievements and contributions to science. Also, common in Western sciences' history is the disregard of other cultures' contributions, traditional or otherwise. For example, the Chinese were particularly innovative, but Europeans (Westerners) easily and quickly adopted Chinese advancements as their own (e.g. paper, moveable print-type, irrigation, gunpowder, and the compass). Such advances and exchanges were largely neglected by Western historical records or are given less attention. This occurs to such an extent that Albert Einstein, who is arguably highly educated, didn't believe that India or China had ever sought to understand the natural world by means of scientific inquiry, even though his algebraic equation $E=mc^2$ is entirely derived from the early mathematical contributions from Islamic scholars and Indian numerical concepts.

The scientific process or way to organize and understand the world is evident in all cultures in the world. There is an innate ability in humans to recognize patterns in nature and allowed humans to decipher poisonous plants from nutritious ones, track constellations, navigate the globe, and develop agriculture, among other things. However, what has shaped me as a researcher is recognizing that the face and formalization of observation, experimentation, and knowledge exchange are different among cultures and this awareness is fundamental to working with the indigenous communities in Papua New Guinea. While my experiences traveling abroad and working with diverse populations greatly influenced how I regard people different than me with dignity and respect, adapting these skills into my scientific pursuits was vital. The book Decolonizing Methodologies by Tuhiwai Smith was perhaps one of the most influential things I read in grad school. I think it should be mandatory reading for all students at the university level, regardless of their field of study.

I recognize that my research falls into the scientific paradigm that scientific methods and theories are the best ways to produce information and improve knowledge (Schick and Vaughn 2011). This cultural lens also determines whether my research questions are worth asking and what methods should be used to answer them. For example, Westerners' view biodiversity as ecologically valuable and the need to map it a valid research endeavor. However, if we were to ask someone from New Guinea what type of research would be most beneficial to their village or country, I doubt that they would say 'map the biodiversity of plants, we need to know!'. In all likelihood, they indigenous people probably have a really good idea of the diversity and distribution of plants proximal to their villages. But such information has yet to be adequately catalogued by Western science. Therefore, here I am to do so and fulfill the other component to my research, which aimed to quantify, collect, and organize information from an indigenous community. Then I will publish this information and claim this information as newly 'discovered'. This is not really so different than the early days of imperialistic ventures and personal gains, but my gains will be through publications and not land grabbing or mineral riches. Because I am not native to PNG and my way of thinking and defining livelihoods and land changes will be skewed to my Western perspective. Recognizing this, I have made an effort to minimize biases and the imperialist nature of my research and have used various measures to improve research objectives and results. For example, I integrated community members into the research process at various stages, data collection and analysis. I also sought feedback on preliminary land-cover change results. Getting the community members to correct and change the land-cover maps was challenging because many have been led to believe that their knowledge is inferior to scientific methods. To overcome this I had to really work hard to extract information and opinions from the community members that differed from the results I presented.

Overall, there are many aspects that are challenging during a PhD and finding the tenacity to complete it is a major part. After spending years reading, writing, re-doing analyses, and questioning your sanity, it is important to sit back and think about what it all means in two ways. First, what does it mean to you personally, and second, how does it contribute to science as a whole. It is one thing to charge ahead and just finish it, and another to really focus on the philosophy aspect of the doctoral degree and your impact on the world and scientific community. I think this latter part lacks in the university setting, because everyone is more focused on results and degrees and less focused on critical thinking. For me, the classes and aspects of my research that facilitated critical thinking and applying knowledge to solve ‘problems’ were much more rewarding and helped me advance as a student to a greater extent. It is important to apply this same line of thought to my next stage in life, the job search. I am just ready for a job, to do something different, and *I feel desperate*. However, when I take a moment to question if what kind of impact to I want to make, I hesitate to take the job for the sake of a job. This is because I never sought my PhD for the degree, and instead as a means to try to gain skills to positively impact the world and do some good. If I ever feel ‘stuck’ or fear changing my job or career path for financial or other reasons, I must remind myself of these things: 1) just cut the cord, 2) don’t misuse your energy, and 3) don’t fear the unknown. Aside from this self-reminder, I have also included a list of lessons learned and suggestions for future graduate students.

6.1 Recommendations to future students

I decided to write this list of suggestions for future or current graduate students in bullet fashion, to make it easy and quick to read. I hope it helps.

- Find support in your cohort and lab, share ideas, and ask questions.
- Talk about your research with people outside of grad school. Sometimes the obvious questions are not obvious when you are entrenched in your field and around people doing the same thing.
- Create the elevator speech that leads people to ask questions.
- Go to talks on a variety of subjects.
- Completely finish one degree before starting the next.
- Practice writing a lot.
- Tailor your publications and research towards the career you want
    - Try not to pigeon-hole yourself with an overly specific skill set/field of study, research and trends can change.
- Have good outlets. No one can be science-y all the time. Go for a run, drink some beers, whatever.
- Think other places: Back of the napkin ideas are not drafted in a lab or behind a computer… change the scene some times.
- Schedule time off and don’t work, every week!
- Be open and honest with a trusted committee member or advisor.

- Find a good committee, how? Ask yourself these questions:
    - How quickly do they respond to emails? Timely?
    - Do you like them and get along with them as a person?
        - While this isn't a necessity, it helps.
    - Talk to other students about their advisor – find commonalities/differences and assess if this is OK with you and what you want as a student.
    - What is their track record with other students? How many graduate students have finished, quit, or changed advisors?
    - Does your advisor have a specific interest in your topic; this will fuel their interest to be more involved and more eager to talk with you.
- Create a timeline, and then rewrite it often.
- Push yourself, but don't beat yourself up too much.
- Realize that academia is a fickle dick and sometimes it is lame.
- Treat yourself.
- Shoot me an email, ask anything (never be afraid to ask questions…)

LITERATURE CITED

Abood, S. A., J. S. H. Lee, Z. Burivalova, J. Garcia-Ulloa, and L. P. Koh. 2015. Relative contributions of the logging, fiber, oil palm, and mining industries to forest loss in Indonesia. Conservation Letters 8:58–67.

Allouche, O., M. Kalyuzhny, G. Moreno-Rueda, M. Pizarro, and R. Kadmon. 2012. Area-heterogeneity tradeoff and the diversity of ecological communities. Proceedings of the National Academy of Sciences 109:17495–17500.

An, L. 2012. Modeling human decisions in coupled human and natural systems: Review of agent-based models. Ecological Modelling 229:25–36.

Anderson, R. P. 2013. A framework for using niche models to estimate impacts of climate change on species distributions. Annals of the New York Academy of Sciences 1297:8–28.

Aphangthong, T. S., and K. Yasuyuki. 2009. Continuity and Discontinuity in Land Use Changes : A Case Study in Northern Lao Villages. Southeast Asian Studies 47:263–286.

Austin, M. P. 2002. Spatial prediction of species distribution: An interface between ecological theory and statistical modelling. Ecological Modelling 157:101–118.

Bailey, J. S., a. Ramakrishna, and G. Kirchhof. 2008. Relationships between important soil variables in moderately acidic soils (pH ≥5.5) in the highlands of Papua New Guinea and management implications for subsistence farmers. Soil Use and Management 24:281–291.

Baldwin, S. L., P. G. Fitzgerald, and L. E. Webb. 2012. Tectonics of the New Guinea region. Annual Review of Earth and Planetary Sciences 40:495–520.

Barr, J. 1999. Drought assessment: the 1997–98 El Niño drought in Papua New Guinea and the Solomon Islands. Disaster Management: Crisis and Opportunity Conference Winter:1–7.

de Barros Ferraz, K. M. P. M., S. F. de Barros Feraz, R. C. de Paula, and C. Breitenmoser. 2012. Species distribution modeling for conservation purposes. Natureza & Conservacao 10:214–220.

Bein, F. L., J. Wagner, and J. Wilson. 2007. Food Garden Capacity and Population Growth : A Case in Papua New Guinea. FOCUS on Geography 50.

Bell, D. M., and D. R. Schlaepfer. 2016. On the dangers of model complexity without ecological justification in species distribution modeling. Ecological Modelling 330:50–59.

Bishop Museum. 2015. Bernice Pauahi Bishop Museum. Available at www.bishopmuseum.org, Accessed July 2015.

Boivin, N. L., M. A. Zeder, D. Q. Fuller, A. Crowther, G. Larson, J. M. Erlandson, T. Denham, and M. D. Petraglia. 2016. Ecological consequences of human niche construction: Examining long-term anthropogenic shaping of global species distributions. Proceedings of the National Academy of Sciences 113:201525200.

Boria, R. A., L. E. Olson, S. M. Goodman, and R. P. Anderson. 2014. Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. Ecological Modelling 275:73–77.

Bourke, R. M. 2001. Intensification of Agricultural Systems in Papua New Guinea. Asia Pacific Viewpoint 42:219–235.

Bourke, R. M. 2012. PNG's population predictions compared with preliminary 2011 census data. http://pacificinstitute.anu.edu.au/outrigger/2012/07/03/pngs-population-predictions-compare-2011-census/.

Bourke, R. M., M. G. Allen, and J. G. Salisbury. 2000. Food Security for Papua New Guinea. Page 330Proceedings of the Papua New Guinea Food and Nutrition 2000 Conference, PNG University of Technology, Lae, 1-300.

Brooks, T. M., R. A. Mittermeier, G. A. B. da Fonseca, J. Gerlach, M. Hoffmann, J. F. Lamoreux, C. G. Mittermeier, J. D. Pilgrim, and A. S. L. Rodrigues. 2006. Global biodiversity conservation priorities. Science (New York, N.Y.) 313:58–61.

Brown, J. L. 2014. SDMtoolbox: A python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. Methods in Ecology and Evolution 5:694–700.

Bryan, J. E., and P. Shearman. 2015. The State of the Forests of Papua New Guinea 2014: Measuring change over the period 2002-2014. Page University of Papua New Guinea. Port Moresby, PNG.

Bryan, J. E., and P. L. Shearman. 2008. PNG resource information system handbook 3rd edition.

Chambers, R. 1994. The origins and practice of participatory rural appraisal. World Development 22:953–969.

Chase, M. W., M. J. M. Christenhusz, M. F. Fay, J. W. Byng, W. S. Judd, D. E. Soltis, D. J. Mabberley, A. N. Sennikov, P. S. Soltis, P. F. Stevens, B. Briggs, S. Brockington, A. Chautems, J. C. Clark, J. Conran, E. Haston, M. M??ller, M. Moore, R. Olmstead, M. Perret, L. Skog, J. Smith, D. Tank, M. Vorontsova, and A. Weber. 2016. An update of the Angiosperm Phylogeny Group classification for the orders and families of flowering plants: APG IV. Botanical Journal of the Linnean Society 181:1–20.

Condit, R., N. Pitman, E. G. L. Jr, J. Chave, R. B. Foster, P. N. V, S. Aguilar, R. Valencia, H. C. Muller-landau, E. Losos, S. P. Hubbell, R. Condit, N. Pitman, E. G. L. Jr, J. Chave, J. Terborgh, R. B. Foster, P. N. V, S. Aguilar, R. Valencia, G. Villa, H. C. Muller-landau, E. Losos, and S. P. Hubbell. 2016. Beta-diversity in tropical forest trees. Science 295:666–669.

Conn, B. J., L. L. Lee, and R. (2004+). (http://www. pngplants. org/PNGdatabase. Kiapranis. 2004. PNGplants database: Plant collections from Papua New Guinea. http://www.pngplants.org/PNGdatabase.

Cronk, Q. C. B., M. Kiehn, W. L. Wagner, and J. F. Smith. 2005. Evolution of Cyrtandra (Gesneriaceae) in the Pacific Ocean: The origin of a supertramp clade. American Journal of Botany 92:1017–1024.

Delang, C. O., and W. M. Li. 2013. Ecological Succession on Fallowed Shifting Cultivation Fields: A Review of the Literature. Springer Briefs, Hong Kong.

Dislich, C., A. C. Keyel, J. Salecker, Y. Kisel, KatrinM.Meyer, Mark Auliya, A. D. Barnes, D. M. Corre, K. Darras, H. Faust, B. Hess, S. Klasen, A. Knohl, H. Kreft, A. Meijide, F. Nurdiansyah, F. Otten, G. Pe'er, S. Steinebach, S. Tarigan, M. H. Tolle, T. Tscharntke, and K. Wiegand. 2016. A review of the ecosystem functions in oil palm plantations, using forests as a reference system. Biological reviews of the Cambridge Philosophical Society:000–000.

Dormann, C. F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carré, J. R. G. Marquéz, B. Gruber, B. Lafourcade, P. J. Leitão, T. Münkemüller, C. Mcclean, P. E. Osborne, B. Reineking, B. Schröder, A. K. Skidmore, D. Zurell, and S. Lautenbach. 2013. Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. Ecography 36:027–046.

Dunn, C. E. 2007. Participatory GIS: a people's GIS? Progress in Human Geography 31:616–637.

Eden, M. 1993. Swidden cultivation in forest and savanna in lowland southwest Papua New Guinea. Human Ecologycology 21:145–166.

Elith, J., C. H. Graham, S. Ferrier, A. Guisan, R. P. Anderson, M. Dudı, R. J. Hijmans, F. Huettmann, J. R. Leathwick, A. Lehmann, J. Li, L. G. Lohmann, B. A. Loiselle, G. Manion, C. Moritz, M. Nakamura, Y. Nakazawa, J. M. Overton, A. T. Peterson, S. J. Phillips, K. Richardson, R. Scachetti-Pereira, R. E. Schapire, S. Williams, M. S. Wisz, and N. E. Zimmermann. 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29:129–151.

Elith, J., S. J. Phillips, T. Hastie, M. Dudík, Y. E. Chee, and C. J. Yates. 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions 17:43–57.

ESRI ArcGIS online data. 2016. Enviornmental Systems Resesarch Institute: ArcGIS Desktop: Release 10.3. Redlands, CA.

Estrella, M., J. Blauert, D. Campilan, J. Gaventa, J. Gonsalves, D. Johnson, and R. Ricafort. 2000. LEARNING FROM CHANGE: Issues and experiences in participatory monitoring and evaluation. Page (M. Estrella, Ed.). Intermediate Technology Publications.

Evangelista, P. H., S. Kumar, T. J. Stohlgren, C. S. Jarnevich, A. W. Crall, J. B. Norman, and D. T. Barnett. 2008. Modelling invasion for a habitat generalist and a specialist plant species. Diversity and Distributions 14:808–817.

Filer, C., R. J. Keenan, B. J. Allen, and J. R. McAlpine. 2009. Deforestation and forest degradation in Papua New Guinea. Annals of Forest Science 66:813–813.

Fox, J., Y. Fujita, D. Ngidang, N. Peluso, L. Potter, N. Sakuntaladewi, J. Sturgeon, and D. Thomas. 2009. Policies, political-economy, and swidden in Southeast Asia. Human Ecology 37:305–322.

Fox, J., R. R. Rindfuss, S. J. Walsh, and V. Mishra, editors. 2003. People and the environment: approaches for linking household and community surveys to remote sensing and GIS. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Fox, J., D. M. Truong, T. A. Rambo, N. P. Tuyen, L. T. Cuc, and S. J. Leisz. 2000. Shifting Cultivation : A New Old Paradigm for Managing Tropical Forests. BioScience 50:521–528.

Fritz, S., I. McCallum, C. Schill, C. Perger, L. See, D. Schepaschenko, M. van der Velde, F. Kraxner, and M. Obersteiner. 2012. Geo-Wiki: An online platform for improving global land cover. Environmental Modelling and Software 31:110–123.

GBIF. 2015. Papua New Guinea and Indonesia occurance-only data. Global Biodiversity Information Facility.

Geist, H. J., and E. F. Lambin. 2002. Proximate Causes and Underlying Driving Forces of Tropical Deforestation. BioScience 52:143.

Gong, P., J. Wang, L. Le Yu, Y. Y. Y. Y. Zhao, L. Liang, Z. Niu, X. Huang, H. Fu, S. Liu, C. Li, X. Li, W. Fu, C. Liu, Y. Xu, X. Wang, Q. Cheng, L. Hu, W. Yao, H. H. Zhang, P. Zhu, Z. Zhao, Y. Zheng, L. Ji, Y. Zhang, H. Chen, A. Yan, J. Guo, L. Wang, X. Liu, T. Shi, M. Zhu, Y. Chen, G. Yang, P. Tang, B. Xu, C. Giri, N. Clinton, Z. Zhu, and J. J. Chen. 2013. Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data. International Journal of Remote Sensing 34:2607–2654.

Hansen, M. C., P. V Potapov, R. Moore, M. Hancher, S. A. Turubanova, and A. Tyukavina. 2013. High-resolution global maps of 21st-centruy forest cover change. Science 342:850–853.

Hanspach, J., I. Kuhn, S. Pompe, and S. Klotz. 2010. Predictive performance of plant species distribution models depends on species traits. Perspectives in Plant Ecology, Evolution and Systematics 12:219–225.

Heads, M. 2001. Regional patterns of biodiversity in New Guinea plants. Botanical Journal of the Linnean Society 136:67–73.

Heads, M. 2006. Biogeography, ecology and tectonics in New Guinea. Journal of Biogeography 33:957–958.

Heads, M. 2009. Dispersal and vicariance. Pages 947–950Molecular panbiogeography of the tropics. University of California Press, Berkely, CA, USA.

Helmer, E. H., M. A. Lefsky, and D. A. Roberts. 2009. Biomass accumulation rates of Amazonian secondary forest and biomass of old-growth forests from Landsat time series and the Geoscience Laser Altimeter System. Journal of Applied Remote Sensing 3:33505.

Herrmann, S. M., A. Anyamba, and C. J. Tucker. 2005. Recent trends in vegetation dynamics in the African Sahel and their relationship to climate. Global Environmental Change 15:394–404.

Herrmann, S. M., I. Sall, and O. Sy. 2014. People and pixels in the Sahel: a study linking coarse-resolution remote sensing observations to land users' perceptions of their changing environment in Senegal. Ecology and Society 19(3).

Hett, C., J.-C. Castella, A. Heinimann, P. Messerli, and J.-L. Pfund. 2012. A landscape mosaics approach for characterizing swidden systems from a REDD+ perspective. Applied Geography 32:608–618.

Hijmans, R. J., S. E. Cameron, J. L. Parra, P. G. Jones, and A. Jarvis. 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25:1965–1978.

Hill, K. C., and R. Hall. 2003. Mesozoic–Cenozoic evolution of Australia's New Guinea margin in a west Pacific context. Geological Society of America Special Papers 372:265–289.

Hoover, J. D. 2015. Modeling plant hotspots in New Guinea and village-scale land-change dynamics in Papua New Guinea (Doctoral Dissertation). Colorado State University, Fort Collins, Colorado, USA.

Hoover, J. D., S. J. Leisz, and M. Laituri. (n.d.). Comparing and combining Landsat satellite imagery and participatory data to assess land-use and land-cover changes in a coastal village in Papua New Guinea. Human Eology.

Hope, G. 2014. The sensitivity of the high mountain ecosystems of New Guinea to climatic change and anthropogenic impact. Arctic Antarctic and Alpine Research 46:777–786.

IPCC Core Writing Team. 2001. Climate change 2001: impacts, adaptation and vulnerability, Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Page (J. J. McCarthy, O. F. Canziani, N. A. Leary, D. J. Dokken, and K. S. White, Eds.). AR3. Cambrige Universtiy Press, Cambrige, UK and New York, USA.

ISRIC -- World Soil Information. 2013. SoilGrids: an automated system for global soil mapping, Accessed Jan. 2015. http://www.isric.org/.

IUCN and UNEP-WCMC. 2016. The World Database on Protected Areas (WDPA), Accessed May 2016. www.protectedplanet.net.

Katovai, E., D. D. Katovai, W. Edwards, and W. F. Laurance. 2015. Forest structure, plant diversity and local endemism in a highly varied New Guinea landscape. Tropical Conservation Science 8:284–300.

Kauth, R. J., and G. S. Thomas. 1976. The Tasselled Cap -- A Graphic Description of the Spectral-Temporal Development of Agricultural Crops as Seen by LANDSAT. Pages 1–13Symposium on Machine Processing of Remotely Sensed Data. Laboratory for Applications of Remote Sensing, West Lafayette, Indiana.

Kenneth, G. 2012. Population of PNG is more than 7 million. http://www.postcourier.com.pg/20120404/news02.htm.

Keppel, G., A. J. Lowe, and H. P. Possingham. 2009. Changing perspectives on the biogeography of the tropical South Pacific: Influences of dispersal, vicariance and extinction. Journal of Biogeography 36:1035–1054.

King, B. H. 2002. Towards a Participatory GIS: Evaluating Case Studies of Participatory Rural Appraisal and GIS in the Developing World. Cartography and Geographic Information Science 29:43–52.

Koczberski, G., and G. N. Curry. 2005. Making a living: Land pressures and changing livelihood strategies among oil palm settlers in Papua New Guinea. Agricultural Systems 85:324–339.

Koczberski, G., G. N. Curry, and V. Bue. 2012. Oil palm, food security and adaptation among smallholder households in Papua New Guinea. Asia Pacific Viewpoint 53:288–299.

Koczberski, G., G. N. Curry, and B. Imbun. 2009. Property rights for social inclusion: Migrant strategies for securing land and livelihoods in Papua New Guinea. Asia Pacific Viewpoint 50:29–42.

Kohl, M., R. Lasco, M. Cifuentes, ??rjan Jonsson, K. T. Korhonen, P. Mundhenk, J. de Jesus Navar, and G. Stinson. 2015. Changes in forest production, biomass and carbon: Results from the 2015 UN FAO Global Forest Resource Assessment. Forest Ecology and Management 352:21–34.

Kremen, C., and A. Miles. 2012. Ecosystem services in biologically diversified versus conventional farming systems: Benefits, externalities, and trade-offs. Ecology and Society 17.

Kumar, S., E. G. LeBrun, T. J. Stohlgren, J. A. Stabach, D. L. McDonald, D. H. Oi, and J. S. LaPolla. 2015. Evidence of niche shift and global invasion potential of the Tawny Crazy ant, Nylanderia fulva. Ecology and Evolution 5:4628–4641.

Laituri, M. 2011. Ingidenous Peoples' Issues and Indigenous Uses of GIS. The SAGE Handbook of GIS and Society:202–221.

Lambin, E. F., H. J. Geist, and E. Lepers. 2003. Dynamics of Land-Use and Land-Cover Change in Tropical Regions. Annual Review of Environment and Resources 28:205–241.

Lambin, E. F., B. L. Turner, H. J. Geist, S. B. Agbola, A. Angelsen, C. Folke, J. W. Bruce, O. T. Coomes, R. Dirzo, P. S. George, K. Homewood, J. Imbernon, R. Leemans, X. Li, E. F. Moran, M. Mortimore, P. S. Ramakrishnan, J. F. Richards, W. Steffen, G. D. Stone, U. Svedin, and T. A. Veldkamp. 2001. The causes of land-use and land-cover change : moving beyond the myths. Global Environmental Change 11:261–269.

Laney, R., and B. L. Turner. 2015. The persistence of self-provisioning among smallholder farmers in northeast Madagascar. Human Ecology 43:811–826.

Lauer, M., and S. Aswani. 2010. Indigenous knowledge and long-term ecological change: Detection, interpretation, and responses to changing ecological conditions in pacific island communities. Environmental Management 45:985–997.

Leisz, S. J., J. B. Burnett, and A. Allison. 2000. Consensus Report Climate Change and Biodiversity in Melanesia: What do we know?

Leisz, S. J., and M. S. Rasmussen. 2012. Mapping fallow lands in Vietnam's north-central mountains using yearly Landsat imagery and a land-cover succession model. International Journal of Remote Sensing 33:6281–6303.

Levine, A. S., and C. L. Feinholz. 2015. Participatory GIS to inform coral reef ecosystem management : Mapping human coastal and ocean uses in Hawaii. Applied Geography 59:60–69.

Li, P., Z. Feng, L. Jiang, C. Liao, and J. Zhang. 2014. A review of swidden agriculture in Southeast Asia. Remote Sensing 6:1654–1683.

Longenecker, K., R. Langston, H. Bolick, and U. Kondio. 2011. Reproduction, Catch, and Size Structure of Exploited Reef-Fishes at Kamiali Wildlife Management Area, Papua New Guinea.

