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Landscape scale spectral-temporal modelling of bamboo-dominated forest succession within the  
Atlantic forest of Southern Brazil

By

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THESIS

Submitted to the Department of Geography and Environmental Studies

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## Abstract

Tropical and subtropical ecosystems have become vulnerable to biological invasion (i.e., bamboo) due to human induced forest fragmentation. Bamboo ecological processes have been found to impede forest development, resulting in a state of arrested succession, which has been found to significantly reduce biodiversity, thus contributing to biotic homogenization. In this study we use a semi-empirical approach to develop a community-level spatially explicit ecological process model (hybrid model) using a time-series of Landsat imagery to describe single-landscape scale ecological processes of a pervasive bamboo species (*Merostachys skvortzovii*) found throughout the Araucaria forest, a critically threatened subtype of Atlantic forest of southern Brazil. The model is subsequently used to map bamboo spatial distribution at a multiple-landscape scale to examine patch pattern throughout a portion of the Araucaria forest. It was determined that the *M. skvortzovii* lifecycle is a synchronized process occurring at single and multiple-landscapes scale and is comprised of four broad lifecycle phases: pioneer predominance, mature bamboo, dieback and pioneer regeneration. Bamboo patch pattern was found to be associated with human settlement and geographic features, with clusters of patches sharing the same shape and size observed at multiple scales.

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## Chapter One:

### 1.0. Introduction

Until recently tropical and subtropical forests have played an integral role in carbon cycling acting as carbon sinks, but with ongoing human-driven forest fragmentation, carbon emissions resulting from deforestation and degradation have rendered tropical forests as a carbon source (Baccini et al., 2017). The loss of this major carbon sink has led to increased carbon emissions which continue to drive climate change at an alarming rate. Human induced fragmentation has resulted in ecological islands which have been found to significantly reduce ecological functionality and biodiversity due to partitioning of functioning assemblages of organisms and alteration of environmental conditions (e.g., edge effects). As a result, remaining fragments have become increasingly vulnerable to natural disturbances (e.g., windthrow, fire, biological invasion, etc.) leading to further degradation.

Ecology is a broad discipline which examines the interactions of organisms within their environment, and encompasses other disciplines, including biology, geography, geology and other earth sciences. However, ecology as a discipline often focuses on community-scale interactions which assumes that communities are closed and isolated (Leibold et al., 2004). Although community focused analyses are important for determining the mechanisms underlying ecological processes, the interconnectedness of adjacent organism communities and their impact on ecological processes is lost at this scale of study (Leibold et al., 2004). Landscape ecology is an emerging discipline which addresses the inherent connectivity between ecological communities and processes at various scales as a result of spatial heterogeneity, which is often due to human interactions with the environment (Wiens et al., 2007). Habitat fragmentation is a multiple-landscape phenomenon and single-landscape processes of fragmentation can only be

understood based on the matrix structure of the landscape to which it belongs (Didham, 2010). The definition of ‘landscape’ in landscape ecological research is context-dependent, but invariably involves spatial patterns produced by processes operating at multiple spatial and temporal scales. These processes lead to some regularity and patchiness in distribution of phenomena over space. Forman and Godron (1986) define a landscape as ‘a heterogeneous land area composed of a cluster of interacting components that is repeated in a similar format throughout.’ In this research, the term ‘single-landscape’ refers to a singular cohesive mosaic of landscape elements which contribute to a pattern spatial heterogeneity, whereas ‘multiple-landscape’ refers to a mosaic of landscapes arbitrarily delineated over a regular tessellation of space (i.e., called a regional scale in Forman 1995). Where community ecology focuses on biotic and abiotic processes and interactions, successional development of an ecosystem, and the abundance and distribution of biodiversity (Allee et al., 1949; Smith & Smith, 2000; Begon et al., 2006), landscape ecology examines how biotic and abiotic processes are influenced by spatial heterogeneity and scale, the interactions of adjacent communities across heterogeneous landscapes, and explores approaches to manage the impacts of spatial heterogeneity (Risser et al., 1984).

The feasibility of landscape ecology as a discipline has increased immensely with the emergence of Geographical Information Systems (GIS), increased availability of spatially rich data sources and improved computer processing capabilities. GIS has provided an environment in which analyses of spatial processes can be undertaken, and spatially exhaustive data (e.g., satellite imagery) coupled with increased processing capabilities (e.g., cloud computing) has augmented the scale at which these analyses can be performed. With continuous technological

advancements, analytical tools to examine spatial processes continue to be developed, thus improving understanding of ecological processes across landscapes at varying scales.

With increasing access to extensive satellite image collections, remote sensing has become a prominent tool for examining ecological processes over time. However, the application of remote sensing techniques for analyzing landscape processes traditionally focuses on ‘snapshot’ approaches, which lack temporal continuity and ignore time. With the opening of the Landsat archives, the ability to study spatial ecological processes has reached new heights, and sophisticated methodologies which employ the spatial-temporal properties of Landsat data through the use of time-series stacks continue to be developed. The use of Landsat time-series stacks enables researchers to look 40+ years into the past, enabling long-term change in ecological processes and patterns to be examined. Spatially explicit models can be derived from Landsat time-series stacks to project future events through integration of short-term *in situ* field observations and satellite imagery. These models have been found to accurately describe mechanisms of forest change and succession, with an emphasis on change event dates (Shroeder et al., 2007; Kennedy et al., 2007; Huang et al. 2009; Vogelmann et al., 2009; Kennedy et al. 2010; Broich et al., 2011; Lehmann et al., 2013; Griffiths et al., 2014; DeVries et al., 2015; Senf et al., 2015; Maus et al., 2016). However, there are inherent trade-offs when developing spatially explicit ecological process models from satellite imagery: spatial generalization is a result of spatial resolution, as well as simplification of a system’s ecological processes. With this knowledge, information derived from these models are relatively crude representations of ecological function and their outputs are to be understood as a further basis for scientific investigation. Therefore, in this research, we aim to derive a spatially explicit ecological process model from a Landsat time-series stack to observe the ecological processes of a biological



invasion (in this case, bamboo) impacting a fragmented and vulnerable ecosystem (in this case, Araucaria forest, subtype of the Atlantic forest) at multiple-scales.

### **1.1. Bamboo as a biological invasion in the Araucaria forest**

The term bamboo is used to describe a group of large woody grasses from the family *Poaceae* and subfamily *Bambusoideae*, which encompasses approximately 1250 species within 75 genera existing in the tropic and sub-tropic regions of the world (Scurlock et al., 2000). Bamboo ecological processes vary amongst species, but it has been discovered that certain species exhibit aggressive regeneration strategies which have been found to impede forest development by excluding adjacent plant communities, resulting in forest degradation and loss of biodiversity (Gratzer et al. 1999; Abe et al. 2002; Griscom, 2002; Narukawa & Yamamoto 2002; Griscom & Ashton, 2006; Lacerda & Kellermann, 2017). In an effort to preserve remaining fragments of tropical and subtropical forests, it is necessary to explore the mechanisms of bamboo ecological processes that drive forest degradation and determine whether the same processes can be observed across multiple-landscapes.

The process of forest fragmentation drastically alters canopy structure and increases the amount of edge of remaining forest fragments, which modifies understorey light climate and leaves fragments vulnerable to illegal extraction and other anthropogenic disturbances. Consequently, remaining fragments predominantly consist of secondary forest, which is characterized by increased number of canopy gaps which receive 2-5% of full sun, in comparison to primary forests, which often have many small canopy openings (<2% full sun) and fewer large gaps (>5% full sun) (Nicotra et al., 1999). As bamboo growth is light driven, forest fragments possess environmental conditions conducive to bamboo expansion, enabling the

invasion of bamboo populations in certain tropical and sub-tropical forests (Griscom, 2002; Griscom & Ashton, 2006; Lacerda & Kellermann, 2017).

The ecological processes of individual bamboo species vary substantially, all of which impact seedling and sapling survival and abundance differently, thus significantly influencing forest development. Lifecycle length varies amongst bamboo species, ranging from three to 120 years, and terminate with a monocarpic dieback event of mass-seeding. Dieback events are comparable to a large-scale disturbance, opening the canopy and releasing resources, such as light availability, soil nutrients and space required for tree recruitment (Taylor & Qin 1992; Abe et al. 2002; Taylor, 2004; Rother et al. 2009). Studies have revealed that the environmental alterations that occur following a dieback event contribute to improved tree germination, regeneration, and tree seedling synchronization (Nakshizuka, 1988; Taylor & Qin, 1992; Abe et al., 2001; Marchesini et al., 2009; Budke et al. 2010). However, other studies have shown that although seedling recruitment may be improved immediately following dieback events, the aggressive regeneration strategies of certain bamboo species results in arrested succession by means of resource competition and mechanical damage (Gratzer et al. 1999; Abe et al. 2002; Griscom, 2002; Narukawa & Yamamoto 2002; Griscom & Ashton, 2006; Lacerda & Kellermann, 2017).

The Atlantic Forest, which is considered one of the world's twenty-five biodiversity hotspots, has been reduced to less than 10% of its original area and is considered the most devastated and threatened ecosystem in the world (Leal & Camara, 2003). The remaining forest is heavily fragmented and exists as a series of minute fragments within an urban and agricultural matrix (Leal & Camara, 2003). In the past century the majority of land conversion occurred in the south of Brazil, the primary agriculture region and geographical range of the *Araucaria*

forest. Additionally, subtropical timber from this region, especially the conifer *Araucaria angustifolia*, was Brazil's primary export product during the 19<sup>th</sup> and 20<sup>th</sup> century (Lacerda et al., 2012). As a result of land conversion and timber exploitation, the remaining Araucaria forest is composed of <1% primary forest and 20-25% as secondary forest of the original landcover (Lacerda et al., 2016). The Araucaria Forest originally covered an area of 216 100 km<sup>2</sup>, but has now been reduced to fragments, the majority being less than 50 hectares in area, scattered across the states of Parana and Santa Catarina (Lacerda, 2016). Due to intensive canopy alteration and increased edge, remaining forest fragments have been left vulnerable to biological invasion which has enabled the invasion of *Merostachys skvortzovii*, a pervasive bamboo species native to the region.

*M. skvortzovii* has a 31 to 33-year lifecycle (Pereira, 1941; Sendulsky, 1995), with the last recorded dieback event occurring between 2003 and 2006 (Luz, 2009; Kellermann, 2011). These dieback events enable regeneration of pioneer tree species, *Mimosa scabrella* and secondary species, *Vernonanthura discolor*, two prominent early successional species within the Araucaria forest. Following a dieback event, *M. scabrella* will initially recruit and form a homogenous canopy, followed by *M. skvortzovii* and *V. discolor*, with the former securing space in the understorey (Kellermann, 2011; Lacerda & Kellermann, 2017). Once *M. skvortzovii* recruits, it will continuously replace itself by clonal growth throughout its lifecycle, increasing in density as it matures and further suppressing regeneration (Lacerda & Kellermann, 2017). These ecological processes have been observed throughout the Embrapa Research Station in Cacador (ERSC), a 1157-hectare forest reserve representing a fragment of secondary Araucaria forest, and are hypothesized to be causing a perpetuated bamboo-dominance cycle throughout the remaining Araucaria forest (Lacerda & Kellermann, 2017).

As the perpetuated bamboo-dominance cycle exhibits non-linear dynamics, it can be related to the ecological theory of adaptive cycling (Holling, 1986). Ecosystems are typically dynamic in nature and change over time, with these changes often being instigated by a disturbance event. Based on the variable which causes the disturbance (e.g., fire, insect, human, etc.), reorganization of organisms that make up a system occurs, causing systems to regenerate differently based on an organism's tolerance to the new environment. Adaptive cycling consists of four main stages which include (1) growth or exploitation of r-strategist species, (2) conservation, which is the securement of resources by K-strategist species, (3) a disturbance event resulting in the collapse of the system and (4) reorganization of organisms to allow development of a new system. The four stages are then divided into two major phases, which are the foreloop and the backloop. The foreloop is the phase of slow incremental growth consisting of stages 1 and 2 and the backloop is the rapid transition and reorganization of one stage to the next stage, which consists of stages 3 and 4. The model is highly relatable to many natural, economic and social systems, and varies from system to system with certain stages being omitted at times.

The perpetuated bamboo-dominance cycle is the result of widespread anthropogenic disturbance which occurred during human settlement. Prior to human establishment in southern Brazil, it is postulated that fire regimes governed ecosystem cycles, which could explain why bamboo populations had not previously been invasive. Based on historical knowledge of the ERSC, it is known that the region within the forest reserve that is most heavily impacted by bamboo populations was continuously harvested until 1974, which is also the same date as the previous dieback event of *M. skvortzovii*. With this historical knowledge we can describe how the adaptive cycle theory directly relates to the perpetuated dominance-cycle. The harvesting

and dieback event which occurred in 1974 represents the third stage of the adaptive cycle. In the fourth stage, reorganization of species for the subsequent cycle is thought to be the result of (1) extraction of adult K-strategist species, which reduces seed availability for dispersal, and (2) the presence of previously established bamboo populations. The first stage of the new cycle is characterized by the recruitment of r-strategist species, which consist of pioneer species, *M. scabrella* and *V. discolor*, and bamboo, *M. skvortzovii*. Bamboo populations quickly secure space and resources, therefore the typical second stage of K-strategist development is omitted in the case of the perpetuated bamboo-dominance cycle. The third stage occurs when bamboo populations dieback. However, in the fourth stage of the cycle, reorganization is a result of further species simplification, resulting from reduced seed dispersal and inability of K-strategist to establish in a bamboo-dominated environment. As a result, the subsequent cycle will be less diverse, and it is anticipated that each proceeding cycle will continue to decline in diversity. Therefore, it is thought that the perpetuated bamboo-dominance cycle is a contributing factor to biotic homogenization, which is a widespread phenomenon occurring throughout the entirety of the Atlantic forest, due to cycle's observed and predicted impact on local taxonomy abundance and disruption in functionality of species assemblages.

The perpetuated bamboo-dominance cycle theory has been hypothesized based on *in situ* observations in the ERSC and it is postulated that the perpetuated bamboo-dominance cycle is a widespread, synchronized phenomenon occurring throughout the remaining Araucaria forest. To determine this, a spatially explicit hybrid spectral-temporal model (hybrid model) was developed by integrating empirical evidence collected from 2006 to 2015 in the ERSC with a Landsat time-series stack from 1984 to 2015, which represents a complete lifecycle of *M. skvortzovii*.

## **1.2. Spatially explicit hybrid spectral-temporal model (hybrid model) development**

At the core of this research is the development of the hybrid model of bamboo-dominated forest succession, which was developed through time-series statistical analysis, local knowledge/field observations, and hypothesized processes of bamboo-dominated forest succession. The development of the hybrid model was based on Kennedy et al. (2007), which used a similar approach to detect change in forest pixels of Landsat time-series based on theoretical spectral-temporal models of forest succession. Kennedy et al. (2007) developed functions based on specific parameters associated with each spectral-temporal model to allow change to be detected in any year of the time-series and for different vegetation types (e.g., coniferous vs. broad-leaved). However, in this study we developed a single spectral-temporal model (hybrid model) of bamboo-dominated forest succession. Unlike the dynamic modelling approach used by Kennedy et al., (2007), our approach is static in nature and assumes synchrony amongst all bamboo populations at a single and multiple-landscape scale.

Extensive data collection from 2006 to 2014 made the study area instrumental to the development and calibration of the hybrid model. The hybrid model was developed in three broad steps: (1) an exploratory changepoint analysis was performed on a spectral-temporal signature extracted from a Landsat time-series stack representative of bamboo-dominated forest succession; (2) changepoints were compared to locally known successional dynamics and empirical evidence; and (3) a trajectory analysis was performed using changepoints as vertices to fit linear models to segments of the time-series.

First, using a Landsat time-series stack from 1984 to 2015, we determined the spectral-temporal signature of bamboo-dominated forest succession by averaging together 28 training spectral-temporal patterns extracted from bamboo-dominated regions within the ERSC. We

subsequently performed a binary segmentation changepoint analysis on the bamboo-dominated forest spectral-temporal signature to identify significant changes in variance, which served to be a determinant of bamboo-dominated forest succession phases. Binary segmentation identifies approximate changepoints in a time-series and is ideal for non-parametric data. This method works by first finding the greatest change in variance within the time-series, and subsequently treats the two resulting segments as individual time-series to be analysed (Edwards & Cavalli-Sforza, 1965). This process is continued until there are no more significant changes in variance detected, or until the user defined number of changepoints has been reached. Central to the development of the hybrid spectral-temporal model was determining the appropriate number of changepoints to be detected. This was achieved through iteration and comparison to empirical evidence; one to ten changepoints were tested, with five changepoints serving to identify the most relevant changepoints within the time-series, which also corroborated with empirical evidence (Kellermann, 2011; Lacerda & Kellermann, 2017).

Long-term datasets from 2006 to 2014 and a 2015 field campaign to the ERSC served to verify correlation between statistically determined changepoints and real-world phases of bamboo-dominated forest succession. Regeneration data were collected in various locations of the ERSC from 2007 to 2014 following bamboo dieback. As *M. skvortzovii* is known to occupy the forest understorey for the majority of its lifecycle, the extracted spectral-temporal signature is representative of the spectral response of pioneer species *M. scabrella* and *V. discolor* occupying the canopy. Therefore, to effectively extrapolate information regarding stages of bamboo-dominated forest succession from the spectral-temporal signature it was important to understand the stages of regeneration of *M. scabrella* and *V. discolor*, which was achieved by interpreting regeneration data. Based on the dataset, it was found that from 2007 to 2009 dense seedling

populations of *M. scabrella* established and quickly developed into homogenous juvenile tree populations (Lacerda & Kellermann, 2017). During this same time period the re-colonization of *M. skvortzovii* was also observed. From 2009 to 2011, a self-thinning process occurred, which significantly reduced *M. scabrella* populations and enabled the development of the secondary succession species, *V. discolor*. Finally, from 2012 to 2014, a vigorous *M. scabrella* adult population emerged into the canopy, which was determined by sampled trees transitioning from a juvenile tree class to an adult tree class (Lacerda & Kellermann, 2017). During the 2015 field campaign, various locations of the ERSC occupied by bamboo populations were visited. GPS points were taken, and qualitative information was recorded regarding the phase of forest succession, which included estimated age of pioneer populations (based on DBH and treefall), presence/absence of regeneration, estimated density of bamboo populations, and canopy openness. The qualitative information enabled us to establish the current stage of forest succession, from which we were able to infer information regarding the previous bamboo lifecycle, which was from approximately 1974 to 2006.

As field data were not available prior to 2006, information regarding successional phases from 1984 to 2005 had to be inferred based on pioneer species lifecycle dynamics. *M. scabrella* is known to have a lifecycle of 20-25 years. A study performed on a *M. scabrella* plantation showed that 75% of adult populations die-off before the age of 20, with the remaining trees showing signs of senescence (Steenbock et al., 2011). *V. discolor* is known to occur with *M. scabrella*, growing in the understory as juveniles, and emerging into the canopy as the *M. scabrella* adult population thins. *V. discolor* has been found to live up to 60 + years (Santos et al., 2011), with a decline in population after 45-50 years. Therefore, with knowledge of these



pioneer population dynamics, it was assumed that pioneers would be present in the canopy from 1984 to 2005, but would be in a state of senescence.

A trajectory analysis was then performed to confirm the inferred stages of bamboo-dominated forest succession. Using the changepoints as vertices, segments were fit with linear models and slope was used to determine phases of bamboo-dominated forest succession. Kennedy et al. (2007) hypothesized the spectral-temporal trajectories of phases of forest succession, which included disturbance, revegetation, and revegetation to stable state. A disturbance event is characterized by an abrupt decrease in spectral values, whereas revegetation is identified by a continuous, gradual increase in spectral values, and revegetation to stable state is characterized by a prolonged period of stable spectral values following a phase of revegetation. Vogelmann et al. (2009) identified that damaged or senescent tree populations exhibited a gradual decrease in spectral values over a prolonged period of time. Therefore, based on the hypothesized trajectories, the modelled segments were aggregated into four broad successional phases, which include (mature/senescence) pioneer predominance (1984 to 2000), mature bamboo (2001 to 2004), bamboo dieback (2005 to 2008) and (juvenile) pioneer regeneration (2009 to 2015), based on the observed slope of the modelled segment trajectories. Pioneer predominance phase exhibited a gradual decrease in spectral values from 1984 to 2000. A distinct increase in spectral values from 2001 to 2004 was determined to be the emergence of mature bamboo into the canopy, as a result of senescent pioneer treefall. Bamboo dieback was determined by an abrupt drop in spectral values from 2005 to 2008, and regeneration was determined by a sharp increase in spectral values from 2009 to 2015. It is important to note that although the dieback phase was statistically determined to occur between 2005 and 2008, in

reality, from 2005 to 2007 a negative slope indicates dieback, whereas from 2007 to 2008, a positive slope indicates regeneration.

### **1.3. Thesis themes & objectives**

The themes and motivations central to this research include determining mechanisms of bamboo forest succession, increased availability of satellite imagery with high spatial-temporal resolution and developing robust methodologies which employ multi-temporal imagery to perform spatial-temporal analyses of bamboo populations at multiple-scales. Spatially explicit ecological process models derived from Landsat time-series stacks are broadly applicable for monitoring forest ecosystems at multiple-scales and have become increasingly feasible to develop with readily available radiometrically corrected Landsat products (e.g., Surface Reflectance Collection 1 Level-2 products) and novel data mining techniques (e.g., Best-Available-Pixel compositing).

The research objectives addressed in this thesis are as follows:

1. Develop a community-level semi-empirical spatially explicit hybrid spectral-temporal model to analyze bamboo-dominated forest succession dynamics and subsequently use the model to map bamboo populations at a single-landscape scale
2. Use new hybrid modelling approach to map bamboo at a multiple-landscape scale, and perform a spatial analysis to explore how bamboo patch distribution is influenced by spatial heterogeneity

We pursue these objectives through detailed model development, assessment, and analysis of bamboo populations in the Araucaria forest, a pine-dominated subtype of the Atlantic forest of Southern Brazil. Given the known ecological processes of bamboo lifecycle (i.e.,

length, dieback date and understorey dynamics), the first chapter of this thesis uses a community-level semi-empirical approach to develop a spatially explicit ecological process model using a time-series of Landsat imagery to model single-landscape scale bamboo ecological processes. Chapter two subsequently addresses the principles of landscape ecology; a multiple-landscape analysis is undertaken which applies the previously developed process model at a multiple-landscape scale to examine the spatial extent at which bamboo ecological processes are occurring and explore how landscape heterogeneity impacts bamboo patch pattern distribution.