Lynam, T., W. De Jong, D. Sheil, T. Kusumanto, and K. Evans. 2007. A Review of Tools for Incorporating Community Knowledge, Preferences , and Values into Decision Making in Natural Resources Management. Ecology and Society 12(1).

Mack, A., and L. E. Alonso. 2000. A biological assessment of the Wapoga River area of Northwestern Irian Jaya, Indonesia. Page Conservation International: A biological assessment of the Wapoga River Area of Northwestern Irian Jaya, Indonesia.

Mandl, N., M. Lehnert, M. Kessler, and S. R. Gradstein. 2010. A comparison of alpha and beta diversity patterns of ferns, bryophytes and macrolichens in tropical montane forests of southern Ecuador. Biodiversity and Conservation 19:2359–2369.

La Manna, L., S. D. Matteucci, and T. Kitzberger. 2011. Modelling Phytophthora disease risk in Austrocedrus chilensis forests of Patagonia. European Journal of Forest Research 131:323–337.

Mather, A. S. 2005. Assessing the world's forests. Global Environmental Change 15:267–280.

Mather, A. S., and C. L. Needle. 2000. The relationships of population and forest trends. The Geographical Journal 166:2–13.

Matthews, R. B., N. G. Gilbert, A. Roach, J. G. Polhill, and N. M. Gotts. 2007. Agent-based land-use models: a review of applications. Landscape Ecology 22:1447–1459.

McAlpine, J. R., and D. F. Freyne. 2001. Land use change and intensification in Papua New Guinea 1975-1996. Asia Pacific viewpoint 42:209–18.

McCall, M. K. 2003. Seeking good governance in participatory-GIS: a review of processes and governance dimensions in applying GIS to participatory spatial planning. Habitat International 27:549–573.

McCall, M. K., and C. E. Dunn. 2012. Geo-information tools for participatory spatial planning: Fulfilling the criteria for "good" governance? Geoforum 43:81–94.

McGavin, G. 2009. Scientific expidition to Mount Bosavi, Southern Highlands, Papua New Guinea. Report.

Mertz, O., S. J. Leisz, A. Heinimann, K. Rerkasem, W. Dressler, V. C. Pham, K. C. Vu, D. Schmidt-Vogt, C. J. P. Colfer, M. Epprecht, C. Padoch, and L. Potter. 2009a. Who counts? Demography of Swidden cultivators in Southeast Asia. Human Ecology 37:281–289.

Mertz, O., C. Padoch, J. Fox, R. A. Cramb, and S. J. Leisz. 2009b. Swidden change in Southeast Asia: Understanding causes and consequences. Human Ecology 37:259–264.

Miettinen, J., C. Shi, and S. C. Liew. 2011. Deforestation rates in insular Southeast Asia between 2000 and 2010. Global Change Biology 17:2261–2270.

Ministry of Forestry. 2010. Ministry of Forestry of Indonesia. Pemantauan Hutan di Indonesia (Forest Monitoring in Indonesia). Overview of the forest monitoring activities by the Ministry of Forestry of Indonesia. (http://www.unredd.net/index.php?option=com_docman&task=doc_download.

Minnegal, M., and P. D. Dwyer. 2000. Responses to a Drought in the Interior Lowlands of Papua New Guinea : A Comparison of Bedamuni and Kubo-Konai. Human Ecology 28:493–525.

Mittermeier, R. A., C. G. Mittermeier, T. M. Brooks, J. D. Pilgrim, W. R. Konstant, G. A. B. da Fonseca, and C. Kormos. 2003. Wilderness and biodiversity conservation. Proceedings of the National Academy of Sciences of the United States of America 100:10309–13.

Morton, J. F. 2007. The impact of climate change on smallholder and subsistence agriculture. Proceedings of the National Academy of Sciences of the United States of America 104:19680–5.

Neall, V. E., and S. A. Trewick. 2008. The age and origin of the Pacific islands: a geological overview. Phil. Trans. R. Soc. B 363:3293–3308.

Nekola, J. C., and P. S. White. 1999. Special Paper: The distance decay of similarity in biogeography and ecology. Journal of Biogeography 26:867–878.

Nelson, P. N., J. Gabriel, C. Filer, M. Banabas, J. A. Sayer, G. N. Curry, G. Koczberski, and O. Venter. 2014. Oil palm and deforestation in Papua New Guinea. Conservation Letters 7:188–195.

Ningal, T., A. E. Hartemink, and A. K. Bregt. 2008. Land use change and population growth in the Morobe Province of Papua New Guinea between 1975 and 2000. Journal of Environmental Management 87:117–124.

Ohtsuka, R. 1994. Subsistence ecology and carying capacity in two Papua New Guinea populations. Journal of Biosocial Science 26:395–407.

de Oliveira, G., T. F. Rangel, M. S. Lima-Ribeiro, L. C. Terribile, and J. A. F. Diniz-Filho. 2014. Evaluating, partitioning, and mapping the spatial autocorrelation component in ecological niche modeling: A new approach based on environmentally equidistant records. Ecography 37:637–647.

Ostrom, E. 2009. A general framework for analyzing sustainability of social-ecological systems. Science (New York, N.Y.) 325:419–22.

Owens, H. L., L. P. Campbell, L. L. Dornak, E. E. Saupe, N. Barve, J. Sober??n, K. Ingenloff, A. Lira-Noriega, C. M. Hensz, C. E. Myers, and A. T. Peterson. 2013. Constraints on interpretation of ecological niche models by limited environmental ranges on calibration areas. Ecological Modelling 263:10–18.

Padoch, C., K. Coffey, O. Mertz, S. J. Leisz, J. Fox, and R. L. Wadley. 2007. The Demise of Swidden in Southeast Asia? Local Realities and Regional Ambiguities. Danish Journal of Geography 107:29–42.

Peterson, A. T., J. Soberon, R. G. Pearson, R. P. Anderson, M. Martinez-Meyer, Enrique, Nakamura, and M. Bastos Araujo. 2011. Ecological Niches and Geographic Distributions. Princeton University Press, Princeton, NJ.

Phillips, S. J., R. P. Anderson, and R. E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling 190:231–259.

Phillips, S. J., and M. Dudık. 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31:161–175.

Phillips, S. J., M. Dudík, J. Elith, C. H. Graham, A. Lehmann, J. Leathwick, and S. Ferrier. 2009. Sample selection bias and presence-only distribution models: Implications for background and pseudo-absence data. Ecological Applications 19:181–197.

Polhemus, D., and J. T. Polhemus. 1998. Assembling New Guinea: 40 million years of island arc accretion as indicated by the distributions of aquatic Heteroptera (Insecta). Biogeography and geological evolution of SE Asia:327–340.

Potapov, P., Y. A. T. S., D. M, L. Laestadius, C. Thies, D. Aksenov, A. Egorov, Y. Yesipova, G. I, K. M. K. A., A. Manisha, E. Tsybikova, and I. Zhuravleva. 2008. Mapping the World's Intact Forest Landscapes by Remote Sensing. Ecology and Society 13(2): 51:16.

Radosavljevic, A., and R. P. Anderson. 2014. Making better Maxent models of species distributions: Complexity, overfitting and evaluation. Journal of Biogeography 41:629–643.

Raes, N., and H. ter Steege. 2007. A null-model for significance testing of presence-only species distribution models. Ecography 30:727–736.

Ramakrishna, A., and S. Bang. 2015. The impacts of climate change on food security and management in Papua New Guinea. Page 29*in* W. Ganpat and W. Isaac, editors.Impacts of Climate Change on Food Security in Small Island Developing States.

Ramanath, M. A., and N. Gilbert. 2004. The Design of Participatory Agent-Based Social Simulations. Journal of Artificial Societies and Social Stimulation 7:1–16.

Raymond, C. M., I. Fazey, M. S. Reed, L. C. Stringer, G. M. Robinson, and A. C. Evely. 2010. Integrating local and scientific knowledge for environmental management. Journal of Environmental Management 91:1766–1777.

Reed, M. S. 2008. Stakeholder participation for environmental management: A literature review. Biological Conservation 141:2417–2431.

Rerkasem, K., D. Lawrence, C. Padoch, D. Schmidt-Vogt, A. D. Ziegler, and T. B. Bruun. 2009. Consequsences of swidden transitions for crop and fallow biodiversity in Southeast Asia. Human Ecology 37:347–360.

Richards, S. J., and B. G. Gamui. 2011. Rapid biological assessments of the Nakanai Mountains and the upper Strickland basin: surveying the biodiversity of Papua New Guinea’s sublime karst environments. RAP Bulletin Biological Assessment 1-60.

Rindfuss, R. R., S. J. Walsh, V. Mishra, J. Fox, and G. P. Dolcemascolo. 2003. Linking household and remotely sensed data. Page *in* J. Fox, R. R. Rindfuss, S. J. Walsh, and V. Mishra, editors. People and the Environment: Approaches for linking Household and Community surveys to Remote Sensing and GIS. Kluwer Academic Publishers, New York.

Rindfuss, R. R., S. J. Walsh, B. L. Turner, J. Fox, and V. Mishra. 2004. Developing a science of land change: challenges and methodological issues. Proceedings of the National Academy of Sciences of the United States of America 101:13976–81.

Roos, M. C., P. J. A. Keßler, S. R. Gradstein, and P. Baas. 2004. Species Diversity and Endemism of Five Major Malesian Islands: Diversity-Area Relationships. Journal of Biogeography 31:1893–1908.

Ruankaew, N., C. LePage, P. Dumrongrojwattana, C. Barnaud, N. Gajaseni, A. van Paassen, and G. Trebuil. 2010. Companion modeling for integraded renewable resource management: A new collaborative approach to create common values for sustainable development. International Journal of Sustainable development and World Ecology 17:15–23.

Schmidt-Vogt, D., S. J. Leisz, O. Mertz, A. Heinimann, P. Messerli, M. Epprecht, P. Van Cu, V. K. Chi, M. Hardiono, and T. M. Dao. 2009a. An Assessment of Trends in the Extent of Swidden in Southeast Asia. Human Ecology 37:269–280.

Schmidt-Vogt, D., S. J. Leisz, O. Mertz, A. Heinimann, P. Messerli, M. Epprecht, P. Van Cu, V. K. Chi, M. Hardiono, and T. M. Dao. 2009b. An Assessment of Trends in the Extent of Swidden An Assessment in Southeast Asia. Human Ecology 37:269–280.

Shearman, P. L., J. Ash, B. Mackey, J. E. Bryan, and B. Lokes. 2009. Forest Conversion and Degradation in Papua New Guinea 1972 – 2002. Biotropica 41:379–390.

Shearman, P. L., and J. Bryan. 2011. A bioregional analysis of the distribution of rainforest cover, deforestation and degradation in Papua New Guinea. Austral Ecology 36:9–24.

Sidder, A. M., S. Kumar, M. Laituri, and J. S. Sibold. 2016. Using spatiotemporal correlative niche models for evaluating the effects of climate change on mountain pine beetle. Ecosphere 7(7):12.

Sirén, A. H. 2007. Population Growth and Land Use Intensification in a Subsistence-based Indigenous Community in the Amazon. Human Ecology 35:669–680.

Stropp, J., R. Ladle, ana C. M. Malhado, H. Joaquín, J. Gaffuri, W. Temperley, J. O. Skøien, and P. Mayaux. 2016. Mapping ignorance: 300 years of knowledge of flowering plants in Africa. Global Ecology and Biogeography 25:1085–1093.

Supriatna, J., Y. de Fretes, A. Mack, Y. P. Yeager, S. Olivieri, J. B. Burnett, I. Wijayanto, S. Suryadi, and A. Suryadi. 1999. The Irian Jaya Biodiversity Conservation Priority- Setting Workshop. Washington, DC.

Syfert, M. M., M. J. Smith, and D. A. Coomes. 2013. The Effects of Sampling Bias and Model Complexity on the Predictive Performance of MaxEnt Species Distribution Models. PLoS ONE 8(2):10.

Takeuchi, W. 2007. Vascular plants of the Kaijende Highlands, Papua New Guinea: Taxonomic and vegetation survey, RAP Bulletin Biological Assessment 25-39.

Tobler, W. R. 1970. A Computer movie simulating urban growth in the Detroit region supplement. Economic Geography 46:234–240.

Trigas, P., M. Panitsa, and S. Tsiftsis. 2013. Elevational gradient of vascular plant species richness and endemism in crete - The effect of post-isolation mountain uplift on a continental island system. PLoS ONE 8 (3):13.

Tuanmu, M.-N., and W. Jetz. 2015. A global, remote sensing-based characterization of terrestrial habitat heterogeneity for biodiversity and ecosystem modelling. Global Ecology and Biogeography 24:1329–1339.

Turner II, B. L., E. F. Lambin, and A. Reenberg. 2007. The emergence of land change science for global environmental change and sustainability. Proceedings of the National Academy of Sciences of the United States of America 104:20666–20672.

Umezaki, M., Y. Kuchikura, and T. Yamauchi. 2000. Impact of Population Pressure on Food Production : An Analysis of Land Use Change and Subsistence Pattern in the Tari Basin in Papua New Guinea Highlands. Human Eology 28:359–381.

Umezaki, M., T. Yamauchi, and R. Ohtsuka. 2002. Time allocation to subsistence activities among the Huli in rural and urban Papua New Guinea. Journal of Biosocial Science 34:133–7.

Veloz, S. D. 2009. Spatially autocorrelated sampling falsely inflates measures of accuracy for presence-only niche models. Journal of Biogeography 36:2290–2299.

Vermote, E., and N. E. Saleous. 2007. LEDAPS surface reflectance product description.

van Vliet, N., O. Mertz, A. Heinimann, T. Langanke, U. Pascual, B. Schmook, C. Adams, D. Schmidt-Vogt, P. Messerli, S. J. Leisz, J.-C. Castella, L. Jørgensen, T. Birch-Thomsen, C. Hett, T. Bech-Bruun, A. Ickowitz, K. C. Vu, K. Yasuyuki, J. Fox, C. Padoch, W. Dressler, and A. D. Ziegler. 2012. Trends, drivers and impacts of changes in swidden cultivation in tropical forest-agriculture frontiers: A global assessment. Global Environmental Change 22:418–429.

Voinov, A., and F. Bousquet. 2010. Modelling with stakeholders☆. Environmental Modelling & Software 25:1268–1281.

Vollering, J., A. Schuiteman, E. de Vogel, R. van Vugt, and N. Raes. 2015. Phytogeography of New Guinean orchids: Patterns of species richness and turnover. Journal of Biogeography:204–214.

Wagner, J. R. 2002. Commons in transition: An analysis of social and ecological change in a coastal rainforest enviroment in Rural Papua New Guinea (Doctoral Dissertation) McGill University, Montreal, CAN, 1-393.

Wakie, T. T., M. Laituri, and P. H. Evangelista. 2016. Assessing the distribution and impacts of Prosopis juliflora through participatory approaches. Applied Geography 66:132–143.

West, P. 2006. Environmental Conservation and Mining: Between Experience and Expectation in the Eastern Highlands of Papua New Guinea. Contemporary Pacific 18:295–314.

Wilbanks, T. J., and R. W. Kates. 1999. Global change in local places: how scale matters. Climate Change 43:601–628.

Wisz, M. S., R. J. Hijmans, J. Li, A. T. Peterson, C. H. Graham, A. Guisan, J. Elith, M. Dudík, S. Ferrier, F. Huettmann, J. R. Leathwick, A. Lehmann, L. Lohmann, B. A. Loiselle, G. Manion, C. Moritz, M. Nakamura, Y. Nakazawa, J. M. Overton, S. J. Phillips, K. S. Richardson, R. Scachetti-Pereira, R. E. Schapire, J. Soberón, S. E. Williams, and N. E. Zimmermann. 2008. Effects of sample size on the performance of species distribution models. Diversity and Distributions 14:763–773.

World Bank. 2016. World Bank population data: http://www.worldbank.org/en/country/png. Accessed May 2016.

World Resources Institute. 2016. Papua New Guinea Exploratory Oil and Natural Gas Mining Concessions. http://pubs.wri.org/pubs_dataset.cfm?PubID=3874.

Wu, J. 2004. Effects of changing scale on landscape pattern analysis: scaling relations. Landscape Ecology 19:125–138.

Yu, L., and P. Gong. 2012. Google Earth as a virtual globe tool for Earth science applications at the global scale: progress and perspectives. International Journal of Remote Sensing 33:3966–3986.

Ziegler, A. D., J. Fox, E. L. Webb, C. Padoch, S. J. Leisz, R. a Cramb, O. Mertz, T. B. Bruun, and T. D. Vien. 2011. Recognizing contemporary roles of swidden agriculture in transforming landscapes of southeast Asia. Conservation Biology 25:846–8.

APPENDIX 1

SUPPLEMENTARY INFORMATION FOR CHAPTER 2 AND 3:

8.1. Structured Survey questions

8.1.1. Coastal and Reef resources

1. Do you collect coastal or reef resources?
2. If yes, what coastal resources do you collect?
3. Resource name:
4. Method used to collect:
5. How often do you collect (resource) per week?
6. Number amount collected per week:
7. For consumption [C] or sale [S]? How much do you consume (%)? How much do you sell (%)?
8. If for sale, how many (kilograms) of (resource) do you sell each year?
9. Has the amount you sell changed since 10 years ago? Why?
10. Where do you go to collect it (local name of location; direction from village)?
11. Is this the same place you went to collect it 10 years ago?
12. Do you collect it year round? If not, what seasons can you collect it in? Why?
13. Do you collect the same amount of (resource) as you did 10 yrs ago?
14. Why has the amount you collect changed?

8.1.2. Land resources

15. Do you cultivate land for crops? If yes, what kind of crops do you cultivate:
16. Crop name:
17. How much area is it grown on?
18. Is it mono-cropped or planted with other crops?
19. How much did you harvest last year?
20. How do you plant your crops? (By hand or with a machine?)
21. How do you cultivate your crops (e.g. how do you weed your crops)? (By hand or with a machine?)
22. How do you harvest your crops? (By hand or with a machine?)
23. Is this crop used for home consumption [C] or for sale [S]? How much do you consume (%)? How much do you sell (%)?
24. If for sale, how many (kilograms) of (crop) do you sell each year?
25. Has the amount you sell changed since 10 years ago? Why?
26. Where is the field you grow this crop (local name of area / direction and distance from home)?
27. Do you plant this crop every year?
28. If not, why do you decide to grow this crop?
29. Did you grow it regularly 10 years ago?
30. If not, why did you start to include it in the crops you grow?

8.1.3. Animal husbandry

31. Do you raise animals (animal husbandry)? Yes No If yes, what animals do you raise:
32. Animal name:
33. How many do you raise?
34. Are your animals penned? Or do they range freely through the community?
35. Where do they forage or where do you get forage for them?
36. Is this animal raised for home consumption [C] or for sale [S]?
37. If for consumption, how many do you consume per year?
38. Do you consume more today than you did 10 years ago?
39. If for sale, how many do you sell each year? Why?
40. Do you sell more today than you did 10 years ago? Why?
41. Did you raise this animal 10 years ago? If not, why did you start to raise it?

8.1.4. Forest Resources

42. Do you collect forest resources (including hunting)? Yes No If yes, what kind of resources do you collect:
43. Name of resource:
44. Method used to collect it:
45. Do you collect this resource year round or seasonally?
46. How much do you collect in a week (when you are able to collect it)?
47. Is this resource for home consumption [C] or for sale [S]?
48. Where do you go to collect it (local name of location; direction from village)?
49. Is this the same place you went to collect it 10 years ago?
50. Do you collect it year round? If not, what seasons can you collect it in? Why?
51. Do you collect the same amount of (resource) as you did 10 yrs ago?
52. Why has this changed?

8.1.5. Comparison of resources used

53. Which location is most important for your livelihood:
54. Coastal areas
55. Reef areas
56. Agricultural land areas
57. Forest areas
58. Why? ____

8.1.6. Other

59. Do you purchase other resources? Yes No If yes, what kind of resources do buy:
60. Name of resource:
61. What time of the year/season do you buy this resource?
62. How much do you buy?
63. Has the amount you buy increased or decreased since 10 years ago?
64. Why has the amount you buy changed since 10 years ago?
65. Does the price change seasonally?
66. Has this changed since10 years?
67. Why has this changed?

8.2. Annual calendar of activities

Table 8.1. Observations of resource quality and importance, household organization and population growth over time as recalled during the oral history interview. Household is referred to as HH.

Approximate time or year	Households divisions / Estimated Population	Garden	Reef	Ocean	Resource importance (among garden, reef and ocean)	Other observations and notes:
		Rank 0-5 (worst to best)				
Before WWII (early 1940's)	10 male households – usually 1-2 men (brothers) per HH / 3-4 women in HH/per 1 man Estimated 100 people	5	5	5	Equal importance	-could get reef/ocean fish along the coast easily -so many fish you could fill up a canoe -taro in gardens was very productive
Rubin marries (early 1960's)	Same as above Estimated 150 people	5	5	5	Equal importance	same as above
Gabo was born (1969)	Same as above Estimated 200 people	5	5	5	Equal importance	-still abundant resources -same as above
School was built (1976)	3 bigger men HH – clans combined to reduce fighting caused by more people Estimated 300 people	5	3	3	Garden is more important	-population grows and more fish are fished so garden becomes more dependable
Flood 1983	Same as 1976 Estimated 400 people	3	3	3	Garden is more important	-taro is taken out by an insect problem -food is disturbed because the soil is inundated with salt from ocean flooding

Fight with neighboring village (1985)	Clans become one group Estimated 450 people	3	3	3	Garden is more important	
Guesthouse built (1996)	Same as 1985 Estimated 600 people	2	2	2	Garden is more important	-population increases even more – many kids -kids fish more by diving, pole and spear so fish population begins to go down -taro is totally gone and replaced by cassava, banana and sweet potato – these new crops also have bug problems -taro is traditionally the best because ancestors used it – the ancestors only knew how to plant taro -many fishing techniques have changed: nets, hooks, poles are used more and boats are used more so access to on the reef and ocean is increased. -fish are frightened by boat motors and the petrol pollutes the water -nets bother the fish and catch turtles which is bad so many fish are scared of nets and goes to the 'deep' ocean -white man fishes too much – not enough for the locals
Today (2011)	Family houses are built Gara and Tabari are recognized but considered one group Estimated 1000 people (census year- 2011)	2	2	1	Garden is more important	

APPENDIX 2

SUPPLEMENTARY INFORMATION FOR CHAPTER 2 AND 3:

9.1. Methods

9.1.1. Satellite image analysis

Figure 8.1 shows the satellite image processing and land-cover classification methods. The first step was to preprocess the scenes with the NASA Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) tool. The LEDAPS tool transforms Landsat data into surface reflectance data through an atmospheric correction process (Vermote and Saleous 2007) and provides top of atmosphere reflectance, cloud masking, and atmospheric corrections. Cloud masks were created for each scene and compiled to create a single cloud mask. A two-pixel buffer expanded the cloud mask area to account for thin clouds not detected by LEDAPS, small gaps between clouds, and cloud shadows. The cloud mask was applied to each scene so that all scenes had the same processing extent. Next, the tasseled cap transformation (Kauth and Thomas 1976) was performed on each scene to create brightness, wetness, and greenness components or bands. The brightness band was subtracted from the wetness band for a wetness-brightness difference index (WBDI). The WBDI was used by Helmer et al. (2009) to classify forest succession in Brazil and proved useful for differentiating forest and agricultural land-cover. Due to the spectral range of the 1972-282 scene, the tasseled cap transformation for MSS data results in a yellowness band instead of a wetness band so the WBDI could not be calculated and was omitted for the 1972-282 scene. The results from the WBDI were classified using the K-means unsupervised classifier into 12 spectrally distinct land-cover classes for each scene. The 12 land-cover classes were reviewed and combined to create a binary map of swidden and non-swidden land-cover. For the 1972-282 scene the k-means classification was performed on the Tasseled Cap bands and land-cover classes were designated appropriately.