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## Chapter Two:

### 2.0. Spectral-temporal modelling of bamboo-dominated forest succession in the Atlantic forest of Southern Brazil

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#### Abstract

With access to collections of continuous satellite imagery over a 40-year period, spectral-temporal patterns extracted from multi-temporal imagery offer a potential new tool to model mechanisms of forest succession and monitor changes in forested landscapes. Specifically, spectral-temporal trajectories associated with successional forest change occurring over prolonged periods of time may enhance periodic ‘snapshot’ monitoring methods, especially for species that exhibit complex and non-linear dynamics. In this paper, Landsat time-series are used to examine the spectral-temporal signatures of bamboo-dominated forest succession occurring within the critically threatened Araucaria Forest, a pine-dominated subtype of the Atlantic Forest in southern Brazil. Alteration of canopy structure through ongoing anthropogenic disturbance has increased understorey light climate and given opportunity for native invasive bamboos to flourish, resulting in loss of biodiversity as a result of arrested succession, which is hypothesized to be caused by the synchrony of bamboo lifecycle dynamics. We aimed to evaluate how spectral-temporal signatures could be used to (1) characterize stages of bamboo-dominated forest succession, (2) identify synchrony of bamboo lifecycle dynamics and (3) classify regions of bamboo-dominated forest. Change point analysis was performed using an extracted sample

spectral-temporal signature and trajectories were fit to the resulting segments using linear regression. Based on slope values of the fitted segments, a novel description incorporating temporal information of bamboo-dominated forest succession was developed which identified four broad phases: pioneer predominance, mature bamboo, dieback and pioneer regeneration. To determine synchrony of bamboo-dominated forest succession, a hybrid model was developed by combining the modelled segments and compared to a 32-year Landsat time-series of vegetation indices by calculating the root-mean square error between each pixel in the study area. The hybrid model proficiently classified regions of bamboo-dominance, achieving between 77% and 90% accuracy, which also indicated lifecycle synchrony of bamboo populations within the study area. To further assess the performance of the hybrid model, a time-weighted dynamic time warping model approach was used to determine synchrony and classify regions of bamboo. The time-weighted dynamic time warping classifier had lower overall accuracy (68% to 82%), but is still considered a useful tool for automated classification purposes that take advantage of multi-temporal imagery. To compare classification performance between ‘snapshot’ and multi-temporal imagery classifiers, a maximum-likelihood classification was performed, which attained lower overall accuracies than the hybrid model (75% and 84%). Overall, the use of spectral-temporal signatures offers a novel and effective approach to both describing and modelling bamboo-dominated forest succession (and forest successional processes more generally) on a single-landscape scale.

## **2.1. Introduction**

The Atlantic Forest, which is considered one of the world’s twenty-five biodiversity hotspots (Myers et al., 2000; Mittermeier et al. 2004), has been reduced to less than 10% of its original area and is considered the most devastated and threatened ecosystem in the world (Leal

& Câmara, 2003). The remaining forest is host to more than 8000 endemic species with over 530 species officially designated as threatened (Myers et al., 2000). As a subtype of the Atlantic Forest, the Subtropical Humid Forests of southern Brazil (FAO, 2005), locally known as Araucaria Forest (IBGE, 2012), has been subjected to intensive fragmentation, resulting in forest fragments of less than 50 hectares which have been heavily altered (Lacerda, 2016). The ongoing degradation of the remaining forests has drastically altered canopy structure which has increased understorey light climate, allowing native bamboos to dominate the forest understorey forming dense clumps which exclude surrounding plant communities (Budke et al. 2010; Lacerda & Kellermann, 2017), contributing to further degrade the remaining Araucaria Forest fragments (Lacerda, 2016).

*Merostachys skvortzovii* is a pervasive bamboo species found throughout Araucaria forest. *M. skvortzovii* is characterized by a 31 to 33-year lifecycle (Pereira, 1941), during which it may dominate the forest understory continuously and terminate with a dieback event of synchronized mass flowering (Griscom & Ashton, 2006; Lacerda & Kellermann, 2017). Once *M. skvortzovii* populations establish themselves in the forest understorey, their monocarpic dieback events have been found to act as disturbance events by opening the canopy and releasing soil nutrients and space (Taylor & Qin 1992; Abe et al. 2002; Taylor, 2004; Rother et al. 2009), enabling regeneration of pioneer species to occur. Within Araucaria forest, *Mimosa scabrella*, a prominent pioneer species, will initially recruit and dominate the canopy, followed by secondary succession species *Vernonanthura discolor* and *M. skvortzovii* (Kellermann, 2011; Lacerda & Kellermann, 2017). Once *M. skvortzovii* recruits, it will continuously replace itself by clonal growth throughout its lifecycle, growing denser as it matures while simultaneously further suppressing regeneration. The way in which pioneer and *M. skvortzovii* population dynamics

coincide is hypothesized to be a synchronized process which control forest succession; due to similar lifecycle lengths of *M. skvortzovii* (31 to 33-years), *M. scabrella* (20 to 25-years), and *V. discolor* (30 to 60-years), gaps created by treefall from senescent pioneer populations enables incoming solar radiation to reach the bamboo-dominated understorey, increasing bamboo growth while impeding the development of tree species. This synchronized process has resulted in a perpetuated bamboo-dominance cycle which has been observed to arrest forest succession in the region (Lacerda & Kellermann, 2017), a phenomenon which has also been observed in the Amazon forest (Griscom & Ashton, 2006).

In forested regions where canopy structure has been altered due to ongoing anthropogenic disturbances, it has been observed that increased understorey light climate has enabled native invasive bamboos to flourish, resulting in reduction of tree regeneration and loss of biodiversity (Lacerda & Kellermann, 2017). With increasing threat to ecologically sensitive regions, such as the Atlantic Forest of southern Brazil, increased knowledge regarding the impact of bamboo-dominance on surrounding plant communities will assist in improving current forest management techniques by emphasizing the need for silvicultural intervention to enable and promote the growth and regeneration of threatened and endangered plant species.

The use of Landsat time-series stacks has proven to serve as a useful tool to observe continuous change and improve understanding of ecological processes occurring at a landscape scale (Kennedy et al., 2007). Methods have been developed in recent years which exploit the use of spectral-temporal signatures to observe mechanisms of forest succession (Broich et al., 2011; Lehmann et al., 2013), identify distinct disturbance events and recovery rates (Huang et al. 2009; Vogelmann et al., 2009; Kennedy et al. 2010; Griffiths et al., 2014; DeVries et al., 2015; Senf et al., 2015) and classify various landcover types (Maus et al., 2016a). The premise of these

methods is the underlying assumption that many natural systems exhibit a distinct temporal progression which can be observed in spectral-space (Kennedy et al., 2007). To analyze ecological processes of bamboo-dominated forests, we investigated whether a spectral-temporal signature extracted from a 32-year Landsat time-series could be used to characterize successional phases of bamboo-dominated forest succession and determine whether bamboo and pioneer population dynamics are synchronized across a single-landscape scale, thus causing a perpetuated bamboo-dominance cycle. While the lifecycle of *M. skvortzovii* has been only recently discovered on a local scale, research interest now centres on identifying the spatial scale and synchrony of these processes occurring across a single-landscape. Utilizing remotely sensed imagery to derive bamboo successional dynamics will support the development of synoptic mapping tools for the Atlantic Forest which will directly support conservation and adaptive management planning. Accordingly, this paper aims to:

1. Identify and characterize the spectral-temporal signature of bamboo-dominated forest succession
2. Determine whether the perpetuated bamboo-dominance cycle is a synchronous process occurring on a single-landscape scale by comparing a 32-year Landsat time-series stack to a hybrid model
3. Compare performance of hybrid model to a time-weighted dynamic time warping model approach to assess the effectiveness of the hybrid model, and more generally spectral-temporal signatures, to determine bamboo lifecycle synchrony and identify regions of bamboo-dominance

## 2.2. Materials and methods

### 2.2.1. Study area

The Embrapa Research Station in Caçador (ERSC) is a 1157-hectare research area located in Caçador, Santa Catarina, Brazil (Figure 2.1). The study area is part of the Subtropical Humid Forest of the Atlantic Forest in Southern Brazil, locally known as Araucaria forest, which is a mixture of temperate and tropical floras (IBGE, 2012; Leite and Klein, 1990), occurring in subtropical highland climate (Cfb: Climate group (C): Temperate; Seasonal precipitation type (f): without dry season; Level of heat (b): warm summer), with high annual precipitation of approximately 1400 mm. However, extensive colonization in the 19<sup>th</sup> century has reduced the biome to 5% of the original forest cover as primary forest, with 20-25% as secondary forest (Lacerda, 2016). The region is characterized by the predominance of the critically endangered late successional species, *Araucaria angustifolia* and *Ocotea porosa* (IBGE, 2012). ERSC is one of the most well-preserved remaining fragments of the Subtropical Humid Forest and has not received any silvicultural intervention in the past 20 years (Lacerda et al., 2012). Prior to that, the forests in the ERSC were subjected to selective logging, significantly reducing areas where the canopy is dominated by *A. angustifolia* (Lacerda, 2016). In 1948, ERSC was established as a forest reserve, although the east end continued to be heavily logged until 1974, which enabled the invasion of bamboo in the forest understorey in the area.

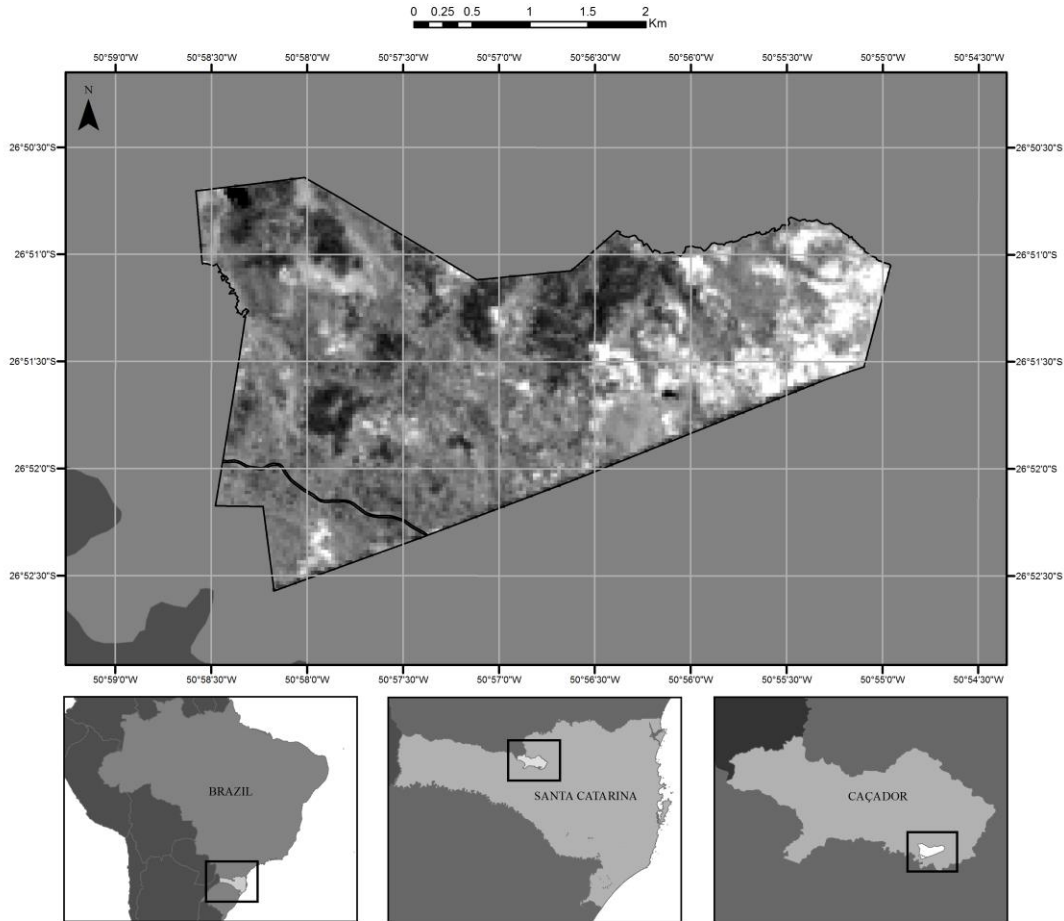


Figure 2.1: Embrapa Research Station in Caçador (ERSC), Caçador, Santa Catarina, Brazil. Landsat 5 TM imagery (SWIR band) from 2007 following a bamboo dieback event, with the light areas denoting regions of bamboo.

The ERSC has previously been classified into three forest types, which include (1) *Araucaria* predominance, (2) degraded forest and (3) bamboo-dominated forest (Lacerda, 2016). *Araucaria* predominance describes areas of forest where canopy is dominated by *Araucaria angustifolia*. Degraded forests are areas of the ERSC that experienced intensive logging in the past and may have been impacted by forest fires, resulting in significant alteration of forest structure and floristic composition. These forests are characterized by open canopies, which enables invasion of bamboo. Bamboo-dominated forests are areas within the ERSC that have been submitted to historical clearcutting in which bamboo populations are dominant with significant suppression of regeneration occurring in the understory (Lacerda et al., 2012; Lacerda



& Kellermann, 2017). The landscape surrounding the ERSC is primarily farmland, commercial forest plantations and small forest fragments resulting from fragmentation or regeneration of abandoned agriculture land (Lacerda, 2016).

### 2.2.2. Data

#### *Reference data collection*

One hundred and ten field samples were used as reference data. Sixty-nine of the field samples were plot data collected in 2006 as part of a forest inventory, which was carried out by stratified random sampling and considered 13 different strata at different slope and elevation classes, based on photo interpretation of a 2004 Ikonos image (Rivera, 2007). The 69 temporary plots were distributed proportionally to the strata areas, 62 of which were 500 m<sup>2</sup> and the remaining seven 250 m<sup>2</sup>. For each plot, all trees >10 cm DBH were identified, and height and DBH were recorded. These 69 plots were later divided into four broad management units, which included: Araucaria predominance, structured forest, degraded forest and bamboo-dominated forest (Lacerda et al., 2012). Structured forest and degraded forest were aggregated into one forest type and designated as degraded forest following Lacerda (2016) mapping of the ERSC. An additional 41 field samples were collected in 2016 during a field campaign. Field sampling regions for the campaign were selected using high resolution imagery from 2004, 2006 and 2014; areas of homogenous forest types (Araucaria predominance, degraded forest and bamboo-dominated forest) were selected to avoid edge effects, with accessibility also influencing selection. In total, the dataset consists of 24 Araucaria predominance, 47 degraded forest and 39 bamboo-dominated forest samples.

### *Imagery and processing*

Landsat imagery was used to examine the spectral-temporal patterns of the ESRC over the 30+ year lifecycle of bamboo, which was acquired using Google Earth Engine. The Landsat time-series stack used for this study consisted of 35 cloud-free images acquired between the months of May and September, to reduce spectral variation caused by seasonality. Years with multiple images were averaged together to create annual composites, with omission of the years 1989, 1992, 1994, 1998 and 2012 due to poor quality imagery. To produce a continuous timeline, raster values were linearly interpolated for each missing year. All cloud free images from 1984 to 2011 were acquired from the Landsat 5 TM Surface Reflectance image collection and images from 2013 to 2015 were acquired from the Landsat 8 OLI Surface Reflectance image collection. Due to the Landsat 7 ETM scan-line-corrector problem, imagery from this sensor were not used.

Surface reflectance is required to accurately derive the Enhanced Vegetation Index (EVI), which was calculated over the Landsat time-series stack using Google Earth Engine code editor. EVI is a canopy reflectance measure developed to optimize the vegetation signal by separating the canopy background signal, while simultaneously reducing atmosphere influences (Huete et al., 2002). EVI values have been found to outperform NDVI in tropical and sub-tropical environments (Huete et al., 2002) as the index has been observed to be more responsive to variation in canopy structure, including leaf area index (LAI), canopy type and architecture and plant physiognomy (Gao et al., 2000). Surface reflectance Climate Data Records (CDR) are generated using Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), specialized software that applies Moderate Resolution Imaging Spectroradiometer (MODIS) atmospheric correction methods to Level-1 Landsat TM or ETM+ data (Ju et al., 2012). Inputs

including water vapor, ozone, geopotential height, aerosol optical thickness and digital elevation are combined with Landsat data and entered into Second Simulation of a Satellite Signal in the Solar Spectrum (6S) radiative transfer models to produce multiple climate data records which include Surface Reflectance (SR) (Ju et al., 2012).

A 32-year Landsat time-series of EVI values was created and a Savitzky-Golay smoothing filter was applied to the time-series stack to reduce year-to-year noise (Savitzky & Golay, 1964). A Savitzky-Golay filter aims to increase signal-to-noise ratio, without reducing the signal, by employing a least-squares-fit convolution (Chen et al., 2004). Smoothing is achieved by fitting polynomials to segments of a larger dataset; a small window preceding and proceeding a value of interest is fit to a polynomial of a certain degree to derive a new smoothed value to replace the value of interest (Chen et al., 2004). For this analysis we used a polynomial order of 2 ( $p=2$ ), with a window size of 5 ( $n=5$ ). Various  $p$  and  $n$  values were tested on a sample spectral-temporal signature of EVI values and the resulting smoothed time-series were visually examined. It was found that increased  $p$  value did not sufficiently reduce year-to-year noise and increased  $n$  value substantially reduced the signal, which eliminated distinct breakpoints in the time-series. Any disturbance events which may occur would still be visible in the smoothed time-series, so long as the smoothing parameters selected do not over generalize the time-series and create a bias.

### *2.2.3. Overview of characterization of successional phases and development of hybrid model*

The overall strategy to characterize bamboo-dominated forest succession and observe its synchrony involved three main steps (Figure 2.2). First, the spectral-temporal signature of bamboo-dominated forest succession was identified (2.2.3.1). Using this spectral-temporal signature, a changepoint analysis was applied to parse the data into segments, which were used

to fit trajectories to determine phases of bamboo-dominated forest succession (2.2.3.2). The resulting modelled segments from the changepoint analysis were then assembled to create a hybrid model (2.2.3.3).

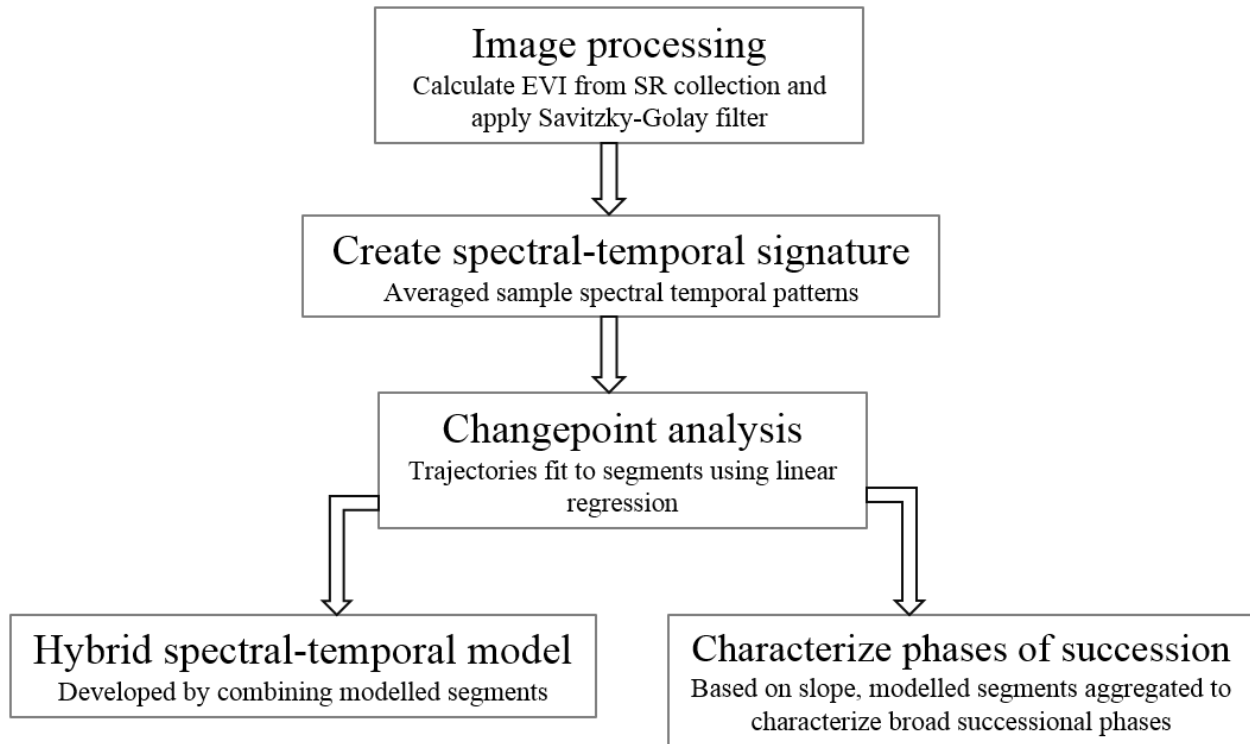


Figure 2.2: Roadmap of methods used to identify the spectral-temporal signature of bamboo-dominated forest, characterize phases of bamboo lifecycle and the subsequent development of the hybrid model. SR refers to surface reflectance.

#### *Determining bamboo-dominated forest succession spectral-temporal signature*

Twenty-eight training points were selected using 2004 Ikonos imagery, 2006 ALOS imagery and 2014 WorldView2 imagery. Based on previous classifications published using these three images, criteria for selecting these training points were (1) bamboo or *V. discolor* are visible in the canopy in the 2004 image (Dlugosz et al., 2005); (2) senescent biomass resulting from dieback is visible in the 2006 image (Luz, 2009); and (3) pioneers are visible in the canopy of the 2014 image (Maran, 2016). Landsat pixels in the middle of these regions were selected to reduce edge effects or spectral-mixing. The individual spectral-temporal patterns of each

selected pixel were then averaged to generate a representative spectral-temporal signature of bamboo-dominated forest succession.

### *Characterizing bamboo-dominated forest succession spectral-temporal signature*

A changepoint analysis was applied to the spectral-temporal signature to identify significant changes in variance that distinguish phases of bamboo-dominated forest succession (Figure 2.3). The distribution of the time-series data is non-parametric, therefore a binary segmentation changepoint analysis was employed. Other more precise changepoint analysis methods (e.g., segment neighbours, pruned exact linear time) require data to be normally distributed (Killick & Eckley, 2014). Binary segmentation determines approximate changepoints in a time-series by first finding the greatest change in mean or variance within the entire time-series, and then treating the two resulting segments as individual time-series to be subsequently analysed (Edwards & Cavalli-Sforza, 1965). This process is continued until there are no more significant changes in variance detected, or until the user defined number of changepoints has been reached. Determining the number of changepoints was done iteratively, and through visual inspection it was found that five changepoints coincided with previous field observations and findings (Table 2.1) (Kellermann, 2011; Lacerda & Kellermann, 2017).