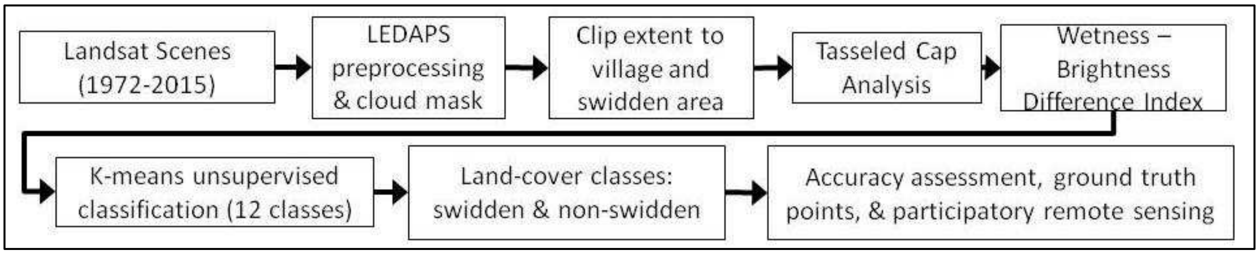

Figure 9.1. Image processing methods used to create and verify the land-cover maps.

9.1.2. Forest cover change analyses

Since only the swidden and village areas are included in the swidden change analyses, we wanted to also assure that larger tracts of forest did not change across the study extent. Thus, change detection was conducted for the available cloud-free images (1987-287, 1992-285, 2003-276, and 2015-301). The 1987 and 1992 scenes were used in the swidden-change time series because they were captured during the dry season, whereas the 2003 and 2015 scenes were captured during other times of the year and not used in the swidden change analyses. In this instance selecting scenes from different seasons was acceptable because we wanted to identify major, anthropogenic changes in forest cover over time (i.e. logged forests). To identify forest cover changes a Normalized Difference Vegetation Index (NDVI) was conducted for each scene. Then the percent of change between time steps was calculated for 1987-1992, 1992-2003, and 2003-2015, and for the whole temporal extent (1987-2015). Any major disturbance in forest cover would result in a high percentage of change between scenes and would form a distinct pattern. To assess any changes in forest cover, we manually reviewed each map for any tracts of forest change that would be akin to resource extraction, such as large swaths of timber extraction, road development, mining, or any other major change in forest cover. Because tropical forests can regenerate quickly, four scenes that are more widely spaced in time may not account for changes between dates. To confirm our results, which show a lack of forest cover changes, we sought ancillary land-cover change information via participatory research (Reed 2008; Raymond et al. 2010).

9.2. Results

9.2.1. Accuracy assessments

For the independent GE images the overall accuracy and Kappa statistic for the GE 2010 image is 92% and 84%, respectively (Table 8.2). The GE 2013 image achieved 95% for overall accuracy and 90% for the Kappa statistic. For the 40-scene dataset, the mean overall accuracy is 93% and Kappa statistic is 83% in Table 8.3.

Table 9.2. Classification accuracy results of the Landsat land-cover maps when referenced against the Google Earth images for 2010 and 2013.

	2010 Google Earth Image					
2010 Landsat Land-Cover Map	Class	Non-swidden	Swidden	Row Total	Users accuracy	Commission error
	Non-swidden	**40**	5	45	95%	5%
	Swidden	3	**52**	55	89%	11%
	Column Total	43	57	**92**		
	Producers accuracy	93%	91%			
	Omission error	7%	9%			
					Overall Accuracy	92%
					Kappa Statistic	84%
	2013 Google Earth Image					
2013 Landsat Land-Cover Map	Class	Non-swidden	Swidden	Row Total	Users accuracy	Commission error
	Non-swidden	**40**	3	43	96%	4%
	Swidden	2	**55**	43	93%	7%
	Column Total	42	58	**85**		
	Producers accuracy	94%	95%			
	Omission error	6%	5%			
					Overall Accuracy	95%
					Kappa Statistic	90%

Table 9.3. Classification accuracy results of the Landsat land-cover maps using visual interpretation of the raw images, averaged across all 40 images.

	Visual interpretation of 40 scenes					
Landsat Land-Cover Map	Class	Swidden	Non-swidden	Row Total	Users accuracy	Commission error
	Swidden	**948**	104	1052	90%	10%
	Non-swidden	142	**2210**	2352	94%	6%
	Column Total	1090	2314	**3158**		
	Producers accuracy	87%	96%			
	Omission error	13%	4%			
					Overall Accuracy	93%
					Kappa Statistic	83%

APPENDIX 3

SUPPLEMENTARY INFORMATION FOR CHAPTER 4

10.1. Appendix 3A: Additional Figures and List of Genera Used in Analysis with AUC Scores

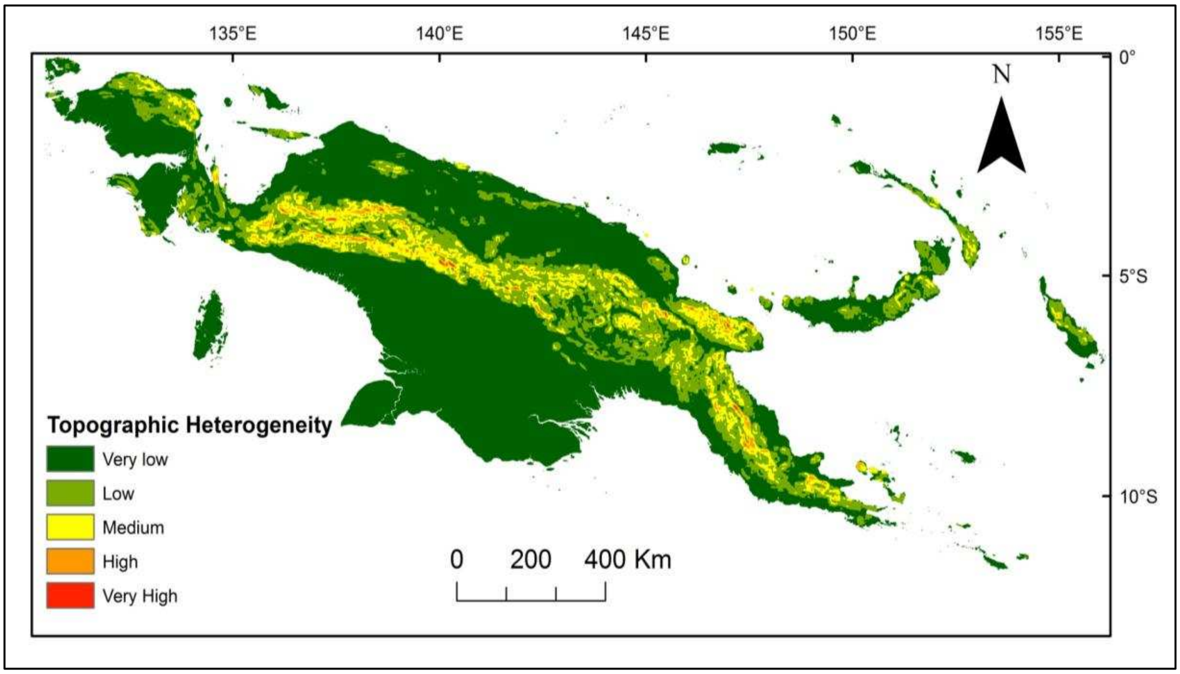

Figure 10.1. Topographic heterogeneity was derived using altitude layer at 1km spatial resolution and the SDMTools in ArcGIS. Green colors represent lower topographic heterogeneity and warm colors represent more topographic heterogeneity. The projection is in Albers Equal-area, WGS84.

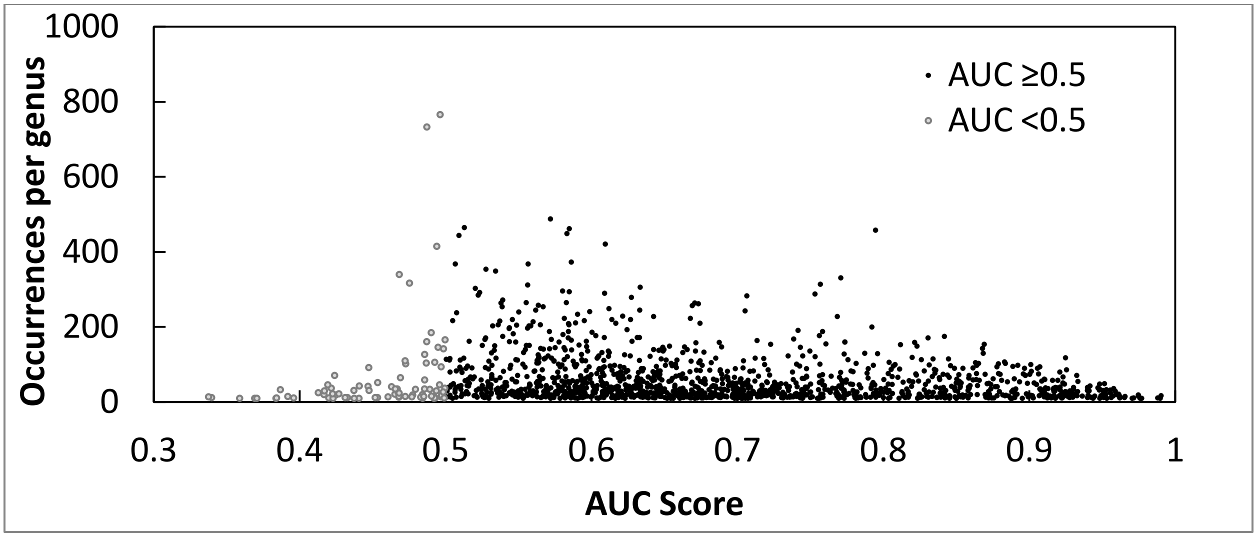

Figure 10.2. The relationship between occurrences per genus and AUC scores, where hollow dots are genera with AUC scores less than 0.5 and black dots are genera with an AUC greater than 0.5.

Table 10.3. The average percentage of contribution for environmental variables used in the model.

Environmental Variable	Average % contribution
Altitude	28.1
Temperature annual range	6.2
Slope (degrees)	6.1
Precipitation seasonality	5.6
Temperature seasonality	5.4
Sine of aspect	4.9
Cosine of aspect	4.7
Variance	4.1
Bulk density	4.0
Annual precipitation	3.8
Coarse fragmentation	3.5
Exposure	3.0
Uniformity	2.8
Precipitation of warmest quarter	2.6
Correlation	2.5
Cation exchange	2.5
Silt	2.3
Organic Carbon	2.2

Evenness	2.1
Soil pH	2.0
Clay	1.7

Table 10.4. Summary and mean results for the genera used in the analyses

	Occurrences	Test AUC
Mean	63	0.6944
Standard deviation	73	0.1285
Most # of occurrences	766	0.9904
Least # of occurrences	10	0.4240
Total genera	1354	
Total occurrences	85481	

Table 10.5. Results for genera with test AUC scores greater than 0.5 and genera with test AUC scores less than 0.5 if occurrences were greater than 50.

Family	Genus	Occurrences after rarify, biases	Test AUC
Acanthaceae	*Acanthus*	25	0.7101
Acanthaceae	*Avicennia*	26	0.7682
Acanthaceae	*Calophanoides*	10	0.6981
Acanthaceae	*Calycacanthus*	59	0.6936
Acanthaceae	*Dicliptera*	27	0.6738
Acanthaceae	*Eranthemum*	12	0.5742
Acanthaceae	*Graptophyllum*	89	0.6054
Acanthaceae	*Hemigraphis*	96	0.6128
Acanthaceae	*Hulemacanthus*	32	0.6018
Acanthaceae	*Hygrophila*	23	0.7404
Acanthaceae	*Jadunia*	18	0.7185
Acanthaceae	*Justicia*	38	0.5844
Acanthaceae	*Lepidagathis*	34	0.61
Acanthaceae	*Pseuderanthemum*	29	0.6204
Acanthaceae	*Ptyssiglottis*	17	0.5196
Acanthaceae	*Ruellia*	16	0.5729
Acanthaceae	*Rungia*	45	0.7044
Acanthaceae	*Staurogyne*	10	0.5532
Acanthaceae	*Thunbergia*	14	0.5027
Achariaceae	*Erythrospermum*	38	0.7846
Achariaceae	*Pangium*	45	0.6311

Achariaceae	*Trichadenia*	22	0.5767
Actinidiaceae	*Saurauia*	373	0.5862
Aizoaceae	*Sesuvium*	13	0.7587
Alangiaceae	*Alangium*	30	0.56
Amaranthaceae	*Achyranthes*	20	0.7692
Amaranthaceae	*Alternanthera*	36	0.5924
Amaranthaceae	*Amaranthus*	26	0.6375
Amaranthaceae	*Celosia*	16	0.6005
Amaranthaceae	*Cyathula*	26	0.717
Amaranthaceae	*Deeringia*	22	0.5618
Amaranthaceae	*Iresine*	10	0.6606
Anacardiaceae	*Buchanania*	110	0.5937
Anacardiaceae	*Campnosperma*	52	0.5416
Anacardiaceae	*Dracontomelon*	40	0.5799
Anacardiaceae	*Euroschinus*	37	0.7652
Anacardiaceae	*Evia*	13	0.6291
Anacardiaceae	*Mangifera*	37	0.5309
Anacardiaceae	*Pleiogynium*	12	0.6184
Anacardiaceae	*Rhus*	65	0.5374
Anacardiaceae	*Semecarpus*	136	0.5974
Anacardiaceae	*Spondias*	28	0.6075
Anastrophyllaceae	*Anastrophyllum*	11	0.9759
Anastrophyllaceae	*Chandonanthus*	21	0.9294
Anastrophyllaceae	*Plicanthus*	30	0.9411
Aneuraceae	*Aneura*	12	0.8901
Aneuraceae	*Riccardia*	77	0.8354
Annonaceae	*Artabotrys*	13	0.5286
Annonaceae	*Cananga*	51	0.7053
Annonaceae	*Cyathocalyx*	67	0.6258
Annonaceae	*Drepananthus*	51	0.7402
Annonaceae	*Goniothalamus*	104	0.5626
Annonaceae	*Haplostichanthus*	49	0.6075
Annonaceae	*Maasia*	21	0.6728
Annonaceae	*Oncodostigma*	10	0.6561
Annonaceae	*Phaeanthus*	27	0.6079
Annonaceae	*Polyalthia*	117	0.6039
Annonaceae	*Popowia*	55	0.5902
Annonaceae	*Pseuduvaria*	98	0.6158
Annonaceae	*Uvaria*	39	0.5071
Annonaceae	*Xylopia*	52	0.5635
Anthocerotaceae	*Anthoceros*	26	0.8003

Apiaceae	*Centella*	27	0.782
Apiaceae	*Chaerophyllum*	38	0.9471
Apiaceae	*Hydrocotyle*	85	0.836
Apiaceae	*Oenanthe*	51	0.8534
Apiaceae	*Oreomyrrhis*	20	0.9505
Apiaceae	*Trachymene*	103	0.8653
Apocynaceae	*Alstonia*	116	0.503
Apocynaceae	*Alyxia*	142	0.5713
Apocynaceae	*Anodendron*	20	0.5377
Apocynaceae	*Cerbera*	94	0.589
Apocynaceae	*Cryptolepis*	15	0.593
Apocynaceae	*Cynanchum*	14	0.6818
Apocynaceae	*Dischidia*	50	0.6382
Apocynaceae	*Heterostemma*	14	0.6367
Apocynaceae	*Hoya*	223	0.5814
Apocynaceae	*Ichnocarpus*	54	0.5479
Apocynaceae	*Lepiniopsis*	19	0.7396
Apocynaceae	*Marsdenia*	90	0.514
Apocynaceae	*Melodinus*	99	0.5798
Apocynaceae	*Micrechites*	18	0.57
Apocynaceae	*Neisosperma*	13	0.6755
Apocynaceae	*Ochrosia*	69	0.6579
Apocynaceae	*Parsonsia*	167	0.5725
Apocynaceae	*Tabernaemontana*	122	0.6117
Apocynaceae	*Toxocarpus*	10	0.572
Apocynaceae	*Voacanga*	40	0.6725
Apocynaceae	*Wrightia*	23	0.7281
Aquifoliaceae	*Ilex*	133	0.6771
Araceae	*Alocasia*	65	0.5318
Araceae	*Cryptocoryne*	10	0.8235
Araceae	*Cyrtosperma*	40	0.6571
Araceae	*Epipremnum*	15	0.647
Araceae	*Holochlamys*	24	0.6422
Araceae	*Homalomena*	52	0.5746
Araceae	*Pothos*	66	0.6063
Araceae	*Rhaphidophora*	42	0.509
Araceae	*Schismatoglottis*	20	0.5679
Araceae	*Scindapsus*	13	0.5006
Araceae	*Spathiphyllum*	14	0.6337
Araliaceae	*Gastonia*	23	0.7933
Araliaceae	*Harmsiopanax*	60	0.8004

Araliaceae	*Mackinlaya*	73	0.5317
Araliaceae	*Osmoxylon*	115	0.5676
Araliaceae	*Polyscias*	172	0.6329
Araliaceae	*Schefflera*	264	0.538
Araucariaceae	*Agathis*	34	0.6332
Araucariaceae	*Araucaria*	50	0.6992
Arecaceae	*Areca*	59	0.6433
Arecaceae	*Arenga*	18	0.5872
Arecaceae	*Brassiophoenix*	14	0.665
Arecaceae	*Calamus*	166	0.4997
Arecaceae	*Calyptrocalyx*	90	0.5442
Arecaceae	*Caryota*	22	0.5763
Arecaceae	*Cyrtostachys*	21	0.5496
Arecaceae	*Heterospathe*	83	0.6349
Arecaceae	*Hydriastele*	102	0.4727
Arecaceae	*Korthalsia*	20	0.6242
Arecaceae	*Licuala*	71	0.6603
Arecaceae	*Linospadix*	24	0.64
Arecaceae	*Livistona*	18	0.5383
Arecaceae	*Metroxylon*	10	0.8108
Arecaceae	*Orania*	30	0.6137
Arecaceae	*Ptychococcus*	23	0.6395
Arecaceae	*Ptychosperma*	44	0.6939
Arecaceae	*Rhopaloblaste*	14	0.5663
Aristolochiaceae	*Aristolochia*	41	0.6968
Asparagaceae	*Cordyline*	117	0.5638
Asparagaceae	*Dracaena*	45	0.558
Aspleniaceae	*Asplenium*	517	0.535
Aspleniaceae	*Diplora*	44	0.5148
Aspleniaceae	*Neottopteris*	52	0.5896
Asteliaceae	*Astelia*	39	0.918
Asteraceae	*Acmella*	16	0.5504
Asteraceae	*Adenostemma*	18	0.7973
Asteraceae	*Ageratum*	46	0.5312
Asteraceae	*Albizia*	51	0.6947
Asteraceae	*Anaphalioides*	36	0.9579
Asteraceae	*Anaphalis*	32	0.9556
Asteraceae	*Arrhenechthites*	35	0.9078
Asteraceae	*Bidens*	36	0.6481
Asteraceae	*Blumea*	111	0.5628
Asteraceae	*Chromolaena*	16	0.7367

Asteraceae	*Crassocephalum*	44	0.5106
Asteraceae	*Cyanthillium*	23	0.6685
Asteraceae	*Dichrocephala*	52	0.793
Asteraceae	*Eclipta*	20	0.6572
Asteraceae	*Elephantopus*	10	0.5785
Asteraceae	*Emilia*	21	0.636
Asteraceae	*Erechtites*	14	0.5257
Asteraceae	*Erigeron*	69	0.7474
Asteraceae	*Euchiton*	48	0.9483
Asteraceae	*Gnaphalium*	15	0.9498
Asteraceae	*Ischnea*	16	0.9574
Asteraceae	*Ixeridium*	54	0.8934
Asteraceae	*Keysseria*	56	0.9086
Asteraceae	*Lactuca*	12	0.9278
Asteraceae	*Lagenophora*	27	0.8313
Asteraceae	*Leptinella*	10	0.9898
Asteraceae	*Melanthera*	39	0.6465
Asteraceae	*Microglossa*	43	0.7696
Asteraceae	*Mikania*	49	0.5054
Asteraceae	*Olearia*	118	0.9249
Asteraceae	*Papuacalia*	19	0.9748
Asteraceae	*Pluchea*	10	0.9761
Asteraceae	*Senecio*	44	0.8646
Asteraceae	*Sigesbeckia*	28	0.72
Asteraceae	*Sonchus*	14	0.9269
Asteraceae	*Synedrella*	14	0.5628
Asteraceae	*Tetramolopium*	34	0.9304
Asteraceae	*Tridax*	11	0.6764
Asteraceae	*Vernonia*	65	0.4691
Asteraceae	*Xerochrysum*	18	0.9011
Asteraceae	*Youngia*	16	0.6924
Athyriaceae	*Callipteris*	42	0.6711
Athyriaceae	*Lunathyrium*	22	0.8421
Azollaceae	*Azolla*	26	0.7497
Balanophoraceae	*Balanophora*	10	0.6709
Balsaminaceae	*Impatiens*	100	0.7187
Bartramiaceae	*Breutelia*	28	0.9274
Bartramiaceae	*Philonotis*	63	0.7445
Begoniaceae	*Begonia*	265	0.5828
Begoniaceae	*Symbegonia*	32	0.9079
Bignoniaceae	*Deplanchea*	12	0.8368

Bignoniaceae	*Dolichandrone*	11	0.6436
Bignoniaceae	*Tecomanthe*	95	0.6196
Bixaceae	*Bixa*	16	0.5496
Blechnaceae	*Blechnum*	223	0.6678
Blechnaceae	*Diploblechnum*	12	0.94
Blechnaceae	*Doodia*	12	0.7037
Blechnaceae	*Stenochlaena*	67	0.5197
Boraginaceae	*Cordia*	44	0.6405
Boraginaceae	*Cynoglossum*	40	0.8584
Boraginaceae	*Heliotropium*	18	0.6744
Boraginaceae	*Myosotis*	33	0.9166
Boraginaceae	*Tournefortia*	34	0.5105
Boraginaceae	*Trigonotis*	82	0.9015
Brassicaceae	*Brassica*	14	0.6928
Brassicaceae	*Cardamine*	68	0.8336
Brassicaceae	*Nasturtium*	12	0.8244
Brassicaceae	*Rorippa*	37	0.7711
Bruchiaceae	*Trematodon*	11	0.8722
Bryaceae	*Brachymenium*	28	0.8796
Bryaceae	*Bryum*	97	0.8461
Bryaceae	*Gemmabryum*	32	0.7951
Bryaceae	*Leptostomum*	16	0.9144
Bryaceae	*Rhodobryum*	41	0.8781
Bryaceae	*Rosulabryum*	18	0.8995
Burmanniaceae	*Burmannia*	57	0.6307
Burseraceae	*Canarium*	203	0.5584
Burseraceae	*Garuga*	21	0.5866
Burseraceae	*Haplolobus*	43	0.6244
Burseraceae	*Protium*	33	0.6461
Calophyllaceae	*Calophyllum*	151	0.5554
Calymperaceae	*Arthrocormus*	23	0.6331
Calymperaceae	*Calymperes*	56	0.6067
Calymperaceae	*Exostratum*	23	0.6894
Calymperaceae	*Leucophanes*	48	0.678
Calymperaceae	*Mitthyridium*	35	0.772
Calymperaceae	*Syrrhopodon*	62	0.641
Campanulaceae	*Isotoma*	12	0.8238
Campanulaceae	*Lobelia*	68	0.8061
Campanulaceae	*Wahlenbergia*	47	0.8289
Cannabaceae	*Celtis*	64	0.673
Cannabaceae	*Gironniera*	62	0.7025

Cannabaceae	*Parasponia*	44	0.6835
Cannabaceae	*Trema*	110	0.4723
Capparaceae	*Capparis*	58	0.6858
Cleomaceae	*Cleome*	17	0.7689
Capparaceae	*Crateva*	25	0.6517
Caprifoliaceae	*Triplostegia*	16	0.9207
Cardiopteridaceae	*Cardiopteris*	29	0.6561
Caryophyllaceae	*Cerastium*	55	0.9334
Caryophyllaceae	*Drymaria*	33	0.7556
Caryophyllaceae	*Sagina*	58	0.8811
Caryophyllaceae	*Stellaria*	16	0.9265
Casuarinaceae	*Casuarina*	57	0.5134
Casuarinaceae	*Gymnostoma*	86	0.5663
Celastraceae	*Celastrus*	34	0.746
Celastraceae	*Loeseneriella*	10	0.7732
Celastraceae	*Perrotettia*	70	0.7563
Celastraceae	*Perrottetia*	52	0.7205
Celastraceae	*Salacia*	43	0.5419
Celastraceae	*Siphonodon*	19	0.5724
Celastraceae	*Stackhousia*	20	0.7309
Restionaceae	*Centrolepis*	35	0.8908
Restionaceae	*Gaimardia*	14	0.8531
Ceratophyllaceae	*Ceratophyllum*	18	0.6144
Cheiropleuriaceae	*Cheiropleuria*	12	0.5654
Chloranthaceae	*Ascarina*	63	0.7458
Chloranthaceae	*Chloranthus*	81	0.6675
Chloranthaceae	*Sarcandra*	11	0.9125
Chrysobalanaceae	*Atuna*	25	0.6273
Chrysobalanaceae	*Maranthes*	48	0.6326
Chrysobalanaceae	*Parastemon*	13	0.5217
Chrysobalanaceae	*Parinari*	42	0.629
Cleomaceae	*Arivela*	12	0.7806
Clusiaceae	*Garcinia*	317	0.4753
Clusiaceae	*Pentaphalangium*	14	0.6659
Combretaceae	*Combretum*	37	0.6303
Combretaceae	*Lumnitzera*	24	0.7313
Combretaceae	*Terminalia*	214	0.56
Commelinaceae	*Amischotolype*	27	0.6698
Commelinaceae	*Aneilema*	11	0.5889
Commelinaceae	*Belosynapsis*	13	0.635
Commelinaceae	*Floscopa*	29	0.6191

Commelinaceae	*Murdannia*	29	0.5454
Commelinaceae	*Pollia*	40	0.6135
Connaraceae	*Connarus*	20	0.6443
Connaraceae	*Rourea*	14	0.6874
Convolvulaceae	*Erycibe*	44	0.6076
Convolvulaceae	*Evolvulus*	14	0.7138
Convolvulaceae	*Ipomoea*	71	0.5494
Convolvulaceae	*Lepistemon*	21	0.7178
Convolvulaceae	*Merremia*	49	0.6898
Coriariaceae	*Coriaria*	21	0.7586
Myssaceae	*Mastixia*	38	0.7287
Corsiaceae	*Corsia*	31	0.7793
Corynocarpaceae	*Corynocarpus*	27	0.5468
Costaceae	*Cheilocostus*	36	0.5777
Costaceae	*Tapeinochilos*	34	0.5518
Cryphaeaceae	*Schoenobryum*	11	0.8423
Crypteroniaceae	*Crypteronia*	11	0.6542
Cucurbitaceae	*Cucumis*	12	0.6139
Cucurbitaceae	*Diplocyclos*	12	0.6504
Cucurbitaceae	*Gynostemma*	17	0.773
Cucurbitaceae	*Luffa*	12	0.6885
Cucurbitaceae	*Melothria*	25	0.6438
Cucurbitaceae	*Momordica*	24	0.5357
Cucurbitaceae	*Mukia*	12	0.8001
Cucurbitaceae	*Neoachmandra*	20	0.8644
Cucurbitaceae	*Neoalsomitra*	17	0.7363
Cucurbitaceae	*Pilogyne*	10	0.7812
Cucurbitaceae	*Trichosanthes*	67	0.5975
Cucurbitaceae	*Urceodiscus*	20	0.8903
Cucurbitaceae	*Zehneria*	51	0.6968
Cunoniaceae	*Acsmithia*	24	0.6015
Cunoniaceae	*Aistopetalum*	16	0.5264
Cunoniaceae	*Caldcluvia*	168	0.7386
Cunoniaceae	*Ceratopetalum*	31	0.6186
Cunoniaceae	*Gillbeea*	14	0.5952
Cunoniaceae	*Opocunonia*	59	0.7747
Cunoniaceae	*Pullea*	48	0.7333
Cunoniaceae	*Schizomeria*	140	0.6656
Cunoniaceae	*Spiraeanthemum*	24	0.7679
Cunoniaceae	*Spiraeopsis*	87	0.835
Cunoniaceae	*Weinmannia*	71	0.6451

Cupressaceae	*Papuacedrus*	113	0.8261
Cyatheaceae	*Cyathea*	421	0.6095
Cyatheaceae	*Dicksonia*	89	0.7897
Cyatheaceae	*Plagiogyria*	54	0.8851
Cycadaceae	*Cycas*	67	0.6389
Cyperaceae	*Bulbostylis*	27	0.7808
Cyperaceae	*Carex*	171	0.8307
Cyperaceae	*Carpha*	24	0.9557
Cyperaceae	*Cyperus*	203	0.5572
Cyperaceae	*Eleocharis*	74	0.6469
Cyperaceae	*Fimbristylis*	171	0.5275
Cyperaceae	*Fuirena*	22	0.6705
Cyperaceae	*Gahnia*	47	0.7923
Cyperaceae	*Hypolytrum*	40	0.5031
Cyperaceae	*Isolepis*	35	0.8737
Cyperaceae	*Kyllinga*	50	0.6081
Cyperaceae	*Lipocarpha*	36	0.7028
Cyperaceae	*Machaerina*	44	0.7597
Cyperaceae	*Mapania*	51	0.5968
Cyperaceae	*Oreobolus*	37	0.9168
Cyperaceae	*Paramapania*	34	0.5242
Cyperaceae	*Pycreus*	61	0.7021
Cyperaceae	*Rhynchospora*	71	0.424
Cyperaceae	*Schoenoplectiella*	33	0.6477
Cyperaceae	*Schoenus*	81	0.7793
Cyperaceae	*Scirpus*	32	0.7732
Cyperaceae	*Scleria*	104	0.5635
Cyperaceae	*Trichophorum*	17	0.8454
Cyperaceae	*Uncinia*	28	0.9332
Cyrtopodaceae	*Bescherellia*	17	0.9022
Daphniphyllaceae	*Daphniphyllum*	98	0.8641
Datiscaceae	*Octomeles*	40	0.6415
Datiscaceae	*Tetrameles*	10	0.7073
Davalliaceae	*Davallia*	241	0.5988
Davalliaceae	*Davallodes*	44	0.8595
Davalliaceae	*Humata*	186	0.6004
Davalliaceae	*Leucostegia*	23	0.5517
Davalliaceae	*Scyphularia*	18	0.7319
Dendrocerotaceae	*Megaceros*	15	0.6479
Dennstaedtiaceae	*Dennstaedtia*	136	0.6713
Dennstaedtiaceae	*Histiopteris*	66	0.81

Dennstaedtiaceae	*Hypolepis*	49	0.8712
Dennstaedtiaceae	*Lindsaea*	349	0.5343
Dennstaedtiaceae	*Microlepia*	78	0.6442
Dennstaedtiaceae	*Odontosoria*	74	0.6154
Dennstaedtiaceae	*Orthiopteris*	16	0.597
Dennstaedtiaceae	*Pteridium*	52	0.7562
Dichapetalaceae	*Dichapetalum*	62	0.599
Dicksoniaceae	*Calochlaena*	47	0.779
Dicranaceae	*Atractylocarpus*	12	0.9653
Dicranaceae	*Braunfelsia*	19	0.9512
Dicranaceae	*Campylopodium*	15	0.8298
Dicranaceae	*Campylopus*	90	0.8968
Dicranaceae	*Cryptodicranum*	51	0.85
Dicranaceae	*Dicranella*	11	0.9151
Dicranaceae	*Dicranoloma*	188	0.7584
Dicranaceae	*Dicranum*	16	0.9749
Dicranaceae	*Holomitrium*	18	0.8841
Dicranaceae	*Leucobryum*	82	0.7086
Dicranaceae	*Leucoloma*	11	0.9621
Dicranaceae	*Octoblepharum*	29	0.7106
Dilleniaceae	*Dillenia*	132	0.5535
Dilleniaceae	*Tetracera*	18	0.5031
Dioscoreaceae	*Dioscorea*	87	0.5106
Dioscoreaceae	*Tacca*	15	0.6914
Dipteridaceae	*Dipteris*	75	0.6625
Dipterocarpaceae	*Anisoptera*	49	0.7299
Dipterocarpaceae	*Hopea*	57	0.7019
Dipterocarpaceae	*Vatica*	43	0.7268
Ditrichaceae	*Ditrichum*	18	0.7147
Droseraceae	*Drosera*	30	0.6756
Drynariaceae	*Aglaomorpha*	68	0.5643
Dryopteridaceae	*Arachniodes*	40	0.748
Dryopteridaceae	*Bolbitis*	76	0.6037
Dryopteridaceae	*Ctenitis*	25	0.8127
Dryopteridaceae	*Didymochlaena*	37	0.6285
Dryopteridaceae	*Dryopolystichum*	15	0.705
Dryopteridaceae	*Dryopteris*	96	0.8069
Dryopteridaceae	*Elaphoglossum*	117	0.7122
Dryopteridaceae	*Lastreopsis*	17	0.7729
Dryopteridaceae	*Lomagramma*	55	0.6355
Dryopteridaceae	*Polystichum*	113	0.7758

Dryopteridaceae	*Rumohra*	17	0.9492
Dryopteridaceae	*Stenolepia*	40	0.9212
Dryopteridaceae	*Teratophyllum*	30	0.5783
Dumortieraceae	*Dumortiera*	31	0.7044
Ebenaceae	*Diospyros*	206	0.5361
Elaeagnaceae	*Elaeagnus*	17	0.5416
Elaeocarpaceae	*Aceratium*	131	0.5315
Elaeocarpaceae	*Dubouzetia*	34	0.6034
Elaeocarpaceae	*Elaeocarpus*	415	0.494
Elaeocarpaceae	*Sericolea*	105	0.8632
Elaeocarpaceae	*Sloanea*	203	0.5323
Entodontaceae	*Entodon*	28	0.9248
Entodontaceae	*Erythrodontium*	11	0.7827
Entodontaceae	*Mesonodon*	21	0.9613
Epacridaceae	*Acrothamnus*	71	0.9326
Epacridaceae	*Leucopogon*	38	0.9402
Epacridaceae	*Styphelia*	61	0.9104
Epacridaceae	*Trochocarpa*	67	0.9232
Equisetaceae	*Equisetum*	83	0.6882
Ericaceae	*Agapetes*	48	0.9242
Ericaceae	*Decatoca*	11	0.9222
Ericaceae	*Dimorphanthera*	331	0.7709
Ericaceae	*Diplycosia*	90	0.8488
Ericaceae	*Gaultheria*	98	0.8922
Ericaceae	*Paphia*	20	0.9594
Ericaceae	*Rhododendron*	458	0.7947
Ericaceae	*Vaccinium*	314	0.7569
Eriocaulaceae	*Eriocaulon*	121	0.7533
Erythroxylaceae	*Erythroxylum*	27	0.5623
Escalloniaceae	*Carpodetus*	106	0.804
Escalloniaceae	*Polyosma*	164	0.7135
Escalloniaceae	*Quintinia*	91	0.8615
Euphorbiaceae	*Acalypha*	94	0.5984
Euphorbiaceae	*Alchornea*	19	0.6813
Euphorbiaceae	*Aleurites*	21	0.7324
Euphorbiaceae	*Aporusa*	14	0.5687
Euphorbiaceae	*Blumeodendron*	27	0.6606
Euphorbiaceae	*Claoxylon*	211	0.5891
Euphorbiaceae	*Cleidion*	24	0.6077
Euphorbiaceae	*Codiaeum*	48	0.5576
Euphorbiaceae	*Croton*	58	0.5345

Euphorbiaceae	*Endospermum*	100	0.5899
Euphorbiaceae	*Euphorbia*	106	0.5639
Euphorbiaceae	*Excoecaria*	12	0.7501
Euphorbiaceae	*Hancea*	16	0.6535
Euphorbiaceae	*Homalanthus*	117	0.5727
Euphorbiaceae	*Macaranga*	368	0.5067
Euphorbiaceae	*Mallotus*	180	0.5805
Euphorbiaceae	*Melanolepis*	20	0.6829
Euphorbiaceae	*Neoscortechinia*	16	0.5808
Euphorbiaceae	*Pimelodendron*	85	0.6141
Euphorbiaceae	*Shirakiopsis*	12	0.7561
Eupomatiaceae	*Eupomatia*	31	0.7031
Fabaceae	*Abrus*	15	0.77
Fabaceae	*Acacia*	115	0.8341
Fabaceae	*Adenanthera*	32	0.6237
Fabaceae	*Aeschynomene*	20	0.7243
Fabaceae	*Alysicarpus*	20	0.6625
Fabaceae	*Andira*	11	0.6677
Fabaceae	*Archidendron*	139	0.5864
Fabaceae	*Bauhinia*	28	0.6079
Fabaceae	*Caesalpinia*	40	0.5628
Fabaceae	*Cajanus*	23	0.8063
Fabaceae	*Calopogonium*	13	0.5073
Fabaceae	*Canavalia*	28	0.7176
Fabaceae	*Cassia*	26	0.5486
Fabaceae	*Chamaecrista*	33	0.7226
Fabaceae	*Codariocalyx*	25	0.6978
Fabaceae	*Crotalaria*	140	0.6426
Fabaceae	*Crudia*	11	0.639
Fabaceae	*Cynometra*	26	0.5752
Fabaceae	*Dalbergia*	33	0.5888
Fabaceae	*Dendrolobium*	34	0.7244
Fabaceae	*Derris*	84	0.5964
Fabaceae	*Desmodium*	150	0.5337
Fabaceae	*Entada*	26	0.6465
Fabaceae	*Erythrina*	22	0.5133
Fabaceae	*Falcataria*	57	0.6779
Fabaceae	*Glycine*	15	0.707
Fabaceae	*Hanslia*	18	0.7004
Fabaceae	*Hylodesmum*	36	0.7983
Fabaceae	*Indigofera*	39	0.7345

Fabaceae	*Inocarpus*	32	0.609
Fabaceae	*Intsia*	53	0.7021
Fabaceae	*Kingiodendron*	17	0.7176
Fabaceae	*Leucaena*	11	0.5889
Fabaceae	*Macropsychanthus*	16	0.583
Fabaceae	*Macroptilium*	10	0.5048
Fabaceae	*Maniltoa*	84	0.6746
Fabaceae	*Millettia*	11	0.582
Fabaceae	*Mimosa*	27	0.773
Fabaceae	*Mucuna*	161	0.4871
Fabaceae	*Ormocarpum*	15	0.6187
Fabaceae	*Paraserianthes*	70	0.5926
Fabaceae	*Phaseolus*	12	0.6059
Fabaceae	*Phylacium*	25	0.5863
Fabaceae	*Phyllodium*	13	0.6381
Fabaceae	*Pithecellobium*	18	0.5207
Fabaceae	*Pongamia*	41	0.6024
Fabaceae	*Pterocarpus*	29	0.5857
Fabaceae	*Pueraria*	35	0.5787
Fabaceae	*Pycnospora*	15	0.7406
Fabaceae	*Racosperma*	10	0.8873
Fabaceae	*Rhynchosia*	16	0.706
Fabaceae	*Schleinitzia*	21	0.8133
Fabaceae	*Senna*	44	0.5935
Fabaceae	*Serianthes*	39	0.5908
Fabaceae	*Smithia*	13	0.6816
Fabaceae	*Strongylodon*	59	0.5244
Fabaceae	*Stylosanthes*	22	0.7041
Fabaceae	*Tadehagi*	12	0.7449
Fabaceae	*Tephrosia*	52	0.6764
Fabaceae	*Trifolium*	10	0.7549
Fabaceae	*Uraria*	22	0.6432
Fabaceae	*Vigna*	42	0.6258
Fagaceae	*Castanopsis*	110	0.6745
Fagaceae	*Lithocarpus*	217	0.5951
Fissidentaceae	*Fissidens*	87	0.8054
Flacourtiaceae	*Itoa*	14	0.7161
Flacourtiaceae	*Osmelia*	24	0.7154
Flacourtiaceae	*Ryparosa*	40	0.539
Flagellariaceae	*Flagellaria*	64	0.6467
Frullaniaceae	*Frullania*	146	0.7432

Funariaceae	*Funaria*	18	0.9232
Gentianaceae	*Exacum*	19	0.5524
Gentianaceae	*Fagraea*	265	0.5553
Gentianaceae	*Gentiana*	86	0.9256
Gentianaceae	*Swertia*	17	0.9243
Geocalycaceae	*Lophocolea*	31	0.8428
Geocalycaceae	*Notoscyphus*	11	0.8744
Geocalycaceae	*Saccogynidium*	15	0.8169
Geraniaceae	*Geranium*	39	0.94
Gesneriaceae	*Aeschynanthus*	193	0.6244
Gesneriaceae	*Agalmyla*	57	0.6546
Gesneriaceae	*Boea*	48	0.8034
Gesneriaceae	*Cyrtandra*	296	0.5802
Gesneriaceae	*Dichrotrichum*	17	0.6967
Gesneriaceae	*Rhynchoglossum*	13	0.8368
Gesneriaceae	*Rhynchotechum*	13	0.6873
Gleicheniaceae	*Dicranopteris*	94	0.497
Gleicheniaceae	*Diplopterygium*	28	0.8721
Gleicheniaceae	*Gleichenia*	136	0.7497
Gleicheniaceae	*Sticherus*	154	0.7228
Gnetaceae	*Gnetum*	188	0.5712
Goodeniaceae	*Scaevola*	120	0.5641
Grammitidaceae	*Calymmodon*	77	0.7889
Grammitidaceae	*Ctenopterella*	24	0.839
Grammitidaceae	*Ctenopteris*	210	0.6744
Grammitidaceae	*Prosaptia*	128	0.7732
Grammitidaceae	*Tomophyllum*	11	0.9226
Grammitidaceae	*Xiphopteris*	36	0.7473
Gunneraceae	*Gunnera*	72	0.8227
Haloragaceae	*Gonocarpus*	47	0.8061
Haloragaceae	*Halorrhagis*	25	0.8407
Haloragaceae	*Myriophyllum*	18	0.8566
Hamamelidaceae	*Sycopsis*	12	0.582
Hanguanaceae	*Hanguana*	10	0.7036
Heliconiaceae	*Heliconia*	23	0.5248
Herbertaceae	*Herbertus*	43	0.9417
Hernandiaceae	*Hernandia*	38	0.7076
Himantandraceae	*Galbulimima*	83	0.7779
Hookeriaceae	*Callicostella*	16	0.6839
Hookeriaceae	*Chaetomitriopsis*	14	0.9103
Hookeriaceae	*Chaetomitrium*	58	0.7715

Hookeriaceae	*Cyathophorum*	13	0.8394
Hookeriaceae	*Cyclodictyon*	11	0.7432
Hookeriaceae	*Distichophyllum*	27	0.7247
Hookeriaceae	*Hypopterygium*	28	0.8171
Hookeriaceae	*Lopidium*	21	0.8917
Hydrangeaceae	*Dichroa*	33	0.5347
Hydrocharitaceae	*Blyxa*	21	0.7572
Hydrocharitaceae	*Najas*	12	0.7023
Hydrocharitaceae	*Vallisneria*	16	0.6548
Hylocomiaceae	*Macrothamnium*	30	0.9177
Hymenophyllaceae	*Abrodictyum*	21	0.5687
Hymenophyllaceae	*Cephalomanes*	123	0.605
Hymenophyllaceae	*Crepidomanes*	139	0.582
Hymenophyllaceae	*Hymenophyllum*	264	0.6708
Hymenophyllaceae	*Macroglena*	26	0.6404
Hymenophyllaceae	*Mecodium*	46	0.7942
Hymenophyllaceae	*Meringium*	86	0.6883
Hymenophyllaceae	*Microgonium*	15	0.6635
Hymenophyllaceae	*Microtrichomanes*	31	0.6744
Hymenophyllaceae	*Nesopteris*	24	0.577
Hymenophyllaceae	*Pleuromanes*	44	0.7249
Hymenophyllaceae	*Reediella*	13	0.6811
Hymenophyllaceae	*Selenodesmium*	74	0.6893
Hymenophyllaceae	*Trichomanes*	234	0.5905
Hymenophyllaceae	*Vandenboschia*	37	0.5359
Hypericaceae	*Hypericum*	103	0.8837
Hypnaceae	*Ctenidium*	11	0.8582
Hypnaceae	*Ectropothecium*	89	0.6986
Hypnaceae	*Elmeriobryum*	10	0.9438
Hypnaceae	*Isopterygium*	15	0.5477
Hypnaceae	*Vesicularia*	18	0.7093
Hypnodendraceae	*Hypnodendron*	149	0.8231
Hypoxidaceae	*Curculigo*	28	0.537
Cardiopteridaceae	*Citronella*	26	0.5284
Stemonuraceae	*Gomphandra*	83	0.6458
Cardiopteridaceae	*Gonocaryum*	67	0.5774
Stemonuraceae	*Medusanthera*	62	0.6223
Metteniusaceae	*Platea*	57	0.587
Icacinaceae	*Polyporandra*	23	0.6476
Icacinaceae	*Pseudobotrys*	26	0.5949
Icacinaceae	*Rhyticaryum*	102	0.5648

Stemonuraceae	*Stemonurus*	32	0.6686
Iridaceae	*Libertia*	31	0.9506
Isoetaceae	*Isoetes*	17	0.9904
Jackiellaceae	*Jackiella*	18	0.9617
Jamesoniellaceae	*Denotarisia*	11	0.8758
Jamesoniellaceae	*Jamesoniella*	14	0.9618
Jamesoniellaceae	*Syzygiella*	18	0.9214
Juglandaceae	*Engelhardia*	33	0.5929
Juglandaceae	*Engelhardtia*	37	0.6627
Juncaceae	*Juncus*	75	0.9064
Juncaceae	*Luzula*	12	0.9511
Jungermanniaceae	*Jungermannia*	58	0.8658
Lamiaceae	*Anisomeles*	24	0.8295
Lamiaceae	*Callicarpa*	177	0.603
Lamiaceae	*Clerodendrum*	175	0.5392
Lamiaceae	*Coleus*	42	0.8468
Lamiaceae	*Faradaya*	68	0.5558
Lamiaceae	*Gmelina*	92	0.608
Lamiaceae	*Hyptis*	49	0.6103
Lamiaceae	*Leucas*	12	0.7847
Lamiaceae	*Ocimum*	31	0.5211
Lamiaceae	*Petraeovitex*	26	0.5065
Lamiaceae	*Platostoma*	10	0.8883
Lamiaceae	*Plectranthus*	138	0.6462
Lamiaceae	*Pogostemon*	45	0.5038
Lamiaceae	*Premna*	109	0.5875
Lamiaceae	*Salvia*	10	0.6048
Lamiaceae	*Scutellaria*	26	0.8343
Lamiaceae	*Teijsmanniodendron*	53	0.7255
Lamiaceae	*Vitex*	98	0.6759
Lamiaceae	*Viticipremna*	15	0.6973
Lamiaceae	*Volkameria*	18	0.7008
Lauraceae	*Actinodaphne*	59	0.6483
Lauraceae	*Alseodaphne*	11	0.6683
Lauraceae	*Beilschmiedia*	43	0.6337
Lauraceae	*Cassytha*	28	0.6492
Lauraceae	*Cinnamomum*	70	0.6213
Lauraceae	*Cryptocarya*	254	0.5388
Lauraceae	*Endiandra*	104	0.4868
Lauraceae	*Litsea*	240	0.5502
Lauraceae	*Neolitsea*	34	0.6911