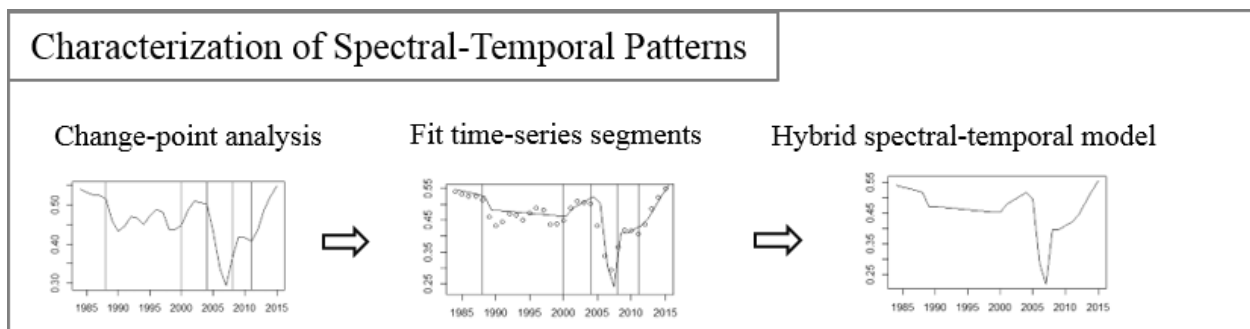


Figure 2.3: Depiction of characterization of bamboo-dominated forest succession spectral-temporal signature and subsequent development of hybrid model.

Table 2.1: The time period that each changepoint occurred within the 32-year time-series.

Changepoint	Years
(1)	1988
(2)	2000
(3)	2004
(4)	2008
(5)	2011

Using the changepoints as vertices, trajectories of each segment were fit using linear regression and were subsequently compared to forest succession temporal-trajectories hypothesized by Kennedy et al. (2007) and Vogelmann et al. (2009). Based on the slope of the fitted values, information regarding the phase of forest succession was extrapolated. Kennedy et al. (2007) hypothesized the spectral-temporal trajectories of four phases of forest succession, which included disturbance, disturbance and revegetation, revegetation, revegetation to stable state and Vogelmann et al. (2009) identified the spectral-temporal trajectory of senescent populations. A disturbance event is characterized by an abrupt decrease in index values, which is followed by either a continued state of disturbance (i.e., land conversion) or revegetation, which is identified by an initial spike in index values, followed by a more gradual increase over time. Revegetation is identified by a continuous, gradual increase in index values and followed by a stable state, which is characterized by a prolonged period of stable index values. Senescent or damaged populations are identified by a gradual decrease in index values over a prolonged period of time (Vogelmann et al., 2009). The modelled segments were aggregated into four broad successional phases, which include (mature/senescence) pioneer predominance, mature bamboo, bamboo dieback and (juvenile) pioneer regeneration based on the observed slope of the modelled segment trajectories.

### *Development of hybrid spectral-temporal model (Hybrid model)*

To evaluate whether the hypothesized perpetuated bamboo-dominance cycle was occurring on a single-landscape scale, a spectral-temporal model representative of bamboo-dominated forest succession was created. We developed a semi-empirical approach to modelling bamboo successional dynamics from the time-series of images. The 32 modelled values of the hybrid model were converted into a 32-year hybrid model raster time-series stack, which was then compared to the 32-year Landsat time-series of smoothed EVI values to determine whether the hybrid model accurately described bamboo-dominated forest succession (Figure 2.4). Bias and Root-mean square error (RMSE) between each pixel in the study area and the hybrid model were computed and summarized, creating raster outputs of both bias and RMSE values.

A local Getis-Ord  $G_i^*$  statistic was calculated for the RMSE output to identify spatial-clustering of errors. Using a local Getis-Ord  $G_i^*$  statistic clustering output of RMSE values is a non-traditional classification method. Typically, this statistic is used to detect statistically significant hot and cold spots of spatially clustered high and low values (Getis & Ord, 1992; Getis & Aldstadt, 2010). In this study, spatial autocorrelation of RMSE values associated with bamboo-dominated forest was assumed based on the (1) existing spatial pattern of bamboo in the ERSC and (2) the RMSE value spread demonstrated by boxplots generated for the three forest types. Through observation of satellite and aerial imagery, it has been observed that approximately a third of the ERSC is visibly occupied by bamboo-dominated forest, the majority of which is coalesced on the eastern edge of the ERSC. With this knowledge, it was assumed that these regions would be characterized by low RMSE values (and other areas as higher RMSE values). Boxplots generated to demonstrate RMSE value spread for the three forest types exemplified this assumption; bamboo-dominated forest exhibited a narrow value spread of low

values, while both Araucaria predominance and degraded forest typically possessed a wider spread of higher RMSE values (Figure 2.8). Based on these preliminary findings, it was hypothesized that the Getis-Ord  $G_i^*$  statistic ‘cold spots’ would generate spatial clusters of bamboo-dominated forest exclusive from other forest types.

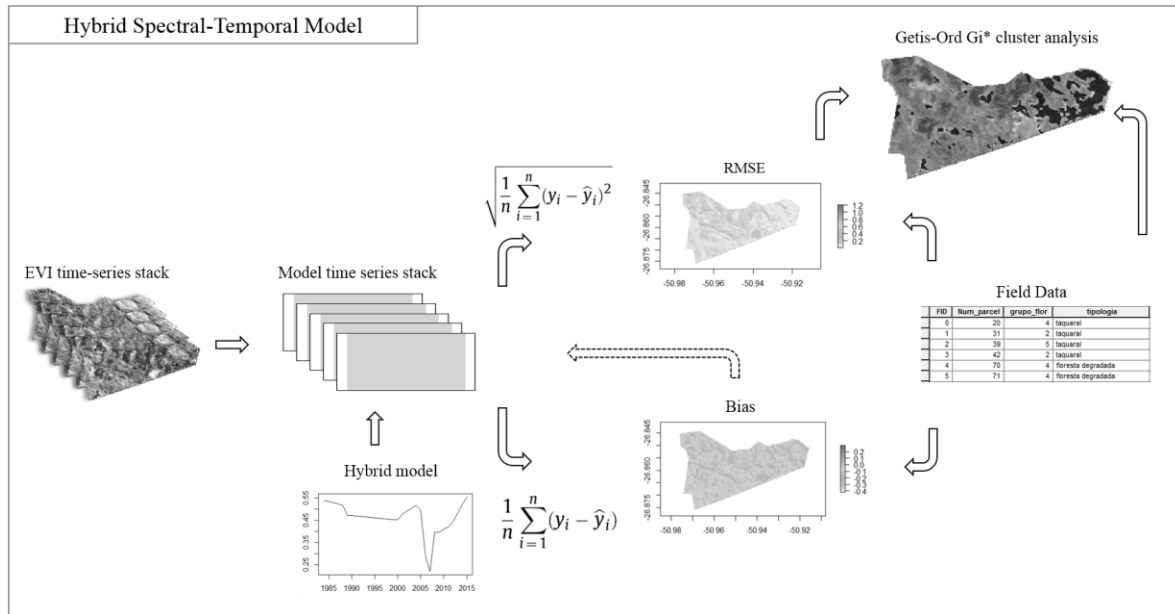


Figure 2.4: Workflow of hybrid modelling; a modelled time-series stack was generated using the developed hybrid model and compared to the 32-year EVI time-series stack and both bias and RMSE were calculated and summarized. A local Getis-Ord  $G_i^*$  statistic was then calculated for the RMSE output to identify spatial-clustering of low errors.

For the Getis-Ord  $G_i$  cluster analysis, queen’s case neighbourhood was used to define the spatial neighbourhood for each pixel. The local sum for each pixel’s neighbours is proportionally compared to the sum of all pixels in a dataset, resulting in a statistically significant Z-score if the local sum is substantially higher or lower than the expected local sum (Getis & Ord, 1992). A simple form of the  $G_i$  statistic is:

$$G_i = \frac{\sum_{j=1}^n w_{ij} x_j}{\sum_{j=1}^n x_j} \quad (1)$$



where  $w_{ij}$  is the spatial weight between pixel  $i$  and  $j$ , and  $x_j$  is the RMSE value of the  $j$ th neighbour of pixel  $i$ . The numerator is the sum of all contiguous neighbouring attributes and the denominator is the sum of all features in the dataset. The sum of both the numerator and the denominator do not include the feature under observation.

The same hybrid modelling workflow was then used to examine the ability of the hybrid model to identify regions of bamboo-dominated forest for each of the four broad phases of the bamboo-dominated forest succession, as well as a 15-year time period from 2001 to 2015. This time period represents the time frame which encapsulates three lifecycle phases (mature bamboo, dieback and pioneer regeneration) which is the portion of the spectral-temporal signature that exhibits the most distinct temporal trajectory based on RMSE values of the modelled segments. Definition of cold spots were based on significance thresholds based on preliminary analysis of the z-score frequencies, but all were at least  $p < 0.05$ .

#### *2.2.4. Time-weighted dynamic time-warping*

The R package dtwSat was used as a comparison to assess the performance of the hybrid model, as it employs spectral-temporal signatures to classify different landcover types and provide further insight into the bamboo lifecycle synchrony (Maus et al., 2016b). The package requires a Landsat time-series stack and a set of training points used to extract time-series information from temporal patterns. Traditionally, dynamic time warping (DTW) is typically used to match two time-dependent sequences,  $X := (x_1, x_2, \dots, x_N)$  of length  $N$  and  $Y := (y_1, y_2, \dots, y_M)$  of length  $M$ . To evaluate the alignment of the sequences certain conditions must be met; (1) the start and end points of  $X$  and  $Y$  must align; (2) monotonicity must be maintained; and (3) continuity is ensured by  $X$  and  $Y$  possessing the same number of nodes, all of which align (Muller, 2007). The inclusion of the time-weighted constraint in the TWDTW algorithm allows

the traditional conditions to be omitted, enabling temporal patterns with different start and end points and number of nodes to classify segments of a longer time-series. A feature of the program is that the TWDTW algorithm employs a logistic weight function as a time constraint which governs the way in which nodes align. The logistic weight permits more flexibility with temporal patterns that may vary in length (e.g., crops cycles that range from 90 to 120 days) (Maus et al., 2016a), and therefore allows the hypothesized synchrony of the perpetuated bamboo-dominance cycle to be tested; if the bamboo dieback events are out of phase, then this algorithm will yield higher accuracies in classifying regions of bamboo-dominated forest than the hybrid model. The logistic weight function is as follows:

$$w = \frac{1}{1 + e^{-\alpha(g(t_1, t_2) - \beta)}} \quad (2)$$

Where  $\alpha$  is steepness,  $g$  is the absolute difference in days between  $t_1, t_2$  and  $\beta$  is the midpoint (Maus et al., 2016b).

To use TWDTW as a method to classify different forest types, a set of time-series samples  $Q_c = \{U_1, U_2, \dots, U_q\}$  where  $U = (u_1, \dots, u_n)$  is a sample of a time-series pattern and  $c$  is class, is then used to classify  $V_{x,y} = (v_1, v_2, \dots, v_m)$ , which is a time-series of pixel locations  $(x, y)$ . All the satellite spatial coverage is then combined into a set of time-series  $S = \{V_1, V_2, \dots, V_s\}$ . Each  $Q_c$  is compared to each  $V_{x,y}$  and the local cost is measured. The cost, or TWDTW distance, between  $Q_c$  and  $V_{x,y}$  will determine the classification of  $V_{x,y}$  (Maus et al., 2016a).

#### *Time-weighted dynamic time warping parameters*

The 32-year smoothed Landsat time-series stack required further processing to improve the program's performance; using changepoints of the four broad successional phases as vertices,

linear models were imposed on the 32-year smoothed Landsat time-series stack, rendering annual modelled values for each pixel in the study area (Figure 2.5). This was done in an attempt to further reduce year-to-year noise, as the original smoothed time-series did not yield acceptable results. Training point data were manually selected to create sample spectral-temporal patterns for the three prominent landcover types of the study area (Araucaria predominance, degraded forest and bamboo-dominated forest). The same 28 training-points used to develop the hybrid model were used to generate the sample spectral-temporal patterns for bamboo-dominated forest, with an additional 14 Araucaria predominance and 34 degraded forest training points selected, based on the approximate proportion of forest types within the ERSC, to create sample patterns.