Lauraceae	*Phoebe*	13	0.5366
Lecythidaceae	*Barringtonia*	143	0.5652
Lecythidaceae	*Planchonia*	33	0.6575
Leeaceae	*Leea*	162	0.6278
Lejeuneaceae	*Acrolejeunea*	32	0.7622
Lejeuneaceae	*Caudalejeunea*	19	0.7473
Lejeuneaceae	*Cheilolejeunea*	61	0.8504
Lejeuneaceae	*Dendrolejeunea*	17	0.6676
Lejeuneaceae	*Drepanolejeunea*	37	0.8589
Lejeuneaceae	*Lejeunea*	98	0.7932
Lejeuneaceae	*Lepidolejeunea*	14	0.7514
Lejeuneaceae	*Lopholejeunea*	46	0.7586
Lejeuneaceae	*Mastigolejeunea*	60	0.8387
Lejeuneaceae	*Ptychanthus*	28	0.8129
Lejeuneaceae	*Pycnolejeunea*	11	0.7314
Lejeuneaceae	*Schiffneriolejeunea*	25	0.7102
Lejeuneaceae	*Spruceanthus*	32	0.889
Lejeuneaceae	*Thysananthus*	69	0.7643
Lembophyllaceae	*Camptochaete*	13	0.8309
Lentibulariaceae	*Utricularia*	51	0.5623
Lepicoleaceae	*Lepicolea*	24	0.9088
Lepidoziaceae	*Acromastigum*	10	0.6231
Lepidoziaceae	*Bazzania*	75	0.8223
Lepidoziaceae	*Kurzia*	10	0.7055
Lepidoziaceae	*Lepidozia*	74	0.841
Lepidoziaceae	*Telaranea*	19	0.6866
Linaceae	*Durandea*	13	0.7884
Linaceae	*Hugonia*	50	0.5945
Linderniaceae	*Lindernia*	50	0.5163
Lindsaeaceae	*Cystodium*	24	0.5956
Lindsaeaceae	*Sphenomeris*	42	0.6177
Lindsaeaceae	*Tapeinidium*	97	0.6553
Loganiaceae	*Geniostoma*	109	0.6683
Loganiaceae	*Mitrasacme*	20	0.7222
Loganiaceae	*Neuburgia*	140	0.5547
Loganiaceae	*Strychnos*	50	0.585
Lomariopsidaceae	*Lomariopsis*	35	0.6501
Lomariopsidaceae	*Nephrolepis*	216	0.5372
Lophocoleaceae	*Chiloscyphus*	17	0.8834
Lophocoleaceae	*Heteroscyphus*	88	0.8112
Lophopyxidaceae	*Lophopyxis*	14	0.8993

Loranthaceae	*Amyema*	257	0.6691
Loranthaceae	*Dactyliophora*	15	0.554
Loranthaceae	*Decaisnina*	117	0.5125
Loranthaceae	*Dendrophthoe*	54	0.5819
Loranthaceae	*Macrosolen*	26	0.6622
Loranthaceae	*Sogerianthe*	39	0.6335
Loxogrammaceae	*Loxogramme*	117	0.6852
Lycopodiaceae	*Huperzia*	245	0.6331
Lycopodiaceae	*Lycopodiella*	123	0.5703
Lycopodiaceae	*Lycopodium*	283	0.7065
Lygodiaceae	*Lygodium*	141	0.5671
Lythraceae	*Duabanga*	25	0.5895
Lythraceae	*Lagerstroemia*	38	0.6732
Lythraceae	*Sonneratia*	36	0.7277
Magnoliaceae	*Magnolia*	63	0.662
Malpighiaceae	*Ryssopterys*	24	0.7078
Malpighiaceae	*Stigmaphyllon*	26	0.7637
Malvaceae	*Abelmoschus*	41	0.6444
Malvaceae	*Abutilon*	11	0.9028
Malvaceae	*Althoffia*	34	0.6125
Malvaceae	*Bombax*	13	0.7342
Malvaceae	*Brachychiton*	25	0.803
Malvaceae	*Brownlowia*	19	0.7183
Malvaceae	*Colona*	19	0.6449
Malvaceae	*Commersonia*	112	0.5493
Malvaceae	*Corchorus*	13	0.6988
Malvaceae	*Gonystylus*	15	0.5108
Malvaceae	*Grewia*	48	0.7502
Malvaceae	*Gyrinops*	26	0.7451
Malvaceae	*Helicteres*	10	0.7695
Malvaceae	*Heritiera*	34	0.5273
Malvaceae	*Hibiscus*	138	0.5334
Malvaceae	*Kleinhovia*	38	0.5722
Malvaceae	*Melochia*	54	0.5487
Malvaceae	*Pimelea*	18	0.8522
Malvaceae	*Pterocymbium*	15	0.5834
Malvaceae	*Pterygota*	15	0.7143
Malvaceae	*Sida*	84	0.6249
Malvaceae	*Sterculia*	162	0.5162
Malvaceae	*Talipariti*	81	0.6201
Malvaceae	*Thespesia*	85	0.6811

Malvaceae	*Trichospermum*	87	0.6051
Malvaceae	*Triumfetta*	66	0.6315
Malvaceae	*Urena*	62	0.5187
Marantaceae	*Cominsia*	29	0.6354
Marantaceae	*Donax*	54	0.6312
Marantaceae	*Phrynium*	54	0.529
Marattiaceae	*Angiopteris*	43	0.685
Marattiaceae	*Marattia*	139	0.6475
Marattiaceae	*Ptisana*	75	0.6458
Marchantiaceae	*Marchantia*	56	0.8181
Mastigophoraceae	*Mastigophora*	62	0.8753
Melastomataceae	*Astronia*	160	0.5778
Melastomataceae	*Astronidium*	81	0.6422
Melastomataceae	*Beccarianthus*	39	0.8526
Melastomataceae	*Catanthera*	15	0.6184
Melastomataceae	*Conostegia*	17	0.7199
Melastomataceae	*Dissochaeta*	25	0.6026
Melastomataceae	*Medinilla*	312	0.5563
Melastomataceae	*Melastoma*	167	0.527
Melastomataceae	*Memecylon*	83	0.5074
Melastomataceae	*Miconia*	11	0.6724
Melastomataceae	*Osbeckia*	40	0.7709
Melastomataceae	*Otanthera*	22	0.6209
Melastomataceae	*Poikilogyne*	105	0.6736
Melastomataceae	*Pternandra*	17	0.5596
Meliaceae	*Aglaia*	368	0.5566
Meliaceae	*Amoora*	30	0.5011
Meliaceae	*Aphanamixis*	80	0.6235
Meliaceae	*Chisocheton*	188	0.5842
Meliaceae	*Dysoxylum*	303	0.5204
Meliaceae	*Toona*	18	0.5563
Meliaceae	*Vavaea*	63	0.5316
Meliaceae	*Xylocarpus*	21	0.7396
Menispermaceae	*Hypserpa*	25	0.57
Menispermaceae	*Legnephora*	10	0.7446
Menispermaceae	*Parabaena*	16	0.647
Menispermaceae	*Pycnarrhena*	14	0.6165
Menispermaceae	*Tinospora*	19	0.546
Menyanthaceae	*Nymphoides*	22	0.6651
Meteoriaceae	*Aerobryopsis*	40	0.836
Meteoriaceae	*Aerobryum*	11	0.8744

Meteoriaceae	*Barbellopsis*	19	0.9124
Meteoriaceae	*Cryptopapillaria*	15	0.8335
Meteoriaceae	*Dicladdiella*	19	0.8819
Meteoriaceae	*Floribundaria*	90	0.8546
Meteoriaceae	*Meteoriopsis*	39	0.8488
Meteoriaceae	*Meteorium*	74	0.8698
Meteoriaceae	*Papillaria*	15	0.922
Metzgeriaceae	*Metzgeria*	50	0.8724
Mniaceae	*Orthomnion*	11	0.6991
Mniaceae	*Plagiomnium*	18	0.9404
Monimiaceae	*Dryadodaphne*	53	0.7745
Monimiaceae	*Kairoa*	10	0.6544
Monimiaceae	*Kibara*	165	0.5862
Monimiaceae	*Levieria*	101	0.7406
Monimiaceae	*Palmeria*	119	0.8198
Monimiaceae	*Steganthera*	126	0.5635
Moraceae	*Antiaris*	21	0.5312
Moraceae	*Antiaropsis*	38	0.7074
Moraceae	*Artocarpus*	112	0.5101
Moraceae	*Ficus*	766	0.4963
Moraceae	*Maclura*	27	0.6184
Moraceae	*Streblus*	83	0.711
Moraceae	*Trophis*	23	0.7675
Myristicaceae	*Endocomia*	27	0.7111
Myristicaceae	*Gymnacranthera*	99	0.5883
Myristicaceae	*Horsfieldia*	254	0.5669
Myristicaceae	*Myristica*	444	0.5092
Myristicaceae	*Virola*	12	0.5917
Myrsinaceae	*Conandrium*	110	0.596
Myrsinaceae	*Moesa*	103	0.6546
Myrsinaceae	*Rapanea*	228	0.7685
Myrsinaceae	*Tapeinosperma*	13	0.6681
Myrtaceae	*Asteromyrtus*	33	0.9529
Myrtaceae	*Corymbia*	95	0.8888
Myrtaceae	*Decaspermum*	210	0.6167
Myrtaceae	*Eucalyptopsis*	22	0.7095
Myrtaceae	*Eucalyptus*	123	0.7448
Myrtaceae	*Eugenia*	238	0.5076
Myrtaceae	*Kania*	51	0.772
Myrtaceae	*Lophostemon*	15	0.8417
Myrtaceae	*Mearnsia*	14	0.7819

Myrtaceae	*Melaleuca*	94	0.8779
Myrtaceae	*Metrosideros*	72	0.645
Myrtaceae	*Myrtella*	13	0.8172
Myrtaceae	*Octamyrtus*	92	0.6582
Myrtaceae	*Rhodamnia*	76	0.6181
Myrtaceae	*Rhodomyrtus*	113	0.5813
Myrtaceae	*Syzygium*	733	0.4872
Myrtaceae	*Tristaniopsis*	12	0.8046
Myrtaceae	*Uromyrtus*	19	0.7205
Myrtaceae	*Welchiodendron*	14	0.9218
Myrtaceae	*Xanthomyrtus*	130	0.8685
Myrtaceae	*Xanthostemon*	23	0.8904
Neckeraceae	*Himantocladium*	38	0.6977
Neckeraceae	*Homaliodendron*	64	0.8586
Neckeraceae	*Neckeropsis*	40	0.6021
Neckeraceae	*Pinnatella*	25	0.6845
Nepenthaceae	*Nepenthes*	101	0.5774
Nephrolepidaceae	*Arthropteris*	45	0.5815
Nothofagaceae	*Nothofagus*	175	0.8419
Notothyladaceae	*Phaeoceros*	13	0.8703
Nyctaginaceae	*Boerhavia*	19	0.7321
Nyctaginaceae	*Ceodes*	14	0.5995
Nyctaginaceae	*Pisonia*	117	0.5683
Nymphaeaceae	*Nymphaea*	21	0.8249
Ochnaceae	*Schuurmansia*	126	0.6227
Oleaceae	*Chionanthus*	109	0.5743
Oleaceae	*Jasminum*	95	0.6445
Oleaceae	*Ligustrum*	17	0.9069
Oleandraceae	*Oleandra*	101	0.553
Onagraceae	*Epilobium*	107	0.8831
Onagraceae	*Ludwigia*	71	0.6086
Ophioglossaceae	*Botrychium*	17	0.9328
Ophioglossaceae	*Helminthostachys*	45	0.7715
Ophioglossaceae	*Ophioderma*	29	0.6573
Ophioglossaceae	*Ophioglossum*	111	0.6329
Opiliaceae	*Cansjera*	10	0.8454
Opiliaceae	*Opilia*	12	0.7042
Orchidaceae	*Acanthephippium*	11	0.709
Orchidaceae	*Acriopsis*	17	0.6536
Orchidaceae	*Aglossorrhyncha*	21	0.7032
Orchidaceae	*Agrostophyllum*	140	0.6497

Orchidaceae	*Apostasia*	18	0.6874
Orchidaceae	*Appendicula*	61	0.5156
Orchidaceae	*Bryobium*	12	0.6824
Orchidaceae	*Bulbophyllum*	249	0.612
Orchidaceae	*Cadetia*	64	0.5929
Orchidaceae	*Calanthe*	122	0.6402
Orchidaceae	*Ceratostylis*	123	0.7348
Orchidaceae	*Coelogyne*	65	0.729
Orchidaceae	*Corybas*	31	0.804
Orchidaceae	*Crepidium*	23	0.7117
Orchidaceae	*Cryptostylis*	11	0.757
Orchidaceae	*Dendrobium*	488	0.5719
Orchidaceae	*Dendrochilum*	39	0.8412
Orchidaceae	*Diplocaulobium*	56	0.5798
Orchidaceae	*Epiblastus*	73	0.8518
Orchidaceae	*Eria*	48	0.7072
Orchidaceae	*Eurycentrum*	14	0.5741
Orchidaceae	*Glomera*	155	0.7607
Orchidaceae	*Glossorhyncha*	103	0.7814
Orchidaceae	*Goodyera*	38	0.6442
Orchidaceae	*Grastidium*	23	0.6388
Orchidaceae	*Hetaeria*	27	0.7502
Orchidaceae	*Lepidogyne*	19	0.6075
Orchidaceae	*Liparis*	112	0.6512
Orchidaceae	*Malaxis*	46	0.5408
Orchidaceae	*Mediocalcar*	99	0.8315
Orchidaceae	*Microtatorchis*	12	0.9527
Orchidaceae	*Neuwiedia*	14	0.7383
Orchidaceae	*Oberonia*	66	0.698
Orchidaceae	*Octarrhena*	39	0.9304
Orchidaceae	*Pedilochilus*	33	0.8281
Orchidaceae	*Pedilonum*	19	0.8543
Orchidaceae	*Peristylus*	35	0.6983
Orchidaceae	*Phaius*	21	0.7429
Orchidaceae	*Pholidota*	25	0.5314
Orchidaceae	*Phreatia*	149	0.6535
Orchidaceae	*Plocoglottis*	34	0.5945
Orchidaceae	*Podochilus*	26	0.5608
Orchidaceae	*Pseuderia*	27	0.6267
Orchidaceae	*Pseudovanilla*	14	0.6273
Orchidaceae	*Pterostylis*	49	0.9516

Orchidaceae	*Spathoglottis*	105	0.5326
Orchidaceae	*Spiranthes*	29	0.6643
Orchidaceae	*Taeniophyllum*	35	0.6885
Orchidaceae	*Tainia*	15	0.8448
Orchidaceae	*Thelymitra*	41	0.8768
Orchidaceae	*Thrixspermum*	17	0.5254
Orchidaceae	*Trichoglottis*	11	0.5859
Orchidaceae	*Trichotosia*	19	0.6534
Orchidaceae	*Vrydagzynea*	21	0.5389
Orchidaceae	*Zeuxine*	10	0.6164
Orobanchaceae	*Buchnera*	22	0.7084
Orobanchaceae	*Euphrasia*	29	0.959
Orthotrichaceae	*Desmotheca*	16	0.9018
Orthotrichaceae	*Macromitrium*	159	0.6876
Orthotrichaceae	*Schlotheimia*	74	0.9004
Orthotrichaceae	*Zygodon*	13	0.9442
Osmundaceae	*Leptopteris*	53	0.8136
Oxalidaceae	*Averrhoa*	12	0.6422
Oxalidaceae	*Oxalis*	89	0.7474
Pandaceae	*Galearia*	44	0.5691
Pandanaceae	*Freycinetia*	196	0.5436
Pandanaceae	*Pandanus*	127	0.4857
Passifloraceae	*Adenia*	17	0.6839
Passifloraceae	*Hollrungia*	22	0.5114
Passifloraceae	*Passiflora*	94	0.6088
Pentaphragmataceae	*Pentaphragma*	18	0.7205
Pentaphylacaceae	*Archboldiodendron*	19	0.8407
Pentaphylacaceae	*Eurya*	191	0.7416
Pentaphylacaceae	*Ternstroemia*	113	0.5482
Peranemaceae	*Acrophorus*	24	0.817
Philesiaceae	*Geitonoplesium*	56	0.712
Mazaceae	*Mazus*	20	0.8698
Phyllanthaceae	*Actephila*	22	0.5448
Phyllanthaceae	*Antidesma*	217	0.5049
Phyllanthaceae	*Aporosa*	96	0.5151
Phyllanthaceae	*Baccaurea*	45	0.6467
Phyllanthaceae	*Breynia*	206	0.5846
Phyllanthaceae	*Bridelia*	46	0.6308
Phyllanthaceae	*Cleistanthus*	35	0.6238
Phyllanthaceae	*Glochidion*	340	0.4683
Phyllanthaceae	*Phyllanthus*	198	0.5438

Phyllocladaceae	*Phyllocladus*	75	0.896
Picrodendraceae	*Choriceras*	10	0.9706
Pinaceae	*Pinus*	10	0.8501
Piperaceae	*Peperomia*	111	0.6085
Piperaceae	*Piper*	449	0.5832
Piperaceae	*Pothomorphe*	13	0.7949
Pittosporaceae	*Pittosporum*	306	0.6334
Plagiochilaceae	*Plagiochila*	130	0.7873
Plagiochilaceae	*Plagiochilion*	28	0.917
Plantaginaceae	*Callitriche*	11	0.9881
Plantaginaceae	*Hebe*	31	0.9399
Plantaginaceae	*Limnophila*	44	0.5771
Plantaginaceae	*Plantago*	51	0.9034
Plantaginaceae	*Veronica*	22	0.9525
Pleuroziaceae	*Pleurozia*	47	0.8737
Poaceae	*Agrostis*	90	0.9057
Poaceae	*Alloteropsis*	31	0.7351
Poaceae	*Anthoxanthum*	38	0.9191
Poaceae	*Apluda*	50	0.6687
Poaceae	*Aristida*	20	0.7752
Poaceae	*Arthraxon*	59	0.8615
Poaceae	*Arundinella*	69	0.7145
Poaceae	*Bothriochloa*	16	0.7683
Poaceae	*Brachiaria*	46	0.7277
Poaceae	*Brachypodium*	29	0.851
Poaceae	*Calamagrostis*	51	0.8506
Poaceae	*Capillipedium*	42	0.8528
Poaceae	*Cenchrus*	68	0.6926
Poaceae	*Centotheca*	63	0.5752
Poaceae	*Chionachne*	27	0.6119
Poaceae	*Chloris*	20	0.6605
Poaceae	*Chrysopogon*	33	0.7441
Poaceae	*Coelachne*	13	0.9299
Poaceae	*Coelorachis*	20	0.6771
Poaceae	*Coix*	63	0.5668
Poaceae	*Cortaderia*	60	0.9107
Poaceae	*Cymbopogon*	31	0.6934
Poaceae	*Cynodon*	13	0.6967
Poaceae	*Cyrtococcum*	57	0.642
Poaceae	*Deschampsia*	71	0.8974
Poaceae	*Dichanthium*	24	0.7954

Poaceae	*Dichelachne*	58	0.9196
Poaceae	*Digitaria*	112	0.6586
Poaceae	*Dimeria*	40	0.709
Poaceae	*Echinochloa*	70	0.6193
Poaceae	*Echinopogon*	33	0.9108
Poaceae	*Ectrosia*	13	0.928
Poaceae	*Ehrharta*	21	0.9305
Poaceae	*Eleusine*	55	0.5946
Poaceae	*Elionurus*	13	0.7358
Poaceae	*Eragrostis*	136	0.6116
Poaceae	*Eremochloa*	10	0.8036
Poaceae	*Eriachne*	34	0.76
Poaceae	*Eulalia*	110	0.7042
Poaceae	*Festuca*	36	0.9129
Poaceae	*Garnotia*	33	0.5066
Poaceae	*Germainia*	15	0.9214
Poaceae	*Hackelochloa*	20	0.7879
Poaceae	*Heteropogon*	16	0.9364
Poaceae	*Hierochloe*	31	0.8493
Poaceae	*Hymenachne*	15	0.6663
Poaceae	*Hyparrhenia*	14	0.8491
Poaceae	*Imperata*	89	0.6356
Poaceae	*Isachne*	158	0.6716
Poaceae	*Ischaemum*	145	0.5812
Poaceae	*Lachnagrostis*	13	0.9421
Poaceae	*Leersia*	35	0.7168
Poaceae	*Leptaspis*	63	0.6646
Poaceae	*Leptochloa*	36	0.7674
Poaceae	*Lophatherum*	25	0.5438
Poaceae	*Melinis*	21	0.7464
Poaceae	*Microstegium*	19	0.6868
Poaceae	*Miscanthus*	65	0.8384
Poaceae	*Mnesithea*	36	0.7917
Poaceae	*Nastus*	101	0.7566
Poaceae	*Neololeba*	31	0.6267
Poaceae	*Ophiuros*	34	0.6972
Poaceae	*Oplismenus*	88	0.582
Poaceae	*Oryza*	20	0.8598
Poaceae	*Ottochloa*	12	0.663
Poaceae	*Panicum*	116	0.7181
Poaceae	*Paspalum*	171	0.5841

Poaceae	*Pennisetum*	33	0.5704
Poaceae	*Perotis*	17	0.7944
Poaceae	*Phragmites*	40	0.6385
Poaceae	*Poa*	102	0.8789
Poaceae	*Pogonatherum*	42	0.647
Poaceae	*Pseudechinolaena*	13	0.7712
Poaceae	*Pseudopogonatherum*	21	0.8246
Poaceae	*Pseudoraphis*	17	0.9208
Poaceae	*Racemobambos*	23	0.7765
Poaceae	*Rottboellia*	14	0.7825
Poaceae	*Rytidosperma*	76	0.879
Poaceae	*Saccharum*	40	0.5572
Poaceae	*Sacciolepis*	101	0.6576
Poaceae	*Schizachyrium*	14	0.7843
Poaceae	*Schizostachyum*	28	0.595
Poaceae	*Scrotochloa*	22	0.6735
Poaceae	*Setaria*	136	0.6491
Poaceae	*Sorghum*	73	0.7584
Poaceae	*Sporobolus*	38	0.6996
Poaceae	*Themeda*	105	0.6821
Poaceae	*Thysanolaena*	28	0.7733
Podocarpaceae	*Dacrycarpus*	154	0.8692
Podocarpaceae	*Dacrydium*	66	0.6934
Podocarpaceae	*Decussocarpus*	14	0.737
Podocarpaceae	*Falcatifolium*	19	0.78
Podocarpaceae	*Nageia*	35	0.5688
Podocarpaceae	*Podocarpus*	229	0.6214
Podocarpaceae	*Prumnopitys*	15	0.6633
Podocarpaceae	*Sundacarpus*	41	0.741
Polygalaceae	*Eriandra*	19	0.6097
Polygalaceae	*Polygala*	132	0.6626
Polygalaceae	*Securidaca*	33	0.5403
Polygalaceae	*Xanthophyllum*	43	0.5654
Polygonaceae	*Homalocladium*	14	0.5862
Polygonaceae	*Muehlenbeckia*	56	0.8309
Polygonaceae	*Persicaria*	146	0.6489
Polygonaceae	*Polygonum*	115	0.6478
Polygonaceae	*Rumex*	18	0.9261
Polypodiaceae	*Belvisia*	200	0.7922
Polypodiaceae	*Colysis*	14	0.6164
Polypodiaceae	*Crypsinus*	57	0.758

Polypodiaceae	*Drynaria*	99	0.472
Polypodiaceae	*Goniophlebium*	64	0.7896
Polypodiaceae	*Grammitis*	153	0.8118
Polypodiaceae	*Lecanopteris*	55	0.563
Polypodiaceae	*Lemmaphyllum*	89	0.6342
Polypodiaceae	*Lepisorus*	23	0.9107
Polypodiaceae	*Leptochilus*	23	0.5835
Polypodiaceae	*Merinthosorus*	18	0.631
Polypodiaceae	*Microsorum*	354	0.5277
Polypodiaceae	*Oreogrammitis*	47	0.905
Polypodiaceae	*Phymatosorus*	65	0.5735
Polypodiaceae	*Platycerium*	12	0.6788
Polypodiaceae	*Polypodium*	41	0.7242
Polypodiaceae	*Pyrrosia*	185	0.4902
Polypodiaceae	*Schellolepis*	72	0.7221
Polypodiaceae	*Scleroglossum*	17	0.7449
Polypodiaceae	*Selliguea*	243	0.7053
Polypodiaceae	*Themelium*	25	0.798
Polytrichaceae	*Dawsonia*	74	0.8801
Polytrichaceae	*Pogonatum*	37	0.8391
Porellaceae	*Porella*	58	0.916
Portulacaceae	*Portulaca*	34	0.6617
Potamogetonaceae	*Potamogeton*	16	0.6593
Pottiaceae	*Anoectangium*	16	0.9449
Pottiaceae	*Barbula*	54	0.8203
Pottiaceae	*Didymodon*	10	0.9532
Pottiaceae	*Hyophila*	37	0.8016
Pottiaceae	*Oxystegus*	12	0.9562
Pottiaceae	*Pseudosymblepharis*	35	0.9073
Pottiaceae	*Trichostomum*	12	0.8151
Primulaceae	*Aegiceras*	29	0.7271
Primulaceae	*Ardisia*	182	0.5464
Primulaceae	*Discocalyx*	66	0.6191
Primulaceae	*Embelia*	94	0.5786
Primulaceae	*Lysimachia*	30	0.928
Primulaceae	*Maesa*	172	0.6088
Primulaceae	*Myrsine*	288	0.7532
Proteaceae	*Alloxylon*	13	0.9624
Proteaceae	*Banksia*	38	0.8485
Proteaceae	*Finschia*	62	0.5955
Proteaceae	*Gevuina*	13	0.8547

Proteaceae	*Grevillea*	58	0.7073
Proteaceae	*Helicia*	228	0.6426
Proteaceae	*Stenocarpus*	14	0.8265
Psilotaceae	*Psilotum*	89	0.6074
Pteridaceae	*Acrostichum*	34	0.6175
Pteridaceae	*Adiantum*	147	0.6638
Pteridaceae	*Antrophyum*	162	0.5965
Pteridaceae	*Ceratopteris*	26	0.7312
Pteridaceae	*Cheilanthes*	63	0.6554
Pteridaceae	*Coniogramme*	24	0.6777
Pteridaceae	*Doryopteris*	25	0.6823
Pteridaceae	*Monogramma*	25	0.5918
Pteridaceae	*Pityrogramma*	28	0.5144
Pteridaceae	*Pteris*	258	0.5636
Pteridaceae	*Syngramma*	58	0.5932
Pteridaceae	*Taenitis*	83	0.6471
Pteridaceae	*Vittaria*	205	0.5487
Pteridiaceae	*Paesia*	22	0.8981
Pterobryaceae	*Calyptothecium*	55	0.8522
Pterobryaceae	*Garovaglia*	100	0.8081
Pterobryaceae	*Neolindbergia*	10	0.8953
Pterobryaceae	*Trachyloma*	31	0.8581
Putranjivaceae	*Drypetes*	30	0.5499
Racopilaceae	*Powellia*	17	0.878
Racopilaceae	*Racopilum*	129	0.7961
Radulaceae	*Radula*	86	0.7211
Ranunculaceae	*Clematis*	121	0.5835
Ranunculaceae	*Ranunculus*	100	0.9011
Rhamnaceae	*Alphitonia*	161	0.5438
Rhamnaceae	*Colubrina*	26	0.5618
Rhamnaceae	*Emmenosperma*	21	0.6969
Rhamnaceae	*Gouania*	44	0.604
Rhamnaceae	*Rhamnus*	57	0.8177
Rhamnaceae	*Ventilago*	13	0.6611
Rhamnaceae	*Ziziphus*	41	0.6185
Rhizogoniaceae	*Hymenodon*	35	0.8161
Rhizogoniaceae	*Hymenodontopsis*	25	0.9225
Rhizogoniaceae	*Pyrrhobryum*	43	0.717
Rhizogoniaceae	*Rhizogonium*	15	0.5399
Rhizophoraceae	*Bruguiera*	54	0.7201
Rhizophoraceae	*Ceriops*	14	0.7246

Rhizophoraceae	*Gynotroches*	58	0.5148
Rhizophoraceae	*Rhizophora*	40	0.7466
Rosaceae	*Acaena*	28	0.8881
Rosaceae	*Potentilla*	94	0.9073
Rosaceae	*Prunus*	220	0.614
Rosaceae	*Pygeum*	22	0.7145
Rosaceae	*Rubus*	220	0.6268
Rubiaceae	*Aidia*	29	0.6089
Rubiaceae	*Airosperma*	19	0.7191
Rubiaceae	*Amaracarpus*	152	0.5915
Rubiaceae	*Anthorrhiza*	13	0.7913
Rubiaceae	*Antirhea*	28	0.5921
Rubiaceae	*Argostemma*	41	0.7357
Rubiaceae	*Atractocarpus*	93	0.5098
Rubiaceae	*Borreria*	34	0.5545
Rubiaceae	*Canthium*	79	0.5113
Rubiaceae	*Coelospermum*	12	0.594
Rubiaceae	*Coprosma*	80	0.921
Rubiaceae	*Coptosapelta*	12	0.6085
Rubiaceae	*Dolianthus*	60	0.8637
Rubiaceae	*Dolicholobium*	48	0.7033
Rubiaceae	*Exallage*	10	0.6519
Rubiaceae	*Galium*	51	0.9231
Rubiaceae	*Gardenia*	142	0.4986
Rubiaceae	*Geophila*	22	0.6181
Rubiaceae	*Guettarda*	14	0.7318
Rubiaceae	*Hedyotis*	120	0.6045
Rubiaceae	*Hydnophytum*	146	0.4949
Rubiaceae	*Ixora*	151	0.5252
Rubiaceae	*Knoxia*	16	0.6161
Rubiaceae	*Lasianthus*	109	0.5297
Rubiaceae	*Lucinaea*	35	0.5227
Rubiaceae	*Mastixiodendron*	52	0.4535
Rubiaceae	*Mitracarpus*	12	0.6229
Rubiaceae	*Mitragyna*	13	0.6827
Rubiaceae	*Morinda*	110	0.5744
Rubiaceae	*Mussaenda*	197	0.5562
Rubiaceae	*Mycetia*	27	0.6635
Rubiaceae	*Myrmecodia*	82	0.5607
Rubiaceae	*Nauclea*	56	0.6196
Rubiaceae	*Neanotis*	19	0.8178

Rubiaceae	*Neolamarckia*	23	0.6603
Rubiaceae	*Neonauclea*	151	0.5574
Rubiaceae	*Nertera*	62	0.8898
Rubiaceae	*Oldenlandia*	81	0.5223
Rubiaceae	*Ophiorrhiza*	98	0.6507
Rubiaceae	*Pachystylus*	29	0.5805
Rubiaceae	*Pavetta*	76	0.6188
Rubiaceae	*Porterandia*	13	0.5498
Rubiaceae	*Psychotria*	465	0.5129
Rubiaceae	*Psydrax*	35	0.6165
Rubiaceae	*Randia*	114	0.5005
Rubiaceae	*Rhadinopus*	10	0.7028
Rubiaceae	*Saprosma*	12	0.5267
Rubiaceae	*Schradera*	52	0.5408
Rubiaceae	*Spermacoce*	92	0.6223
Rubiaceae	*Tarenna*	83	0.5612
Rubiaceae	*Timonius*	292	0.5234
Rubiaceae	*Uncaria*	91	0.5181
Rubiaceae	*Urophyllum*	82	0.6932
Rubiaceae	*Versteegia*	24	0.5594
Rubiaceae	*Wendlandia*	53	0.669
Rubiaceae	*Xanthophytum*	15	0.6346
Rutaceae	*Acronychia*	147	0.6892
Rutaceae	*Citrus*	25	0.6731
Rutaceae	*Clausena*	11	0.6755
Rutaceae	*Euodia*	74	0.6171
Rutaceae	*Evodiella*	16	0.8138
Rutaceae	*Flindersia*	93	0.5545
Rutaceae	*Geijera*	11	0.9716
Rutaceae	*Glycosmis*	18	0.6851
Rutaceae	*Halfordia*	43	0.5157
Rutaceae	*Lunasia*	33	0.6806
Rutaceae	*Melicope*	462	0.5848
Rutaceae	*Micromelum*	79	0.6322
Rutaceae	*Murraya*	10	0.8501
Rutaceae	*Tetractomia*	19	0.6185
Rutaceae	*Wenzelia*	19	0.6266
Rutaceae	*Zanthoxylum*	55	0.5841
Sabiaceae	*Meliosma*	91	0.7039
Salicaceae	*Casearia*	160	0.5481
Salicaceae	*Flacourtia*	41	0.6825

Salicaceae	*Homalium*	57	0.6322
Santalaceae	*Cladomyza*	76	0.8639
Santalaceae	*Dendromyza*	67	0.7475
Santalaceae	*Dendrotrophe*	20	0.632
Santalaceae	*Exocarpos*	66	0.77
Santalaceae	*Notothixos*	30	0.5582
Santalaceae	*Santalum*	32	0.9481
Santalaceae	*Scleropyrum*	34	0.58
Santalaceae	*Viscum*	28	0.5673
Sapindaceae	*Alectryon*	61	0.6836
Sapindaceae	*Allophylus*	96	0.6128
Sapindaceae	*Arytera*	44	0.5252
Sapindaceae	*Cardiospermum*	10	0.5905
Sapindaceae	*Cnesmocarpon*	10	0.5297
Sapindaceae	*Cupaniopsis*	73	0.5998
Sapindaceae	*Dictyoneura*	35	0.6608
Sapindaceae	*Dodonaea*	83	0.8281
Sapindaceae	*Elattostachys*	31	0.7194
Sapindaceae	*Ganophyllum*	21	0.525
Sapindaceae	*Guioa*	98	0.5447
Sapindaceae	*Harpullia*	209	0.5843
Sapindaceae	*Jagera*	39	0.6161
Sapindaceae	*Lepisanthes*	22	0.5155
Sapindaceae	*Mischocarpus*	61	0.634
Sapindaceae	*Pometia*	65	0.6184
Sapindaceae	*Sarcopteryx*	52	0.5641
Sapindaceae	*Toechima*	30	0.5919
Sapindaceae	*Tristiropsis*	28	0.582
Sapotaceae	*Burckella*	30	0.7005
Sapotaceae	*Chrysophyllum*	12	0.6426
Sapotaceae	*Madhuca*	14	0.724
Sapotaceae	*Magodendron*	10	0.6999
Sapotaceae	*Palaquium*	71	0.6431
Sapotaceae	*Planchonella*	148	0.5967
Sapotaceae	*Pleioluma*	46	0.6232
Sapotaceae	*Pouteria*	80	0.5769
Saxifragaceae	*Astilbe*	21	0.8728
Scapaniaceae	*Gottschelia*	15	0.9657
Scapaniaceae	*Scapania*	17	0.9215
Schistochilaceae	*Gottschea*	32	0.9213
Schistochilaceae	*Schistochila*	72	0.844

Schizaeaceae	*Schizaea*	127	0.5932
Scrophulariaceae	*Buddleja*	30	0.7153
Scrophulariaceae	*Parahebe*	50	0.8988
Selaginellaceae	*Selaginella*	285	0.5224
Sematophyllaceae	*Acroporium*	60	0.7383
Sematophyllaceae	*Meiothecium*	12	0.7303
Sematophyllaceae	*Sematophyllum*	10	0.918
Sematophyllaceae	*Trismegistia*	45	0.7168
Sematophyllaceae	*Warburgiella*	15	0.9164
Simaroubaceae	*Ailanthus*	18	0.688
Simaroubaceae	*Picrasma*	13	0.6801
Simaroubaceae	*Quassia*	19	0.6102
Smilacaceae	*Smilax*	92	0.4474
Solanaceae	*Lycianthes*	80	0.7378
Solanaceae	*Nicotiana*	13	0.621
Solanaceae	*Solanum*	279	0.6274
Sphagnaceae	*Sphagnum*	71	0.8588
Sphenostemonaceae	*Sphenostemon*	76	0.8034
Spiridentaceae	*Spiridens*	66	0.8452
Splachnaceae	*Tetraplodon*	10	0.9771
Staphyleaceae	*Turpinia*	62	0.6775
Stemonaceae	*Stemona*	10	0.756
Sterculiaceae	*Ambroma*	13	0.6352
Styracaceae	*Bruinsmia*	16	0.5499
Styracaceae	*Styrax*	18	0.6291
Symplocaceae	*Symplocos*	262	0.6733
Tectariaceae	*Pleocnemia*	55	0.6747
Tectariaceae	*Tectaria*	123	0.6266
Theaceae	*Adinandra*	43	0.5158
Theaceae	*Gordonia*	68	0.5825
Theaceae	*Terustroemia*	59	0.4857
Thelypteridaceae	*Amphineuron*	33	0.5947
Thelypteridaceae	*Christella*	38	0.5966
Thelypteridaceae	*Coryphopteris*	48	0.7776
Thelypteridaceae	*Cyclosorus*	88	0.5295
Thelypteridaceae	*Macrothelypteris*	18	0.5671
Thelypteridaceae	*Parathelypteris*	23	0.9298
Thelypteridaceae	*Plesioneuron*	62	0.6897
Thelypteridaceae	*Pneumatopteris*	117	0.5346
Thelypteridaceae	*Pronephrium*	55	0.6531
Thelypteridaceae	*Pseudophegopteris*	14	0.9231

Thelypteridaceae	*Sphaerostephanos*	272	0.5392
Thelypteridaceae	*Thelypteris*	61	0.5456
Thuidiaceae	*Pelekium*	18	0.633
Thuidiaceae	*Thuidium*	85	0.672
Thymelaeaceae	*Drapetes*	38	0.9112
Thymelaeaceae	*Kelleria*	34	0.9484
Thymelaeaceae	*Phaleria*	145	0.5751
Thymelaeaceae	*Thecanthes*	19	0.7012
Thymelaeaceae	*Wikstroemia*	39	0.7917
Tiliaceae	*Microcos*	132	0.6122
Trachypodaceae	*Trachypus*	10	0.9484
Trichocoleaceae	*Trichocolea*	56	0.8242
Trimeniaceae	*Trimenia*	79	0.7708
Triuridaceae	*Sciaphila*	22	0.5558
Typhaceae	*Typha*	19	0.8718
Urticaceae	*Boehmeria*	39	0.6472
Urticaceae	*Cypholophus*	172	0.6314
Urticaceae	*Debregeasia*	24	0.7162
Urticaceae	*Dendrocnide*	92	0.5273
Urticaceae	*Elatostema*	294	0.5848
Urticaceae	*Gonostegia*	37	0.6855
Urticaceae	*Laportea*	67	0.5171
Urticaceae	*Lecanthus*	17	0.9172
Urticaceae	*Leucosyke*	113	0.5934
Urticaceae	*Maoutia*	78	0.6076
Urticaceae	*Nothocnide*	67	0.5317
Urticaceae	*Oreocnide*	54	0.5842
Urticaceae	*Pilea*	177	0.7562
Urticaceae	*Pipturus*	245	0.5618
Urticaceae	*Poikilospermum*	112	0.5027
Urticaceae	*Pouzolzia*	51	0.6001
Urticaceae	*Procris*	132	0.6072
Urticaceae	*Urticastrum*	32	0.6994
Verbenaceae	*Calocarpa*	28	0.5757
Verbenaceae	*Clerodendron*	45	0.6572
Verbenaceae	*Lantana*	11	0.6038
Verbenaceae	*Stachytarpheta*	39	0.5017
Verbenaceae	*Verbena*	16	0.8861
Violaceae	*Rinorea*	42	0.5887
Violaceae	*Viola*	115	0.8447
Vitaceae	*Cayratia*	82	0.5397

Vitaceae	*Cissus*	106	0.4926
Vitaceae	*Nothocissus*	25	0.5505
Vitaceae	*Tetrastigma*	80	0.5031
Vittariaceae	*Vaginularia*	16	0.615
Winteraceae	*Belliolum*	22	0.7237
Winteraceae	*Bubbia*	96	0.7427
Winteraceae	*Drimys*	159	0.8215
Winteraceae	*Takhtajania*	42	0.8194
Winteraceae	*Tasmannia*	143	0.868
Winteraceae	*Zygogynum*	160	0.7737
Woodsiaceae	*Athyrium*	46	0.7835
Woodsiaceae	*Deparia*	13	0.8259
Woodsiaceae	*Diplazium*	290	0.609
Xanthorrhoeaceae	*Dianella*	98	0.5318
Xyridaceae	*Xyris*	40	0.6122
Zingiberaceae	*Alpinia*	220	0.5458
Zingiberaceae	*Curcuma*	44	0.6085
Zingiberaceae	*Etlingera*	58	0.6326
Zingiberaceae	*Hornstedtia*	43	0.6012
Zingiberaceae	*Pleuranthodium*	38	0.5944
Zingiberaceae	*Riedelia*	206	0.565

Table 10.6. Comparison of test AUC and null AUC scores for select genera.

Family	**Genus**	**Occurrences after rarify, biases**	**Test AUC**	**Null AUC**
Nothofagaceae	*Nothofagus*	175	0.8419	0.503006
Ericaceae	*Rhododendron*	458	0.7947	0.504158
Apocynaceae	*Alstonia*	116	0.503	0.505113
Rosaceae	*Acaena*	28	0.8881	0.504384

10.2. Appendix 3B: Genera Not Included In Study Due To Low Auc Scores

Table 10.7. Summary of results for genera not included in the study

	Occurrences	**Test AUC**
Mean	21	0.4434
Standard deviation	11	0.0532
Most # of occurrences	46	0.4995
Least # of occurrences	10	0.1989
Total genera	62	
Total occurrences	1284	

Table 10.8. Genera with test AUC scores less than 0.5 and occurrences fewer than 50.

Family	**Genus**	**Occurrences (after rarify, biases)**	**Test AUC**
Acanthaceae	*Leptosiphonium*	22	0.4226
Annonaceae	*Mitrella*	31	0.4372
Apocynaceae	*Asclepias*	10	0.3692
Apocynaceae	*Kopsia*	10	0.4843
Apocynaceae	*Papuechites*	35	0.4856
Apocynaceae	*Tylophora*	43	0.4409
Araceae	*Amydrium*	20	0.4167
Araceae	*Colocasia*	12	0.4328
Arecaceae	*Gronophyllum*	26	0.4675
Aristolochiaceae	*Pararistolochia*	12	0.4312
Asclepiadaceae	*Sarcolobus*	30	0.4937
Bignoniaceae	*Pandorea*	37	0.4217
Calophyllaceae	*Mammea*	18	0.4973
Celastraceae	*Lophopetalum*	14	0.3376
Clethraceae	*Clethra*	10	0.4374
Commelinaceae	*Commelina*	37	0.4995
Euphorbiaceae	*Briedelia*	10	0.3589
Euphorbiaceae	*Omalanthus*	35	0.4656
Euphorbiaceae	*Spathiostemon*	27	0.4984
Fabaceae	*Centrosema*	10	0.4407
Fabaceae	*Flemingia*	20	0.4842
Fabaceae	*Paraderris*	11	0.3842
Fabaceae	*Sesbania*	11	0.3959
Hymenophyllaceae	*Gonocormus*	12	0.3397

Hypoxidaceae	*Molineria*	11	0.4991
Lamiaceae	*Dysophylla*	13	0.468
Lamiaceae	*Orthosiphon*	15	0.468
Lejeuneaceae	*Leptolejeunea*	10	0.4921
Malvaceae	*Abroma*	19	0.4248
Melastomataceae	*Creochiton*	10	0.4229
Menispermaceae	*Stephania*	46	0.4193
Moraceae	*Parartocarpus*	25	0.4128
Moraceae	*Prainea*	15	0.3919
Musaceae	*Musa*	13	0.483
Myrsinaceae	*Fittingia*	21	0.4653
Myrtaceae	*Acmena*	12	0.4534
Olacaceae	*Anacolosa*	14	0.497
Orchidaceae	*Chilopogon*	11	0.493
Orchidaceae	*Corymborkis*	12	0.4518
Orchidaceae	*Dipodium*	13	0.1989
Orchidaceae	*Habenaria*	34	0.4794
Orchidaceae	*Robiquetia*	14	0.492
Orchidaceae	*Thelasis*	11	0.4925
Orchidaceae	*Tropidia*	14	0.4769
Orobanchaceae	*Striga*	15	0.4851
Phyllanthaceae	*Bischofia*	41	0.463
Poaceae	*Axonopus*	19	0.4775
Poaceae	*Bambusa*	46	0.4959
Poaceae	*Ichnanthus*	22	0.4269
Rhizophoraceae	*Carallia*	42	0.4469
Rubiaceae	*Cyclophyllum*	34	0.4892
Rubiaceae	*Gynochthodes*	31	0.4476
Sabiaceae	*Sabia*	14	0.4606
Salicaceae	*Xylosma*	15	0.4724
Sapindaceae	*Sarcotoechia*	10	0.3707
Scrophulariaceae	*Lymnophila*	10	0.3838
Sematophyllaceae	*Taxithelium*	24	0.4682
Solanaceae	*Physalis*	30	0.417
Vitaceae	*Ampelocissus*	11	0.42
Vittariaceae	*Haplopteris*	35	0.4669
Zingiberaceae	*Amomum*	33	0.3868
Zingiberaceae	*Zingiber*	16	0.4904

10.3. Appendix 3c: Genera with too few occurrences to be included in the model

Table 10.9. Summary of genera with too few occurrences to run initially and after rarify and biases were conducted.

	Number of Genera	Occurrences
Too few to run (after rarify, biases)	178	~1600
Too few occurrences initially	905	3241

Table 10.10. List of genera with too few occurrences to run after rarify and biases were conducted and too few occurrences initially.