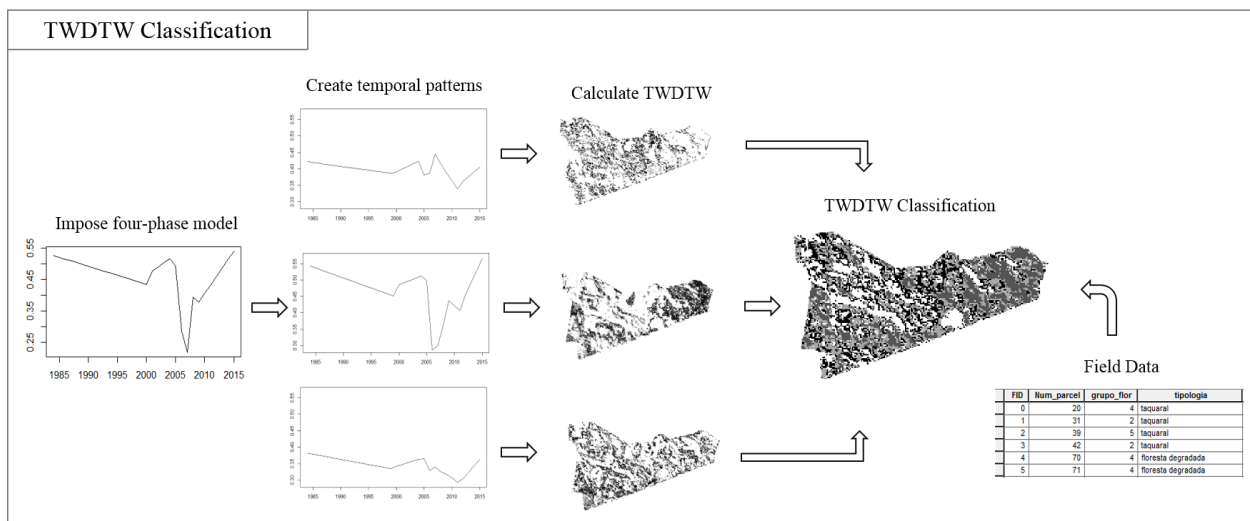


Figure 2.5: Workflow of TWDTW classifier; a simplified four-phase hybrid model is imposed on the 32-year EVI time-series stack, and template temporal patterns were extracted using training points. The template patterns are compared to each pixel time-series and the distance to align template patterns and individual pixels is calculated and output as a ‘TWDTW distance’ raster. The three resulting ‘TWDTW distance’ rasters are then combined, and pixels with the lowest cost are selected for the final classification.

Maus et al. (2016a) tested a range of time delays to determine  $\beta$  as a parameter for the TWDTW equation. For this study, the program was found to produce the most accurate outputs

when the parameters were set to  $\alpha = -0.01$  and  $\beta = 1$ , which enables minimal time-warping, but still serves as a necessary constraint to maintain the temporal structure. Both a 32-year (1984 to 2015) and a 16-year time-series (2000 to 2015) were evaluated.

The TWDTW classifier was run three times (Table 2.2); both the 32-year and 16-year time-series were run separately to determine which time-series yielded superior results. For both, each time-series was treated as a singular temporal pattern (i.e., Model run (1):1984 to 2015; Model run (2): 2000 to 2015). An additional classification was performed (i.e., Model run (3)) to identify whether the 16-year temporal pattern could successfully classify regions of bamboo-dominance when applied to the 32-year time-series stack, which yields two classified maps from the time periods of 1984 to 1999 and 2000 to 2015.

Table 2.2: Parameters used for each of the three TWDTW model runs.  $S$  is the EVI time-series of  $V_{x,y}$  used as an input in the model to be compared to samples of time-series patterns of different classes ( $Q_c$ ). Number of  $Q_c$  is the number of classes used for the classification.  $Q_c$  length is the length of time-series pattern samples of  $Q_c$ .  $\alpha$  is slope and  $\beta$  is midpoint of the logistic function.

Model run	$S$ (EVI time-series)	Number of $Q_c$	$Q_c$ length	$\alpha$	$\beta$
(1)	1984 to 2015	3	32-year	-0.01	1
(2)	2000 to 2015	3	16-year	-0.01	1
(3)	1984 to 2015	3	16-year	-0.01	1

### 2.2.5. Maximum likelihood classification

To compare efficacy of both the hybrid model and TWDTW algorithm as classification methods, a maximum likelihood classification was employed on four satellite images representative of each of the four lifecycle phases; 2000 (pioneer predominance), 2004 (mature bamboo), 2008 (dieback), 2015 (pioneer regeneration). These four time periods were selected to provide snapshots of the progression of bamboo-dominated forest succession, with each date

being the last date of the four phases' time intervals. Maximum likelihood is one of the most prominent supervised classification algorithms used in remote sensing. The algorithm uses probability densities of user-defined classes to predict the inclusion of a pixel in each class category (Strahler, 1980). Samples (pixels) are selected which are representative of a particular class, and based on these samples, the parametric mean and dispersion matrix for the class are estimated (Strahler, 1980). Observations are then compared to each class parametric mean and dispersion matrix and the probability of an observation's inclusion in each class is calculated, and subsequently appointed to the class with the highest probability (Strahler, 1980). The same training samples used for both the hybrid model and the TWDTW classification were used for the maximum likelihood classification.

#### *2.2.6. Validation*

To determine the initial accuracy of the hybrid model, boxplots were created for six relevant time periods, which included the 32-year time-series (1984 to 2015), 15-year time-series (2001 to 2015) and each of the four lifecycle phases, using the extracted bias and RMSE values from the field sample reference data. To demonstrate response variability of other forest types to the hybrid model, both Araucaria predominance and degraded forest were included as variables for the boxplots. As the purpose of this study is to identify regions of bamboo-dominated forest, to assess the accuracy of the hybrid model, TWDTW model and Maximum Likelihood classification output maps, both Araucaria predominance and degraded forest field samples were combined and designated as secondary forest, creating a presence/absence output of bamboo-dominated regions.

Overall agreement and the allocation and quantity disagreement were calculated using a method developed by Pontius and Millones (2011). The underlying assumption of this method is

that both reference data and classification output data are a perfect match, as opposed to Kappa coefficient, which assumes randomness between both datasets. This method mathematically converts sample error matrices into estimated unbiased population matrices, a step which is often overlooked when performing an accuracy assessment (Pontius & Millones, 2011). Quantity disagreement refers to the less than perfect match in the proportions of classes (e.g., secondary forest and bamboo-dominated forest) between reference data and classification output data. Allocation disagreement refers to the omission and commission of pixels between classes (e.g., secondary forest and bamboo-dominated forest) of reference data and classification output data. Total disagreement is calculated by summing quantity disagreement and allocation disagreement and overall agreement is derived from subtracting total disagreement from 100.

## **2.3. Results**

### *2.3.1. Characterization of bamboo-dominated forest succession*

Based on the modelled segments, distinct phases of bamboo-dominated forest succession can be observed, which include senescence, disturbance and subsequent regeneration. Between 1984 to 2000, the time-series has a negative slope, showing gradual decrease in EVI values, with a more rapid decrease occurring between 1984 and 1988, and a much more gradual decrease between 1989 and 2000. The two segments are thought to (1) represent the die-off of *M. scabrella* populations and (2) the subsequent emergence of *V. discolor* into the canopy alongside the remaining senescent *M. scabrella* population, resulting in a gradual decrease in EVI values until 2000. In 2001, a positive slope indicates an increase in EVI values, which is thought to be the emergence of mature bamboo into the canopy, as a result of gap formation from treefall of senescent *M. scabrella* and *V. discolor* populations. In 2005, there is a sharp drop in EVI values,

with a corresponding negative slope, which characterizes a dieback event. Subsequently, slope becomes positive and a spike in EVI values occur, indicating pioneer regeneration. Based on these spectral-temporal trajectories, bamboo-dominated forest succession can be characterized into four broad phases, which include pioneer predominance, mature bamboo, bamboo dieback and pioneer regeneration (Figure 2.6, Table 2.3). However, it is important to note that between 2007 and 2008 in the dieback phase (2005 to 2008) there is a positive slope, which indicates regeneration. Therefore, it is important to understand that the actual dying and detection of senescent bamboo biomass occurs between 2005 to 2007, with 2007 to 2008 being the first year of regeneration.



Figure 2.6: Developed hybrid model, showing both training ('Train') and modelled ('Model') spectral values, and defined four broad phases: pioneer predominance, mature bamboo, dieback, pioneer regeneration.

Table 2.3: The four phases and time intervals of the complete perpetuated bamboo-dominance cycle, as observed in a 32-year time-series. RMSE values and slope are shown to demonstrate precision of each modelled segment and slope as an indicator of succession phase.

Broad Phase	Time Interval	RMSE	Slope
Pioneer predominance	1984 to 1988	0.002	-0.006
	1989 to 2000	0.022	-0.002
Mature Bamboo	2001 to 2004	0.014	0.013
Bamboo Dieback	2005 to 2008	0.045	-0.041
Pioneer regeneration	2009 to 2011	0.016	0.012
	2012 to 2015	0.005	0.037

### 2.3.2. Hybrid model performance

All boxplots generated for the six time periods indicated that bamboo-dominated forest consistently had median values closest to zero, compared to both Araucaria predominance and degraded forest, for both bias and RMSE outputs, and generally exhibited a value spread with strong central tendency. In all cases, bamboo-dominated forest had the smallest value range and spread between the first and third quartile.

The value spread of the bias boxplots indicate that the hybrid model consistently over predicts, which is shown by negative median values for all time periods and a value range that is predominantly negative values, with exception to dieback (Figure 2.7). The 15-year time period had the smallest and most unbiased first to third quartile spread. Pioneer predominance and mature bamboo had the first and second largest value range between the first and third quartile, respectively. Comparing bamboo-dominated forest value spread to the other two forest types, it is noted that generally only the fourth quartile group of Araucaria predominance overlaps with the range of bamboo-dominated forest, whereas consistently the third quartile group of degraded forest aligns with the second quartile group of bamboo-dominated forest.



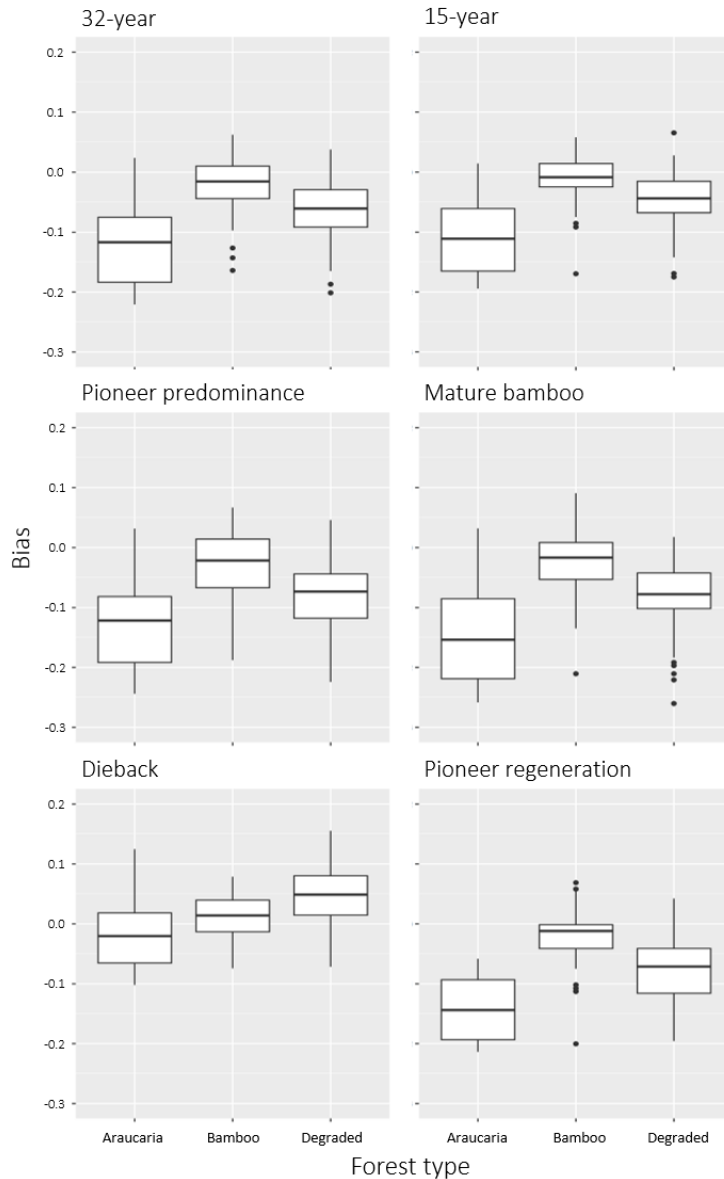


Figure 2.7: Boxplots showing bias of the three forest types when compared to the 32-year EVI time-series stack.