Too few occurrences to run (after rarify, biases, all are <10)		***Too few occurrences initially***		
Family	**Genus**	***Family***	***Genus***	**Occurrences**
Acanthaceae	*Asystasia*	Acanthaceae	*Ancylacanthus*	1
Achariaceae	*Hydnocarpus*	Acanthaceae	*Aphelandra*	3
Acoraceae	*Acorus*	Acanthaceae	*Barleria*	2
Alismataceae	*Caldesia*	Acanthaceae	*Blechum*	6
Amaryllidaceae	*Crinum*	Acanthaceae	*Brunoniella*	2
Anacardiaceae	*Gluta*	Acanthaceae	*Dipteracanthus*	5
Annonaceae	*Fissistigma*	Acanthaceae	*Gendarussa*	3
Annonaceae	*Friesodielsia*	Acanthaceae	*Geunsia*	6
Annonaceae	*Meiogyne*	Acanthaceae	*Isoglossa*	2
Annonaceae	*Miliusa*	Acanthaceae	*Nelsonia*	3
Annonaceae	*Rauwenhoffia*	Acanthaceae	*Odontonema*	1
Apocynaceae	*Allamanda*	Acanthaceae	*Pachystachys*	1
Apocynaceae	*Carissa*	Acanthaceae	*Peristrophe*	4
Apocynaceae	*Catharanthus*	Acanthaceae	*Phlogacanthus*	2
Apocynaceae	*Secamone*	Acanthaceae	*Polytrema*	2
Araceae	*Aglaonema*	Acanthaceae	*Psacadocalymma*	1
Araceae	*Amorphophallus*	Acanthaceae	*Rhaphidospora*	5
Araceae	*Pistia*	Acanthaceae	*Sanchezia*	5
Araceae	*Syngonium*	Acanthaceae	*Strobilanthes*	2
Araceae	*Typhonium*	Acrobolbaceae	*Lethocolea*	1
Arecaceae	*Elaeis*	Acrobolbaceae	*Tylimanthus*	8
Arecaceae	*Pinanga*	Adelanthaceae	*Wettsteinia*	2
Asparagaceae	*Agave*	Adoxaceae	*Viburnum*	2
Asteraceae	*Cosmos*	Aizoaceae	*Trianthema*	6
Asteraceae	*Eleutheranthera*	Alismataceae	*Sagittaria*	5
Asteraceae	*Epaltes*	Alseuosmiaceae	*Periomphale*	1
Asteraceae	*Helianthus*	Alseuosmiaceae	*Wittsteinia*	4
Asteraceae	*Tithonia*	Alstroemeriaceae	*Luzuriaga*	3
Asteraceae	*Zinnia*	Amaranthaceae	*Aerva*	2
Balantiopsidaceae	*Isotachis*	Amaranthaceae	*Chenopodium*	8
Bignoniaceae	*Spathodea*	Amaranthaceae	*Psilotrichum*	1

Bignoniaceae	*Tecoma*	Amaranthaceae	*Ptilotus*	1
Bixaceae	*Cochlospermum*	Amaryllidaceae	*Proiphys*	1
Boraginaceae	*Argusia*	Amblystegiaceae	*Calliergon*	9
Boraginaceae	*Ehretia*	Amblystegiaceae	*Drepanocladus*	2
Brassicaceae	*Capsella*	Amblystegiaceae	*Limprichtia*	3
Cannaceae	*Canna*	Anacardiaceae	*Anacardium*	4
Caprifoliaceae	*Lonicera*	Anacardiaceae	*Koordersiodendron*	1
Caricaceae	*Carica*	Anacardiaceae	*Solenocarpus*	3
Caryophyllaceae	*Silene*	Anacardiaceae	*Toxicodendron*	7
Celastraceae	*Bhesa*	Annonaceae	*Alphonsea*	3
Celastraceae	*Euonymus*	Annonaceae	*Anaxagorea*	1
Celastraceae	*Gymnosporia*	Annonaceae	*Annona*	2
Chrysobalanaceae	*Hunga*	Annonaceae	*Cyathostemma*	3
Commelinaceae	*Tradescantia*	Annonaceae	*Desmos*	1
Convolvulaceae	*Operculina*	Annonaceae	*Enicosanthum*	3
Convolvulaceae	*Porana*	Annonaceae	*Huberantha*	7
Cucurbitaceae	*Benincasa*	Annonaceae	*Mitrephora*	3
Cucurbitaceae	*Cucurbita*	Annonaceae	*Petalolophus*	6
Cucurbitaceae	*Lagenaria*	Annonaceae	*Rollinia*	1
Cucurbitaceae	*Sechium*	Antheliaceae	*Anthelia*	1
Cyperaceae	*Actinoscirpus*	Apiaceae	*Andriana*	2
Cyperaceae	*Diplacrum*	Apiaceae	*Apium*	2
Cyperaceae	*Lepironia*	Apiaceae	*Cyclospermum*	4
Cyperaceae	*Remirea*	Apiaceae	*Lisaea*	1
Ditrichaceae	*Garckea*	Apiaceae	*Osmorhiza*	2
Euphorbiaceae	*Hevea*	Apiaceae	*Scandix*	3
Euphorbiaceae	*Jatropha*	Apocynaceae	*Bleekeria*	1
Euphorbiaceae	*Manihot*	Apocynaceae	*Brachystelma*	3
Euphorbiaceae	*Ricinus*	Apocynaceae	*Calotropis*	4
Fabaceae	*Aganope*	Apocynaceae	*Chilocarpus*	2
Fabaceae	*Brownea*	Apocynaceae	*Clitandropsis*	2
Fabaceae	*Butea*	Apocynaceae	*Delphyodon*	8
Fabaceae	*Calliandra*	Apocynaceae	*Dischidiopsis*	1
Fabaceae	*Castanospermum*	Apocynaceae	*Ervatamia*	5
Fabaceae	*Clitoria*	Apocynaceae	*Gymnema*	9
Fabaceae	*Cullen*	Apocynaceae	*Nerium*	1
Fabaceae	*Dumasia*	Apocynaceae	*Pachycarpus*	1
Fabaceae	*Enterolobium*	Apocynaceae	*Rejoua*	9
Fabaceae	*Eriosema*	Apocynaceae	*Saba*	1
Fabaceae	*Galactia*	Apocynaceae	*Trachelospermum*	2
Fabaceae	*Gliricidia*	Araceae	*Anthurium*	1
Fabaceae	*Lablab*	Araceae	*Arum*	1
Fabaceae	*Lathyrus*	Araceae	*Lasia*	7
Fabaceae	*Lonchocarpus*	Araceae	*Lemna*	4
Fabaceae	*Lupinus*	Araceae	*Pedicellarum*	1
Fabaceae	*Macrotyloma*	Araceae	*Raphidophora*	1
Fabaceae	*Mundulea*	Araceae	*Spirodela*	9
Fabaceae	*Neptunia*	Araceae	*Xanthosoma*	1
Fabaceae	*Ormosia*	Araliaceae	*Boerlagiodendron*	5
Fabaceae	*Pachyrhizus*	Araliaceae	*Delarbrea*	4
Fabaceae	*Peltophorum*	Araliaceae	*Meryta*	2
Fabaceae	*Pericopsis*	Araliaceae	*Plerandra*	4
Fabaceae	*Prosopis*	Arecaceae	*Borassus*	4

Fabaceae	*Psophocarpus*	Arecaceae	*Clinostigma*	5
Fabaceae	*Saraca*	Arecaceae	*Cocos*	1
Fabaceae	*Sophora*	Arecaceae	*Corypha*	1
Fabaceae	*Tamarindus*	Arecaceae	*Drymophloeus*	8
Fabaceae	*Vicia*	Arecaceae	*Gulubia*	8
Fabaceae	*Zornia*	Arecaceae	*Iguanura*	1
Goodeniaceae	*Goodenia*	Arecaceae	*Nypa*	4
Halimedaceae	*Halimeda*	Arecaceae	*Oraniopsis*	3
Hydrocharitaceae	*Enhalus*	Arecaceae	*Paralinospadix*	2
Hydrocharitaceae	*Halophila*	Arecaceae	*Physokentia*	2
Hydrocharitaceae	*Ottelia*	Arecaceae	*Sabal*	1
Hymenophyllaceae	*Callistopteris*	Arecaceae	*Saribus*	2
Icacinaceae	*Merrilliodendron*	Arecaceae	*Thrinax*	1
Lamiaceae	*Ceratanthus*	Arecaceae	*Veitchia*	1
Lamiaceae	*Tectona*	Asclepiadaceae	*Gymnanthera*	5
Lauraceae	*Dehaasia*	Asclepiadaceae	*Ischnostemma*	2
Lauraceae	*Nothaphoebe*	Asclepiadaceae	*Phyllanthera*	7
Lauraceae	*Persea*	Asclepiadaceae	*Stephanotis*	1
Loganiaceae	*Spigelia*	Asparagaceae	*Arthropodium*	4
Lythraceae	*Pemphis*	Asparagaceae	*Eustrephus*	5
Malpighiaceae	*Tristellateia*	Asparagaceae	*Romnalda*	6
Malvaceae	*Camptostemon*	Asparagaceae	*Thysanotus*	6
Malvaceae	*Ceiba*	Aspleniaceae	*Hymenasplenium*	6
Malvaceae	*Durio*	Aspleniaceae	*Loxoscaphe*	2
Malvaceae	*Gossypium*	Asteraceae	*Acanthospermum*	2
Malvaceae	*Malvastrum*	Asteraceae	*Artemisia*	1
Malvaceae	*Ochroma*	Asteraceae	*Aster*	1
Melastomataceae	*Pachycentria*	Asteraceae	*Bedfordia*	3
Melastomataceae	*Sonerila*	Asteraceae	*Brachycome*	2
Meliaceae	*Melia*	Asteraceae	*Brachyscome*	6
Menispermaceae	*Macrococculus*	Asteraceae	*Camptacra*	9
Molluginaceae	*Mollugo*	Asteraceae	*Celmisia*	1
Monimiaceae	*Matthaea*	Asteraceae	*Centratherum*	8
Moraceae	*Broussonetia*	Asteraceae	*Cirsium*	1
Moraceae	*Morus*	Asteraceae	*Conyza*	5
Myrtaceae	*Gossia*	Asteraceae	*Cotula*	6
Myrtaceae	*Kjellbergiodendron*	Asteraceae	*Crepis*	3
Myrtaceae	*Leptospermum*	Asteraceae	*Dicoma*	1
Myrtaceae	*Myrtus*	Asteraceae	*Glossocardia*	3
Myrtaceae	*Psidium*	Asteraceae	*Helichrysum*	3
Nelumbonaceae	*Nelumbo*	Asteraceae	*Hypochaeris*	1
Nyctaginaceae	*Mirabilis*	Asteraceae	*Lagenocypsela*	6
Ochnaceae	*Brackenridgea*	Asteraceae	*Laphangium*	2
Orchidaceae	*Cleisostoma*	Asteraceae	*Lepidaploa*	4
Orchidaceae	*Eulophia*	Asteraceae	*Myriactis*	8
Orchidaceae	*Flickingeria*	Asteraceae	*Phacellothrix*	2
Orchidaceae	*Grammatophyllum*	Asteraceae	*Phrygia*	1
Orchidaceae	*Hylophila*	Asteraceae	*Piora*	4
Orchidaceae	*Nervilia*	Asteraceae	*Pterocaulon*	8
Phyllanthaceae	*Sauropus*	Asteraceae	*Pyrethrum*	1
Plantaginaceae	*Angelonia*	Asteraceae	*Raoulia*	2
Plantaginaceae	*Russelia*	Asteraceae	*Rhamphogyne*	1
Plumbaginaceae	*Aegialitis*	Asteraceae	*Solidago*	1

Plumbaginaceae	*Plumbago*	Asteraceae	*Sparganophorus*	1
Poaceae	*Dactyloctenium*	Asteraceae	*Sphaeranthus*	5
Poaceae	*Dendrocalamus*	Asteraceae	*Sphaeromorphaea*	7
Poaceae	*Ectrosiopsis*	Asteraceae	*Spilanthes*	6
Poaceae	*Elymus*	Asteraceae	*Strobocalyx*	1
Poaceae	*Eriochloa*	Asteraceae	*Tanacetum*	4
Poaceae	*Lepturus*	Asteraceae	*Vittadinia*	2
Poaceae	*Lolium*	Asteraceae	*Wedelia*	7
Poaceae	*Thuarea*	Asteraceae	*Xanthium*	3
Podocarpaceae	*Retrophyllum*	Athyriaceae	*Acystopteris*	2
Polygalaceae	*Salomonia*	Athyriaceae	*Anisocampium*	1
Polygonaceae	*Antigonon*	Athyriaceae	*Diplaziopsis*	9
Pteridaceae	*Gaga*	Athyriaceae	*Dryoathyrium*	3
Restionaceae	*Dapsilanthus*	Balanophoraceae	*Langsdorffia*	6
Rubiaceae	*Bikkia*	Bartramiaceae	*Anacolia*	4
Rubiaceae	*Cinchona*	Bartramiaceae	*Conostomum*	2
Rubiaceae	*Coffea*	Bartramiaceae	*Fleischerobryum*	3
Rubiaceae	*Paederia*	Bartramiaceae	*Leiomela*	8
Rubiaceae	*Pentas*	Bataceae	*Batis*	4
Rubiaceae	*Sarcocephalus*	Batrachospermaceae	*Batrachospermum*	3
Rubiaceae	*Scyphiphora*	Berberidaceae	*Caulophyllum*	1
Rutaceae	*Clymenia*	Bignoniaceae	*Jacaranda*	2
Rutaceae	*Triphasia*	Bignoniaceae	*Lamiodendron*	6
Santalaceae	*Ginalloa*	Bignoniaceae	*Saritaea*	1
Sapindaceae	*Dimocarpus*	Blechnaceae	*Woodwardia*	8
Sapindaceae	*Nephelium*	Boraginaceae	*Bothriospermum*	5
Sapindaceae	*Rhysotoechia*	Boraginaceae	*Carmona*	7
Sapindaceae	*Synima*	Boraginaceae	*Coldenia*	3
Sapotaceae	*Manilkara*	Boraginaceae	*Halgania*	1
Sapotaceae	*Mimusops*	Boraginaceae	*Lithospermum*	1
Sapotaceae	*Pichonia*	Boraginaceae	*Trichodesma*	2
Sematophyllaceae	*Radulina*	Brachytheciaceae	*Cirriphyllum*	1
Simaroubaceae	*Soulamea*	Brachytheciaceae	*Eurhynchium*	1
Solanaceae	*Capsicum*	Brachytheciaceae	*Platyhypnidium*	8
Solanaceae	*Datura*	Brachytheciaceae	*Rhynchostegiella*	4
Talinaceae	*Talinum*	Brachytheciaceae	*Unclejackia*	3
Tectariaceae	*Pteridrys*	Brassicaceae	*Papuzilla*	3
Verbenaceae	*Duranta*	Brassicaceae	*Raphanus*	2
Verbenaceae	*Phyla*	Bryaceae	*Imbribryum*	5
Zingiberaceae	*Globba*	Bryaceae	*Mielichhoferia*	4
Zingiberaceae	*Hedychium*	Bryaceae	*Orthodontium*	4
Zygophyllaceae	*Tribulus*	Bryaceae	*Ptychostomum*	1
		Burmanniaceae	*Thismia*	2
		Burseraceae	*Bursera*	1
		Burseraceae	*Rosselia*	4
		Burseraceae	*Scutinanthe*	2
		Buxbaumiaceae	*Buxbaumia*	6
		Calymperaceae	*Thyridium*	1
		Calypogeiaceae	*Mnioloma*	1
		Campanulaceae	*Cyclocodon*	9
		Campanulaceae	*Hippobroma*	4
		Campanulaceae	*Pratia*	6
		Campanulaceae	*Ruthiella*	2

		Capparaceae	*Celome*	4
		Cardiopteridaceae	*Peripterygium*	4
		Caryophyllaceae	*Agrostemma*	1
		Caryophyllaceae	*Colobanthus*	2
		Caryophyllaceae	*Polycarpaea*	7
		Caryophyllaceae	*Scleranthus*	9
		Casuarinaceae	*Ceuthostoma*	2
		Caulacanthaceae	*Catenella*	1
		Caulerpaceae	*Caulerpa*	6
		Celastraceae	*Maytenus*	7
		Celastraceae	*Pleurostylia*	2
		Cephaloziaceae	*Cephalozia*	1
		Cephaloziaceae	*Metahygrobiella*	3
		Cephaloziaceae	*Nowellia*	3
		Cephaloziaceae	*Odontoschisma*	3
		Cephaloziaceae	*Schiffneria*	1
		Cephaloziellaceae	*Cephaloziella*	1
		Cephaloziellaceae	*Cylindrocolea*	3
		Characeae	*Lychnothamnus*	1
		Chenopodiaceae	*Salicornia*	1
		Chrysobalanaceae	*Cyclandrophora*	1
		Chrysobalanaceae	*Dactyladenia*	2
		Chrysobalanaceae	*Licania*	3
		Cladophoraceae	*Chaetomorpha*	1
		Cladophoraceae	*Pithophora*	1
		Cladophoraceae	*Rhizoclonium*	2
		Cleomaceae	*Hemiscola*	3
		Cleomaceae	*Tarenaya*	2
		Clusiaceae	*Kayea*	9
		Clusiaceae	*Mesua*	9
		Clusiaceae	*Nouhuysia*	2
		Clusiaceae	*Ochrocarpos*	1
		Colchicaceae	*Gloriosa*	3
		Combretaceae	*Quisqualis*	9
		Commelinaceae	*Aclisia*	3
		Commelinaceae	*Cartonema*	1
		Commelinaceae	*Cyanotis*	8
		Commelinaceae	*Dictyospermum*	5
		Commelinaceae	*Forrestia*	4
		Commelinaceae	*Rhopalephora*	1
		Commelinaceae	*Tricarpelema*	1
		Convolvulaceae	*Hewittia*	1
		Convolvulaceae	*Xenostegia*	1
		Corallinaceae	*Cheilosporum*	1
		Corallinaceae	*Jania*	1
		Costaceae	*Costus*	1
		Crassulaceae	*Bryophyllum*	3
		Crassulaceae	*Kalanchoe*	1
		Cryphaeaceae	*Acrocryphaea*	1
		Cucurbitaceae	*Bryonia*	2
		Cucurbitaceae	*Bryonopsis*	7
		Cucurbitaceae	*Cyclanthera*	1
		Cucurbitaceae	*Gomphogyne*	2

		Cucurbitaceae	*Muckia*	2
		Cucurbitaceae	*Muellerargia*	4
		Cucurbitaceae	*Papuasicyos*	5
		Cucurbitaceae	*Thladiantha*	2
		Culcitaceae	*Culcita*	7
		Cunoniaceae	*Geissois*	1
		Cupressaceae	*Cryptomeria*	3
		Cupressaceae	*Libocedrus*	2
		Cyatheaceae	*Alsophila*	5
		Cyatheaceae	*Sphaeropteris*	4
		Cymodoceaceae	*Cymodocea*	9
		Cymodoceaceae	*Halodule*	6
		Cymodoceaceae	*Syringodium*	3
		Cyperaceae	*Baumea*	2
		Cyperaceae	*Bolboschoenus*	3
		Cyperaceae	*Capitularia*	1
		Cyperaceae	*Capitularina*	9
		Cyperaceae	*Cladium*	8
		Cyperaceae	*Exocarya*	4
		Cyperaceae	*Lepidosperma*	2
		Cyperaceae	*Scirpodendron*	4
		Cyperaceae	*Thoracostachyum*	4
		Cystocloniaceae	*Fimbrifolium*	3
		Daltoniaceae	*Distichophyllidium*	3
		Daltoniaceae	*Lepidopilum*	3
		Dennstaedtiaceae	*Ithycaulon*	2
		Dicksoniaceae	*Cibotium*	2
		Dicnemonaceae	*Eucamptodon*	3
		Dicnemonaceae	*Synodontia*	3
		Dicranaceae	*Campylopodiella*	3
		Dicranaceae	*Chorisodontium*	3
		Dicranaceae	*Cladopodanthus*	4
		Dicranaceae	*Dichodontium*	4
		Dicranaceae	*Dicranodontium*	9
		Dicranaceae	*Dicranoweisia*	2
		Dicranaceae	*Microcampylopus*	3
		Dipteridaceae	*Phymatodes*	3
		Dipterocarpaceae	*Shorea*	9
		Ditrichaceae	*Rhamphidium*	4
		Ditrichaceae	*Wilsoniella*	7
		Dryopteridaceae	*Arcypteris*	4
		Dryopteridaceae	*Chlamydogramme*	9
		Dryopteridaceae	*Hypodematium*	4
		Dryopteridaceae	*Stenosemia*	3
		Elaeocarpaceae	*Peripentadenia*	2
		Elatinaceae	*Elatine*	4
		Encalyptaceae	*Encalypta*	1
		Entodontaceae	*Plagiotheciopsis*	6
		Entodontaceae	*Trachyphyllum*	5
		Eriocaulaceae	*Syngonanthus*	3
		Euphorbiaceae	*Agrostistachys*	3
		Euphorbiaceae	*Bischoffia*	1
		Euphorbiaceae	*Chamaesyce*	6

		Euphorbiaceae	*Dimorphocalyx*	4
		Euphorbiaceae	*Flueggia*	2
		Euphorbiaceae	*Fontainea*	6
		Euphorbiaceae	*Gymnanthes*	1
		Euphorbiaceae	*Hura*	2
		Euphorbiaceae	*Koilodepas*	5
		Euphorbiaceae	*Leptopus*	1
		Euphorbiaceae	*Octospermum*	1
		Euphorbiaceae	*Ptychopyxis*	7
		Euphorbiaceae	*Ryparia*	1
		Euphorbiaceae	*Sapium*	1
		Euphorbiaceae	*Suregada*	9
		Euphorbiaceae	*Syndyophyllum*	4
		Euphorbiaceae	*Trigonostemon*	6
		Euphorbiaceae	*Wetria*	4
		Fabaceae	*Abarema*	9
		Fabaceae	*Acaciella*	1
		Fabaceae	*Anadenanthera*	4
		Fabaceae	*Aphyllodium*	4
		Fabaceae	*Archidendropsis*	9
		Fabaceae	*Austrosteenisia*	8
		Fabaceae	*Calpurnia*	1
		Fabaceae	*Colvillea*	2
		Fabaceae	*Desmanthus*	1
		Fabaceae	*Lotononis*	1
		Fabaceae	*Lotus*	1
		Fabaceae	*Lysiphyllum*	4
		Fabaceae	*Neonotonia*	2
		Fabaceae	*Ototropis*	1
		Fabaceae	*Pararchidendron*	9
		Fabaceae	*Prioria*	3
		Fabaceae	*Solori*	2
		Fagaceae	*Pasania*	9
		Fagaceae	*Quercus*	8
		Flacourtiaceae	*Scolopia*	7
		Funariaceae	*Physcomitrium*	3
		Galaxauraceae	*Galaxaura*	2
		Gelidiaceae	*Gelidium*	5
		Gentianaceae	*Centaurium*	1
		Gentianaceae	*Cotylanthera*	8
		Gentianaceae	*Lisianthus*	1
		Gesneriaceae	*Dichotrichum*	1
		Gesneriaceae	*Episcia*	1
		Gesneriaceae	*Epithema*	1
		Gesneriaceae	*Monophyllaea*	7
		Gesneriaceae	*Oxychlamys*	1
		Gesneriaceae	*Paraboea*	1
		Gesneriaceae	*Sinningia*	1
		Gesneriaceae	*Trichosporum*	2
		Gnetaceae	*Thoa*	1
		Goodeniaceae	*Calogyne*	2
		Goodeniaceae	*Leschenaultia*	2
		Goodeniaceae	*Velleia*	4

		Grammitidaceae	*Acrosorus*	5
		Grammitidaceae	*Chrysogrammitis*	3
		Grammitidaceae	*Nematopteris*	1
		Grammitidaceae	*Radiogrammitis*	7
		Grimmiaceae	*Grimmia*	5
		Gymnomitriaceae	*Gymnomitrion*	1
		Halymeniaceae	*Halymenia*	2
		Hernandiaceae	*Illigera*	1
		Himantandraceae	*Himantandra*	1
		Hookeriaceae	*Bryobrothera*	1
		Hookeriaceae	*Calyptrochaeta*	5
		Hookeriaceae	*Eriopus*	6
		Hookeriaceae	*Hookeria*	1
		Hookeriaceae	*Hookeriopsis*	5
		Hookeriaceae	*Pterygophyllum*	6
		Hydrocharitaceae	*Hydrilla*	6
		Hydrocharitaceae	*Hydrocharis*	3
		Hydrocharitaceae	*Thalassia*	7
		Hymenophyllaceae	*Didymoglossum*	1
		Hymenophyllaceae	*Polyphlebium*	4
		Hypnaceae	*Ectropotheciopsis*	4
		Hypnaceae	*Giraldiella*	1
		Hypnaceae	*Glossadelphus*	9
		Hypnaceae	*Gollania*	4
		Hypnaceae	*Hypnum*	3
		Hypnaceae	*Leucomium*	4
		Hypnaceae	*Macrothamniella*	6
		Hypnaceae	*Rhizohypnella*	3
		Hypnaceae	*Taxiphyllum*	7
		Hypnaceae	*Trachythecium*	9
		Hypnodendraceae	*Mniodendron*	8
		Hypnodendraceae	*Sciadocladus*	1
		Hypoxidaceae	*Hypoxis*	3
		Icacinaceae	*Iodes*	1
		Icacinaceae	*Phytocrene*	7
		Iridaceae	*Sisyrinchium*	7
		Iridaceae	*Tritonia*	4
		Joinvilleaceae	*Joinvillea*	3
		Jubulaceae	*Jubula*	4
		Juncaginaceae	*Cycnogeton*	2
		Juncaginaceae	*Triglochin*	2
		Lamiaceae	*Clinopodium*	1
		Lamiaceae	*Cymaria*	3
		Lamiaceae	*Glossocarya*	7
		Lamiaceae	*Marsypianthes*	4
		Lamiaceae	*Mesona*	7
		Lamiaceae	*Mesosphaerum*	1
		Lamiaceae	*Satureja*	2
		Lamiaceae	*Teucrium*	4
		Lamiaceae	*Teysmanniodendron*	1
		Lauraceae	*Brassiodendron*	1
		Lauraceae	*Lindera*	3
		Lauraceae	*Notaphoebe*	1

		Lejeuneaceae	*Acanthocoleus*	2
		Lejeuneaceae	*Diplasiolejeunea*	1
		Lejeuneaceae	*Harpalejeunea*	1
		Lejeuneaceae	*Leucolejeunea*	5
		Lejeuneaceae	*Metalejeunea*	4
		Lejeuneaceae	*Microlejeunea*	3
		Lejeuneaceae	*Myriocoleopsis*	1
		Lejeuneaceae	*Otolejeunea*	5
		Lejeuneaceae	*Papillolejeunea*	9
		Lejeuneaceae	*Phaeolejeunea*	2
		Lejeuneaceae	*Plagiolejeunea*	1
		Lejeuneaceae	*Prionolejeunea*	1
		Lejeuneaceae	*Stictolejeunea*	1
		Lejeuneaceae	*Trachylejeunea*	1
		Lejeuneaceae	*Trocholejeunea*	9
		Lejeuneaceae	*Tuyamaella*	4
		Lepidoziaceae	*Arachniopsis*	3
		Lepidoziaceae	*Neolepidozia*	2
		Lepidoziaceae	*Psiloclada*	9
		Lepidoziaceae	*Zoopsis*	8
		Leptodontaceae	*Caduciella*	8
		Leskeaceae	*Duthiella*	3
		Leskeaceae	*Lindbergia*	6
		Leskeaceae	*Pseudoleskeopsis*	4
		Leskeaceae	*Schwetschkea*	3
		Leucodontaceae	*Forsstroemia*	6
		Liliaceae	*Drakaina*	7
		Linaceae	*Ixionanthes*	1
		Lindsaeaceae	*Osmolindsaea*	1
		Loganiaceae	*Mitreola*	1
		Lomariopsidaceae	*Cyclopeltis*	9
		Lomariopsidaceae	*Thysanosoria*	1
		Lomentariaceae	*Gelidiopsis*	1
		Lophocoleaceae	*Conoscyphus*	4
		Lophocoleaceae	*Leptoscyphus*	3
		Lophoziaceae	*Denotrarisia*	3
		Loranthaceae	*Amylotheca*	9
		Loranthaceae	*Bakerella*	4
		Loranthaceae	*Cyne*	4
		Loranthaceae	*Loranthus*	5
		Loranthaceae	*Phrygilanthus*	4
		Loranthaceae	*Scurrula*	1
		Lythraceae	*Ammannia*	5
		Lythraceae	*Cuphea*	7
		Lythraceae	*Lawsonia*	1
		Lythraceae	*Lythrum*	3
		Magnoliaceae	*Talauma*	1
		Malpighiaceae	*Malpighia*	3
		Malpighiaceae	*Rhyssopteris*	1
		Malvaceae	*Aquilaria*	5
		Malvaceae	*Eleutherostylis*	3
		Malvaceae	*Fioria*	5
		Malvaceae	*Hildegardia*	1

		Malvaceae	*Kosteletzkya*	1
		Malvaceae	*Malachra*	1
		Malvaceae	*Malva*	3
		Malvaceae	*Malvaviscus*	2
		Malvaceae	*Melhania*	3
		Malvaceae	*Papuodendron*	9
		Malvaceae	*Pentapetes*	1
		Malvaceae	*Pterospermum*	1
		Marantaceae	*Calathea*	1
		Marantaceae	*Clinogyne*	1
		Marantaceae	*Megaphrynium*	1
		Marantaceae	*Phacelophrynium*	4
		Marantaceae	*Stachyphrynium*	1
		Marattiaceae	*Marrattia*	4
		Marattiaceae	*Pecopteris*	1
		Matoniaceae	*Phanerosorus*	5
		Melastomataceae	*Bamlera*	2
		Melastomataceae	*Clidemia*	4
		Melastomataceae	*Diplectria*	8
		Melastomataceae	*Everettia*	3
		Melastomataceae	*Hederella*	5
		Melastomataceae	*Heteroblemma*	2
		Melastomataceae	*Heterocentron*	6
		Melastomataceae	*Hypenanthe*	1
		Melastomataceae	*Kibessia*	1
		Melastomataceae	*Macrolenes*	1
		Melastomataceae	*Phyllapophysis*	1
		Melastomataceae	*Tibouchina*	3
		Meliaceae	*Anthocarapa*	6
		Meliaceae	*Carapa*	1
		Meliaceae	*Clemensia*	1
		Meliaceae	*Didymocheton*	2
		Meliaceae	*Epicharis*	1
		Meliaceae	*Lansium*	2
		Meliaceae	*Pseudoclausena*	1
		Meliaceae	*Reinwardtiodendron*	1
		Meliaceae	*Sandoricum*	7
		Meliaceae	*Synoum*	7
		Meliaceae	*Turraea*	9
		Menispermaceae	*Albertisia*	8
		Menispermaceae	*Carronia*	4
		Menispermaceae	*Cocculus*	1
		Menispermaceae	*Limacia*	1
		Menispermaceae	*Pachygone*	5
		Menispermaceae	*Sarcopetalum*	4
		Menispermaceae	*Tinomiscium*	9
		Meteoriaceae	*Barbella*	8
		Meteoriaceae	*Chrysocladium*	1
		Mimosaceae	*Albizzia*	9
		Mniaceae	*Orthomniopsis*	7
		Monachosoraceae	*Monachosorum*	4
		Monimiaceae	*Anthobembix*	2
		Monimiaceae	*Faika*	2

		Monimiaceae	*Hedycarya*	7
		Monimiaceae	*Monimia*	1
		Monimiaceae	*Tetrasynandra*	1
		Monimiaceae	*Wilkiea*	6
		Moraceae	*Dammaropsis*	2
		Moraceae	*Malaisia*	2
		Moraceae	*Paratrophis*	1
		Moraceae	*Pseudotrophis*	1
		Moringaceae	*Moringa*	5
		Musaceae	*Ensete*	3
		Myristicaceae	*Knema*	3
		Myrsinaceae	*Grenacheria*	7
		Myrsinaceae	*Hymenandra*	1
		Myrsinaceae	*Labisia*	5
		Myrsinaceae	*Loheria*	9
		Myrtaceae	*Acmenosperma*	2
		Myrtaceae	*Baeckea*	9
		Myrtaceae	*Cleistocalyx*	2
		Myrtaceae	*Mosiera*	1
		Myrtaceae	*Myrceugenia*	1
		Myrtaceae	*Osbornia*	6
		Myrtaceae	*Pilidiostigma*	2
		Myrtaceae	*Syncarpia*	3
		Neckeraceae	*Neomacounia*	1
		Neckeraceae	*Porotrichum*	1
		Neckeraceae	*Thamnobryum*	7
		Nelumbonaceae	*Nelumbium*	1
		Notothyladaceae	*Notothylas*	4
		Nymphaeaceae	*Hydrostemma*	8
		Olacaceae	*Ximenia*	7
		Oleaceae	*Linociera*	5
		Oleaceae	*Myxopyrum*	7
		Ophioglossaceae	*Japanobotrychum*	1
		Ophioglossaceae	*Sceptridium*	2
		Opiliaceae	*Champereia*	1
		Opiliaceae	*Lepionurus*	2
		Orchidaceae	*Acanthophippium*	5
		Orchidaceae	*Adenoncos*	4
		Orchidaceae	*Amblyanthe*	7
		Orchidaceae	*Anoectochilus*	9
		Orchidaceae	*Aphyllorchis*	2
		Orchidaceae	*Ascoglossum*	1
		Orchidaceae	*Calcearia*	1
		Orchidaceae	*Calochilus*	2
		Orchidaceae	*Calymmanthera*	2
		Orchidaceae	*Cephalantheropsis*	3
		Orchidaceae	*Cestichis*	1
		Orchidaceae	*Chamaeanthus*	3
		Orchidaceae	*Cheirostylis*	8
		Orchidaceae	*Chitonanthera*	5
		Orchidaceae	*Chrysoglossum*	2
		Orchidaceae	*Cirrhopetalum*	1
		Orchidaceae	*Claderia*	1

		Orchidaceae	*Coelandria*	2
		Orchidaceae	*Collabium*	2
		Orchidaceae	*Corymborchis*	2
		Orchidaceae	*Cylindrolobus*	3
		Orchidaceae	*Cymbidium*	8
		Orchidaceae	*Cyphochilus*	6
		Orchidaceae	*Cystorchis*	2
		Orchidaceae	*Didymoplexis*	3
		Orchidaceae	*Dienia*	2
		Orchidaceae	*Diglyphosa*	3
		Orchidaceae	*Dimorphorchis*	4
		Orchidaceae	*Epidendrum*	2
		Orchidaceae	*Epipogium*	9
		Orchidaceae	*Erythrodes*	6
		Orchidaceae	*Eucosia*	1
		Orchidaceae	*Euphlebium*	2
		Orchidaceae	*Galeola*	5
		Orchidaceae	*Geodorum*	5
		Orchidaceae	*Giulianettia*	7
		Orchidaceae	*Hapalochilus*	1
		Orchidaceae	*Herpethophytum*	1
		Orchidaceae	*Hippeophyllum*	7
		Orchidaceae	*Hymeneria*	2
		Orchidaceae	*Kuhlhasseltia*	1
		Orchidaceae	*Laelianthe*	1
		Orchidaceae	*Lecanorchis*	4
		Orchidaceae	*Luisia*	7
		Orchidaceae	*Malleola*	6
		Orchidaceae	*Micropera*	4
		Orchidaceae	*Microstylis*	1
		Orchidaceae	*Mycaranthes*	4
		Orchidaceae	*Myrmechis*	1
		Orchidaceae	*Oxyglossellum*	2
		Orchidaceae	*Oxysepala*	2
		Orchidaceae	*Parapteroceras*	1
		Orchidaceae	*Pelma*	2
		Orchidaceae	*Phalaenopsis*	1
		Orchidaceae	*Pinalia*	6
		Orchidaceae	*Platanthera*	1
		Orchidaceae	*Platylepis*	1
		Orchidaceae	*Poaephyllum*	6
		Orchidaceae	*Porphyrodesme*	2
		Orchidaceae	*Pristiglottis*	5
		Orchidaceae	*Pseudoliparis*	1
		Orchidaceae	*Pteroceras*	2
		Orchidaceae	*Renanthera*	7
		Orchidaceae	*Rhinerrhiza*	1
		Orchidaceae	*Rhinerrhizopsis*	7
		Orchidaceae	*Rhynchophreatia*	3
		Orchidaceae	*Ridleyella*	8
		Orchidaceae	*Saccoglossum*	6
		Orchidaceae	*Saccolabiopsis*	1
		Orchidaceae	*Salacistis*	6

		Orchidaceae	*Sarcanthopsis*	6
		Orchidaceae	*Sarcochilus*	8
		Orchidaceae	*Sarcoglottis*	2
		Orchidaceae	*Sayeria*	2
		Orchidaceae	*Schoenorchis*	7
		Orchidaceae	*Sepalosiphon*	1
		Orchidaceae	*Sestochilos*	1
		Orchidaceae	*Stereosandra*	2
		Orchidaceae	*Stigmatodactylus*	8
		Orchidaceae	*Trachoma*	3
		Orchidaceae	*Tuberolabium*	3
		Orchidaceae	*Vanda*	9
		Orchidaceae	*Vandopsis*	4
		Orchidaceae	*Vanilla*	8
		Orobanchaceae	*Aeginetia*	9
		Orobanchaceae	*Centranthera*	7
		Orthotrichaceae	*Groutiella*	3
		Orthotrichaceae	*Macrocoma*	4
		Orthotrichaceae	*Orthotrichum*	9
		Osmundaceae	*Cladophlebis*	1
		Osmundaceae	*Osmunda*	1
		Oxalidaceae	*Biophytum*	5
		Oxalidaceae	*Xanthoxalis*	2
		Pallaviciniaceae	*Podomitrium*	5
		Pallaviciniaceae	*Symphyogyna*	7
		Pallaviciniaceae	*Symphyogynopsis*	4
		Pandanaceae	*Benstonea*	7
		Pandanaceae	*Sararanga*	6
		Papaveraceae	*Argemone*	1
		Passifloraceae	*Tacsonia*	2
		Pedaliaceae	*Ceratotheca*	1
		Pentoxylaceae	*Taeniopteris*	1
		Peraceae	*Chaetocarpus*	1
		Peranemaceae	*Diacalpe*	5
		Phellinaceae	*Phelline*	3
		Philydraceae	*Helmholtzia*	4
		Phyllanthaceae	*Distichirhops*	6
		Phyllanthaceae	*Flueggea*	3
		Phyllanthaceae	*Margaritaria*	2
		Phyllanthaceae	*Notoleptopus*	1
		Phyllanthaceae	*Synostemon*	1
		Phyllodrepaniaceae	*Mniomalia*	1
		Phyllogoniaceae	*Phyllogonium*	3
		Phytolaccaceae	*Phytolacca*	2
		Picrodendraceae	*Austrobuxus*	7
		Picrodendraceae	*Petalostigma*	4
		Piperaceae	*Macropiper*	6
		Pittosporaceae	*Citriobatus*	7
		Plagiochilaceae	*Chiastocaulon*	6
		Plagiotheciaceae	*Plagiothecium*	8
		Plantaginaceae	*Adenosma*	7
		Plantaginaceae	*Antirrhinum*	2
		Plantaginaceae	*Bacopa*	7

		Plantaginaceae	*Ellisiophyllum*	8
		Plantaginaceae	*Gratiola*	3
		Plantaginaceae	*Lophospermum*	6
		Plantaginaceae	*Maurandya*	5
		Plantaginaceae	*Mecardonia*	3
		Plantaginaceae	*Scoparia*	7
		Plantaginaceae	*Stemodia*	5
		Poaceae	*Aegopogon*	4
		Poaceae	*Ancistragrostis*	4
		Poaceae	*Andropogon*	3
		Poaceae	*Australopyrum*	4
		Poaceae	*Bromus*	9
		Poaceae	*Chionochloa*	2
		Poaceae	*Cleistochloa*	8
		Poaceae	*Danthonia*	9
		Poaceae	*Deyeuxia*	3
		Poaceae	*Dinochloa*	1
		Poaceae	*Diplanche*	2
		Poaceae	*Enneapogon*	9
		Poaceae	*Enteropogon*	5
		Poaceae	*Entolasia*	3
		Poaceae	*Gastridium*	1
		Poaceae	*Gigantochloa*	3
		Poaceae	*Hemarthria*	8
		Poaceae	*Manisuris*	2
		Poaceae	*Monostachya*	1
		Poaceae	*Muhlenbergia*	6
		Poaceae	*Perostis*	1
		Poaceae	*Phalaris*	5
		Poaceae	*Polytrias*	3
		Poaceae	*Spinifex*	5
		Poaceae	*Stenotaphrum*	4
		Poaceae	*Stipa*	2
		Poaceae	*Tripogon*	8
		Poaceae	*Tripsacum*	3
		Poaceae	*Triraphis*	1
		Poaceae	*Trisetum*	3
		Poaceae	*Urochloa*	6
		Poaceae	*Vulpia*	6
		Podostemaceae	*Torrenticola*	6
		Polygalaceae	*Bredemeyera*	4
		Polypodiaceae	*Dendroconche*	1
		Polypodiaceae	*Dendroglossa*	1
		Polypodiaceae	*Drymoglossum*	6
		Polypodiaceae	*Drynariopsis*	7
		Polypodiaceae	*Grammatopteridium*	2
		Polypodiaceae	*Holostachyum*	2
		Polypodiaceae	*Microsorium*	1
		Polypodiaceae	*Paragramma*	2
		Polypodiaceae	*Phymatopsis*	1
		Polypodiaceae	*Thylacopteris*	6
		Polypodiaceae	*Xiphopterella*	3
		Polytrichaceae	*Atrichum*	2

		Polytrichaceae	*Notoligotrichum*	5
		Polytrichaceae	*Oligotrichum*	2
		Polytrichaceae	*Psilopilum*	1
		Pontederiaceae	*Eichhornia*	5
		Pontederiaceae	*Monochoria*	6
		Pottiaceae	*Chionoloma*	5
		Pottiaceae	*Gymnostomiella*	3
		Pottiaceae	*Hydrogonium*	1
		Pottiaceae	*Streptopogon*	4
		Pottiaceae	*Timmiella*	2
		Pottiaceae	*Tortella*	2
		Pottiaceae	*Tortula*	1
		Pottiaceae	*Weissia*	5
		Primulaceae	*Samolus*	4
		Proteaceae	*Bleasdalea*	7
		Proteaceae	*Leucadendron*	2
		Proteaceae	*Oreocallis*	8
		Proteaceae	*Ptychocarpa*	2
		Pseudolepicoleaceae	*Temnoma*	7
		Pteridaceae	*Aleuritopteris*	9
		Pteridaceae	*Austrogramme*	9
		Pteridaceae	*Calciphilopteris*	4
		Pteridaceae	*Craspedodictyum*	2
		Pterobryaceae	*Euptychium*	4
		Pterobryaceae	*Pireella*	1
		Pterobryaceae	*Pterobryidium*	3
		Pterobryaceae	*Symphysodontella*	4
		Ptychomniaceae	*Hampeella*	4
		Racopilaceae	*Powelliopsis*	4
		Racopilaceae	*Timokoponenia*	9
		Restionaceae	*Leptocarpus*	4
		Rhabdoweisiaceae	*Rhabdoweisia*	1
		Rhamnaceae	*Berchemia*	2
		Rhamnaceae	*Cryptandra*	1
		Rhamnaceae	*Rhamnella*	6
		Rhamnaceae	*Sageretia*	4
		Rhipogonaceae	*Rhipogonum*	6
		Rhipogonaceae	*Ripogonum*	4
		Rhizophoraceae	*Agatea*	1
		Rhizophoraceae	*Crossostylis*	1
		Rhizophoraceae	*Pellacalyx*	1
		Rhodomelaceae	*Chondrophycus*	3
		Rhodomelaceae	*Laurencia*	4
		Rhodomelaceae	*Lophocladia*	1
		Rhodomelaceae	*Murrayella*	3
		Rhodomelaceae	*Polysiphonia*	4
		Rhodomelaceae	*Stictosiphonia*	3
		Ricciaceae	*Riccia*	2
		Rosaceae	*Fragaria*	3
		Rosaceae	*Spiraea*	5
		Rubiaceae	*Adina*	1
		Rubiaceae	*Anotis*	5
		Rubiaceae	*Arcytophyllum*	2

		Rubiaceae	*Badusa*	1
		Rubiaceae	*Breonia*	1
		Rubiaceae	*Caelospermum*	2
		Rubiaceae	*Calycosia*	9
		Rubiaceae	*Cephaelis*	5
		Rubiaceae	*Chaetostachydium*	2
		Rubiaceae	*Chassalia*	2
		Rubiaceae	*Cowiea*	4
		Rubiaceae	*Dentella*	9
		Rubiaceae	*Diodia*	4
		Rubiaceae	*Diplospora*	2
		Rubiaceae	*Discospermum*	1
		Rubiaceae	*Guettardella*	1
		Rubiaceae	*Gynochtodes*	1
		Rubiaceae	*Houstonia*	1
		Rubiaceae	*Hyperacanthus*	1
		Rubiaceae	*Hypobathrum*	1
		Rubiaceae	*Kajewskiella*	7
		Rubiaceae	*Litosanthes*	1
		Rubiaceae	*Mapouria*	1
		Rubiaceae	*Maschalocorymbus*	1
		Rubiaceae	*Maschalodesme*	6
		Rubiaceae	*Metadina*	4
		Rubiaceae	*Oxyceros*	4
		Rubiaceae	*Palicourea*	8
		Rubiaceae	*Petunga*	1
		Rubiaceae	*Pogonolobus*	3
		Rubiaceae	*Psilanthus*	2
		Rubiaceae	*Rhodopentas*	1
		Rubiaceae	*Richardia*	2
		Rubiaceae	*Tarennoidea*	3
		Rubiaceae	*Thecagonum*	5
		Rubiaceae	*Trukia*	3
		Rutaceae	*Aegle*	2
		Rutaceae	*Atalantia*	8
		Rutaceae	*Echinocitrus*	1
		Rutaceae	*Luvunga*	5
		Rutaceae	*Medicosma*	1
		Rutaceae	*Merope*	1
		Rutaceae	*Monanthocitrus*	2
		Rutaceae	*Perryodendron*	8
		Saccolomataceae	*Saccoloma*	3
		Salviniaceae	*Salvinia*	6
		Sapindaceae	*Aphania*	1
		Sapindaceae	*Crossonephelis*	1
		Sapindaceae	*Diploglottis*	8
		Sapindaceae	*Euphoria*	1
		Sapindaceae	*Harpulia*	3
		Sapindaceae	*Lepiderema*	2
		Sapindaceae	*Mischarytera*	7
		Sapindaceae	*Sapindus*	5
		Sapotaceae	*Achradotypus*	2
		Sapotaceae	*Beccariella*	2

		Sapotaceae	*Chelonespermum*	2
		Sapotaceae	*Niemeyera*	3
		Sapotaceae	*Pycnandra*	2
		Sapotaceae	*Sarcosperma*	2
		Sapotaceae	*Sersalisia*	9
		Scapaniaceae	*Diplophyllum*	2
		Schistochilaceae	*Paraschistochila*	1
		Schizaeaceae	*Actinostachys*	8
		Scrophulariaceae	*Artanema*	1
		Scrophulariaceae	*Derwentia*	1
		Scrophulariaceae	*Ilysanthos*	1
		Scrophulariaceae	*Masus*	2
		Seligeriaceae	*Blindia*	3
		Sematophyllaceae	*Acanthocladium*	2
		Sematophyllaceae	*Acanthorrhynchium*	5
		Sematophyllaceae	*Clastobryophilum*	1
		Sematophyllaceae	*Clastobryopsis*	1
		Sematophyllaceae	*Clastobryum*	7
		Sematophyllaceae	*Mastopoma*	5
		Sematophyllaceae	*Meiotheciella*	1
		Sematophyllaceae	*Papillidiopsis*	2
		Sematophyllaceae	*Rhaphidorrhynchium*	2
		Sematophyllaceae	*Rhaphidostegium*	3
		Simaroubaceae	*Brucea*	6
		Simaroubaceae	*Samadera*	5
		Siphonocladaceae	*Boergesenia*	1
		Siphonocladaceae	*Ventricaria*	2
		Solanaceae	*Browallia*	1
		Solanaceae	*Brugmansia*	4
		Solanaceae	*Brunfelsia*	3
		Solanaceae	*Cestrum*	7
		Solanaceae	*Cyphomandra*	4
		Solanaceae	*Nicandra*	3
		Solanaceae	*Salpichroa*	2
		Solanaceae	*Solandra*	1
		Solanaceae	*Streptosolen*	1
		Sorapillaceae	*Sorapilla*	3
		Sphenophyllaceae	*Sphenophyllum*	1
		Splachnobryaceae	*Splachnobryum*	6
		Staphyleaceae	*Staphylea*	1
		Stemonuraceae	*Hartleya*	7
		Stemonuraceae	*Urandra*	9
		Stemonuraceae	*Whitmorea*	5
		Sterculiaceae	*Keraudrenia*	2
		Sterculiaceae	*Leptonychia*	5
		Styracaceae	*Simplocos*	1
		Symplocaceae	*Cordyloblaste*	1
		Tectariaceae	*Ataxipteris*	2
		Tectariaceae	*Ctenitopsis*	6
		Tectariaceae	*Dryopsis*	1
		Tectariaceae	*Heterogonium*	2
		Theaceae	*Camellia*	3
		Thelypteridaceae	*Mesophlebion*	5

		Thelypteridaceae	*Metathelypteris*	5
		Thuidiaceae	*Aequatoriella*	3
		Thuidiaceae	*Herpetineuron*	1
		Thuidiaceae	*Orthothuidium*	8
		Tiliaceae	*Pentace*	1
		Trachypodaceae	*Diaphanodon*	4
		Trentepholiaceae	*Printzina*	2
		Treubiaceae	*Treubia*	3
		Trichocoleaceae	*Leiomitra*	3
		Triuridaceae	*Andruris*	1
		Udoteaceae	*Chlorodesmis*	3
		Udoteaceae	*Tydemania*	1
		Udoteaceae	*Udotea*	2
		Urticaceae	*Distemon*	4
		Urticaceae	*Elatostemma*	9
		Urticaceae	*Gibbsia*	7
		Urticaceae	*Parietaria*	5
		Urticaceae	*Pellionia*	5
		Urticaceae	*Pseudopipturus*	7
		Urticaceae	*Villebrunea*	7
		Verbenaceae	*Lippia*	1
		Vitaceae	*Parthenocissus*	1
		Vitaceae	*Vitis*	6
		Vittariaceae	*Rheopteris*	4
		Wiesnerellaceae	*Wiesnerella*	3
		Woodsiaceae	*Allantodia*	1
		Woodsiaceae	*Gymnocarpium*	4
		Xanthorrhoeaceae	*Caesia*	8
		Zingiberaceae	*Eriolopha*	3
		Zingiberaceae	*Geanthus*	6
		Zingiberaceae	*Plagiostachys*	3