The RMSE boxplots show that the six time periods share similar median values (Figure 2.8). The 15-year time period, dieback and the 32-year time-series have the smallest first to third quartile range, respectively, and do not overlap with both Araucaria predominance and degraded forest. Mature bamboo has the largest first to third quartile spread, with the third quartile group overlapping the most with the second quartile group of the degraded forest. Both pioneer predominance and pioneer regeneration have similar first to third quartile value ranges, but it can

be observed that pioneer predominance overlaps with degraded forest similarly to mature bamboo, whereas pioneer regeneration has less overlap with the second quartile group.

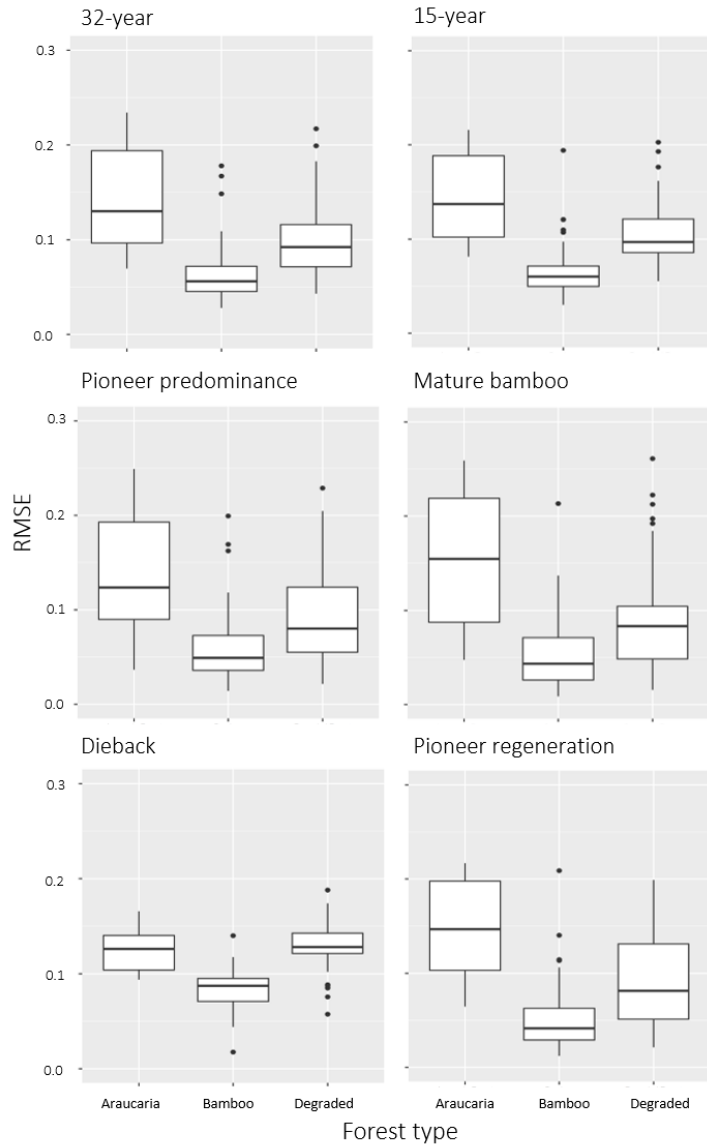


Figure 2.8: Boxplots showing RMSE of the three forest types when compared to the 32-year EVI time-series stack.

With the resulting Z-scores from the local Getis-Ord  $G_i^*$ , unique threshold values were selected for each of the six hybrid model outputs, based on visual assessment of Z-score frequency histograms (Table 2.4). As RMSE serves as a measure of model fit, the resulting Z-scores are indicative of model performance, suggesting that regions of RMSE values closest to

zero would be representative of bamboo-dominance. Therefore, the resulting spatial clustering demonstrates the hybrid model's distance from being able to perfectly predict regions of bamboo-dominance.

Table 2.4: Z-score thresholds selected to indicate regions of accurate hybrid model performance.

Hybrid Model	Threshold (Z-score)
32-year	-2.2
15-year	-2.2
Pioneer predominance	-2.1
Mature bamboo	-2.1
Dieback	-2.0
Pioneer regeneration	-2.2

An accuracy assessment was performed for the six Getis-Ord Gi maps (Figure 2.9, Table 2.5). The 15-year time-series achieved the highest overall agreement of 90%. The dieback phase had the second highest overall agreement which was 87% and both the 32-year times series and pioneer regeneration had an overall agreement of 85%. Pioneer predominance and mature bamboo had the lowest accuracies, receiving an overall agreement of 82% and 77%, respectively.

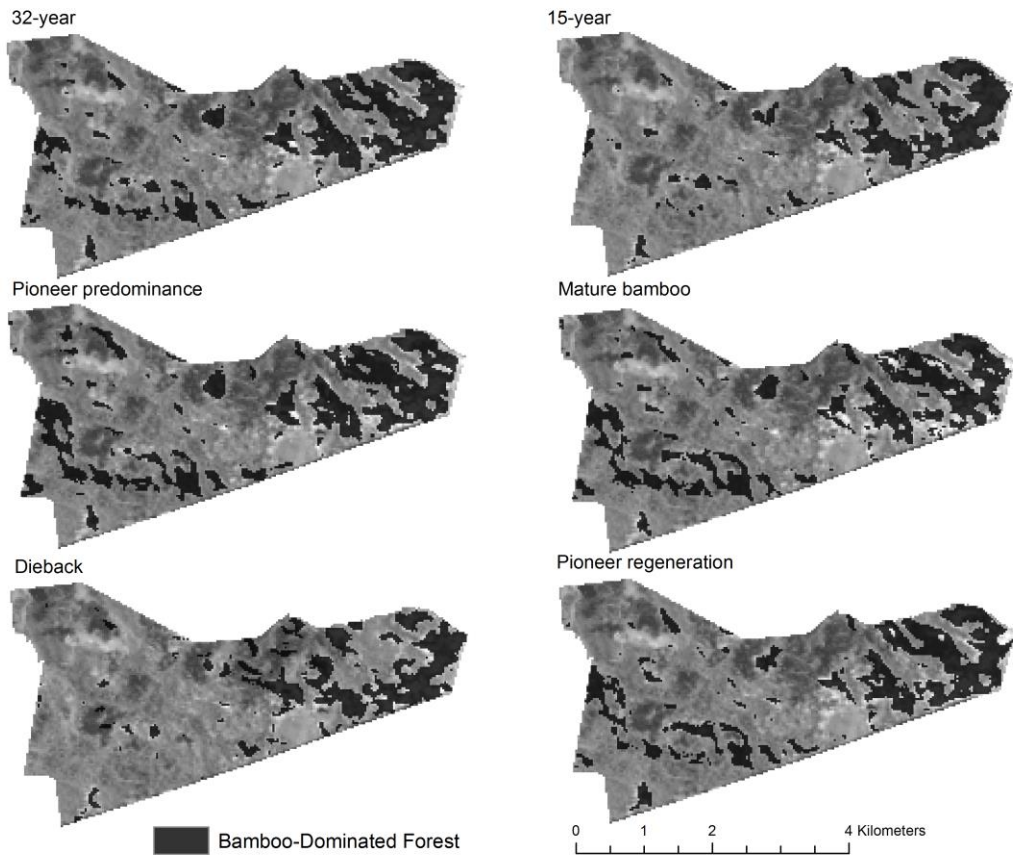


Figure 2.9: Spatial-clustering of RMSE outputs depicting the hybrid model’s ability to predict bamboo-dominated regions.

Table 2.5: Overall agreement, quantity disagreement, allocation disagreement and estimated area of the hybrid model outputs, using Getis-Ord Gi to identify spatial clustering of RMSE values.

Hybrid Model	Overall Agreement (%)	Quantity Disagreement (%)	Allocation Disagreement (%)	Estimated Area (ha)
32-year	85	6	10	226
15-year	90	8	3	172
Pioneer predominance	82	5	13	266
Mature bamboo	77	9	14	244
Dieback	87	9	4	169
Pioneer regeneration	85	7	9	233

### 2.3.3. Time-weighted dynamic time warping performance

The accuracy assessment revealed that the 16-year time-series was more successful at identifying regions of bamboo-dominated forest than the 32-year time-series (Figure 2.10, Table 2.6). Model run (1) (32-year time-series) yielded an overall agreement of 77%, while model run (2) (16-year time-series) achieved an overall agreement of 82%. The two outputs from model run (3) yielded very different results; the time period from 1984 to 1999 (pioneer predominance) yielded an overall agreement of 68%, whereas the proceeding time period (2000 to 2015) yielded an accuracy of 80%.

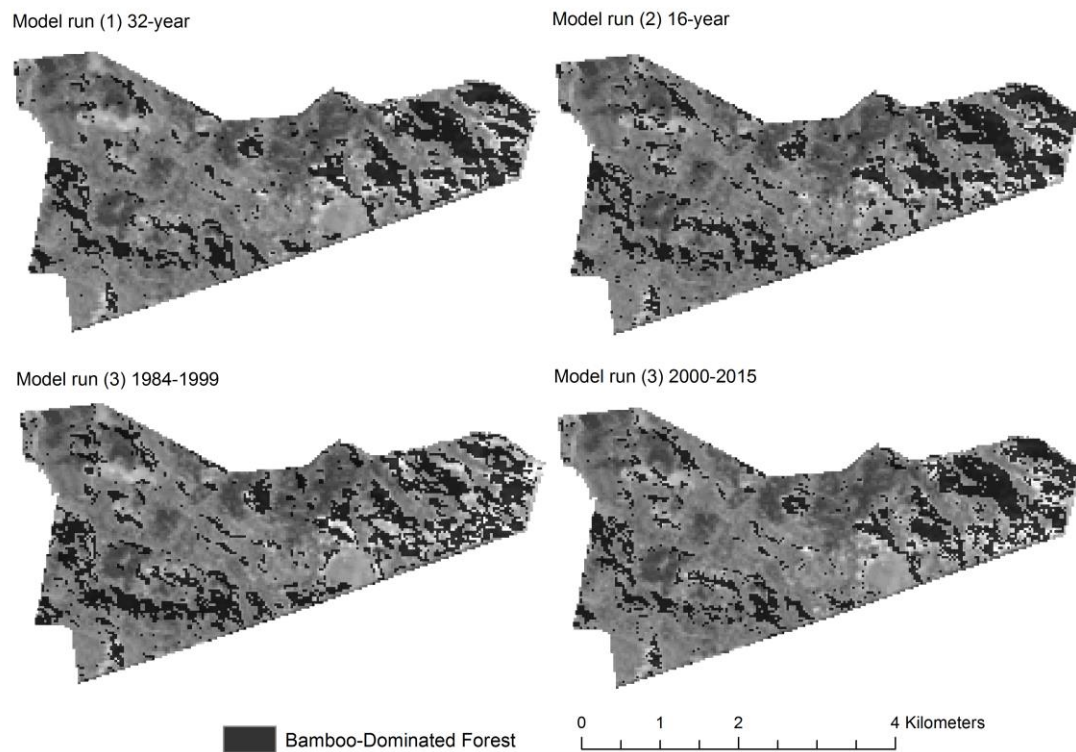


Figure 2.10: Classification of bamboo-dominated forest regions using the TWDTW algorithm.

Table 2.6: Overall agreement, quantity disagreement, allocation disagreement and estimated area of TWDTW classification.

Model run	Overall Agreement (%)	Quantity Disagreement (%)	Allocation Disagreement (%)	Estimated Area (ha)
(1) 32-year	77	3	15	246
(2) 16-year	82	9	14	279
(3) 1984 to 1999	68	8	24	300
(3) 2000 to 2015	80	8	12	244

#### *2.3.4. Maximum likelihood classification performance*

It was found that the Maximum Likelihood classification was most successful at classifying the 2008 image (dieback), garnering an overall accuracy of 84%. Both the 2000 (pioneer predominance) and 2015 (pioneer regeneration) images achieved a fairly accurate overall agreement of 79% (Figure 2.11, Table 2.7). Comparatively, the 2004 image classification received a lower overall accuracy of 75%.

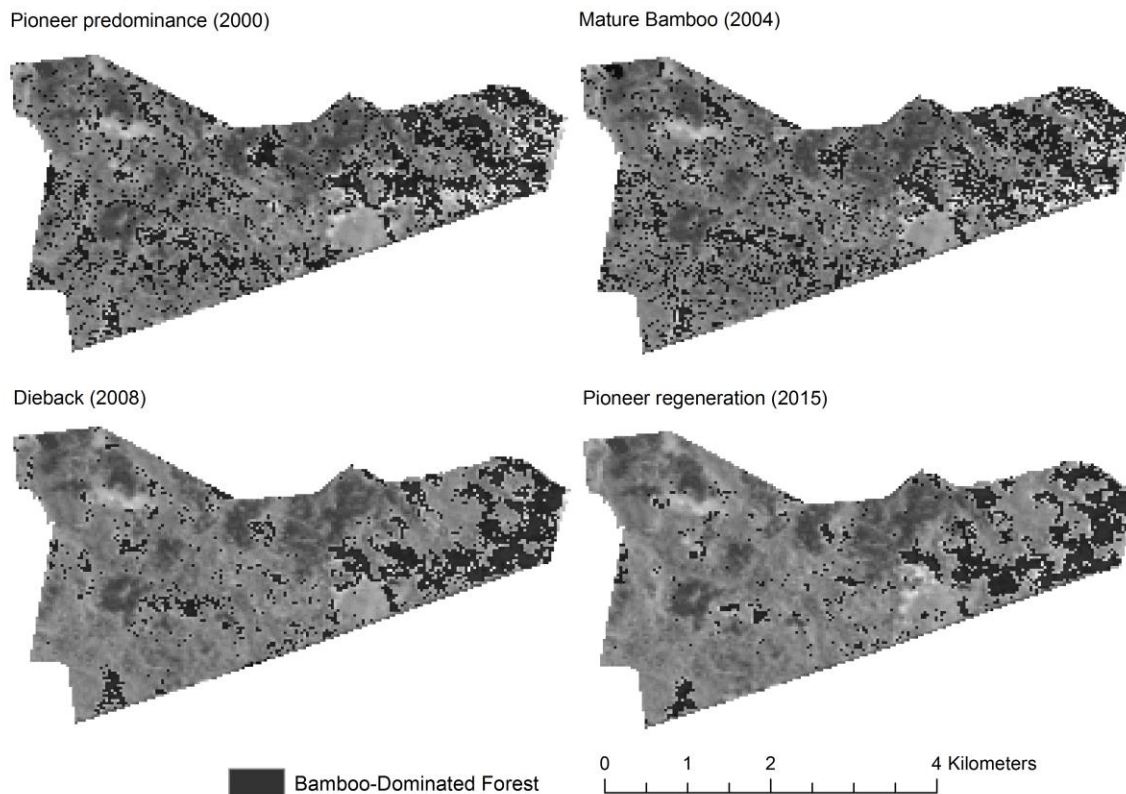


Figure 2.11: Classification of bamboo-dominated regions using the maximum likelihood algorithm.

Table 2.7: Overall agreement, quantity disagreement and allocation disagreement of Maximum Likelihood classification.

Maximum Likelihood Classification	Overall Agreement (%)	Quantity Disagreement (%)	Allocation Disagreement (%)	Estimated Area (ha)
Pioneer predominance (2000)	79	11	10	263
Mature bamboo (2004)	75	9	16	273
Dieback (2008)	84	7	9	181
Pioneer regeneration (2015)	79	9	12	154

### 2.3.5. Comparison of classification performances

Overall, the hybrid model consistently outperformed the TWDTW and Maximum-Likelihood classifiers, with the TWDTW model achieving the lowest overall accuracies of the

three classifiers. Generally, the three classifiers consistently produced outputs which possessed two specific configurations (i.e., similar classification and misclassification of pixel locations), which influenced the estimated area occupied by bamboo. The two hybrid models (i.e., 15-year and dieback) which had the highest accuracies had an estimated area of approximately 170 ha and maintained a similar configuration. All other model outputs with lower overall accuracy from the hybrid model and TWDTW model possessed a similar configuration, in which two large areas of degraded forest were consistently misclassified as bamboo-dominated forest, resulting in an estimated total area ranging from 226 to 300 ha.

## **2.4. Discussion**

### *2.4.1 Hybrid model performance*

The initial purpose of the hybrid model was to perform an exploratory analysis to identify whether bamboo-dominated forest exhibited a unique spectral-temporal trajectory and identify whether this trajectory was common to all bamboo-dominated forest throughout the study area, thus indicating synchrony. The 32-year hybrid model, representing one full bamboo lifecycle, had an overall agreement of 85%, indicating that the *in situ* observed perpetuated bamboo-dominance cycle is a synchronous process occurring throughout the ERSC, which further suggests that this process is also occurring throughout the remaining fragments of Araucaria forest. The overall agreement of 90% for the 15-year time period, which encapsulates the phases of mature bamboo, dieback and pioneer regeneration, further suggests the synchrony of bamboo-dominated forest succession and also demonstrates the efficacy of the 15-year time period to detect bamboo-dominated regions. State-wide synchronized monocarpic dieback events of *Merostachys skvortzovii* have been recorded from 1843 to 1876-1877, 1909-1910, 1938-1940, 1973-1975 (Pereira, 1941; Sendulsky, 1995) and 2003-2006 (Liebsch & Reginato, 2009;



Kellermann, 2011), therefore it is certain that the 15-year period encapsulates the 2003 to 2006 dieback event, as well as the preceding mature bamboo lifecycle phase and proceeding pioneer regeneration phase. The 15-year time period is characterized by a distinct spectral-temporal signature due to the abrupt drop in index values as a result of the dieback event. When each of these three phases were individually used to classify regions of bamboo dominance, overall agreement for each phase was lower than the 15-year period, indicating that the 15-year time-series is a superior spectral-temporal model for classifying bamboo dominated regions.

For both pioneer predominance and mature bamboo, certain portions of the study area representative of degraded forest were consistently misclassified, which was also observed by an increase of the total estimated area of almost 100 hectares. The RMSE boxplots of both phases show that there is considerable overlap between bamboo-dominated and degraded forest, indicating that both forest types share similar values, which could be the reason for the consistent misclassification. Similarly to both the pioneer predominance and mature bamboo phases, the canopy of degraded forest is heterogenous in nature, possessing a wide variation in structure and diversity, as in the past, selective logging was aimed at the most valuable tree species resulting in a heterogenous canopy under which the bamboos could thrive (Lacerda, 2016). Although bamboo-dominance in the understorey is widespread within the study area, the discontinuity of the canopy tends to mask its occurrence, which is attributed to the inconsistency in identifying bamboo-dominated regions in the degraded forest type. The same pattern was observed in the Araucaria predominance; when the tree stratum below the Araucaria canopy is absent, it enables the development of bamboos resulting in further uncertainty in the classification due to the presence of Araucaria in the canopy.

#### *2.4.2 Comparison of model performances*

Comparatively, the TWDTW model yielded lower overall agreement than the hybrid model. Initially the classification was performed using the same 32-year time-series used as an input for the hybrid model, however, yielded poor overall agreement. As the hybrid model demonstrated acceptable overall agreement for each of the four phases of the lifecycle, linear models representative of the four phases were applied to the time-series stack in order to reduce year -to-year spectral variation, which improved overall agreement. Similarly to the 15-year hybrid model, the 16-year temporal pattern proved to acquire the most accurate results; 82% for model run (2) (16-year temporal pattern applied to a 16-year time-series) and 80% for model run (3) (16-year temporal pattern applied to a 32-year time-series). For the same reasons previously mentioned, it is thought that the 15-year or 16-year temporal pattern is therefore a more robust input to identify regions of bamboo, and further suggests the synchrony of bamboo lifecycle.

Both the hybrid model and the TWDTW outputs yielded similar classification configurations, and therefore the TWDTW consistently misclassified the same degraded forest regions. Also, TWDTW is somewhat computationally intensive, requiring anywhere from two to eight hours to process a 32-raster stack, with each raster possessing 33880 cells at 30 metre resolution (CPU 2.6 GHz; 4 GB ram). However, TWDTW offers an opportunity to automate classification of bamboo dominated regions; in the case of the hybrid model, the user can only compare specified time periods to a time-series with the same time periods, whereas with the TWDTW, a temporal pattern representative of bamboo-dominated forest succession (e.g., the 16-year time-series), can be used to classify smaller segments of a larger time-series.

Overall, the hybrid model outperformed the maximum likelihood classification for all four successional phases, showing the functionality of the hybrid model and the advantages of

using multi-temporal imagery. Although the maximum likelihood classifier acquired reasonable overall accuracies, the use of ‘snapshot’ classifiers gives limited insight into the history of forest development; *M. skvortzovii* occupies the forest understorey for the majority of its lifecycle, making it very challenging to detect during the pioneer predominance and pioneer regeneration phases. Therefore, by extracting spectral-temporal signatures from multi-temporal imagery, it is possible to determine whether bamboo exists in the understorey based on the temporal progression of the pixel under investigation, e.g., the distinct drop in EVI values of dieback followed by the sharp increase in EVI values of pioneer regeneration.

#### *2.4.3 Hybrid model and in situ observations*

Results from the three modelling methods used in this study indicate that spectral-temporal signatures are a viable tool from which mechanisms of bamboo-dominated forest succession can be extrapolated, regions of bamboo-dominance can be identified, and further demonstrates how the use of multi-temporal imagery can improve classification results. The hybrid model achieved the highest accuracy and gives the most insight into the ecological processes of bamboo-dominated forest succession occurring across the single-landscape. It also has the ability to capture and classify the four phases of bamboo-dominated forest succession into discrete events and demonstrates that the perpetuated bamboo dominance cycle is a widespread, synchronous phenomenon occurring throughout the ERSC and other Araucaria forest fragments as observed in the Santa Catarina State Forest Inventory (Vibrans et al., 2013).

Understanding the mechanisms of bamboo-dominated forest succession is crucial in order to improve forest health and vitality and also to promote and develop silvicultural practices to better manage the dwindling fragments of Araucaria Forest. The inclusion of certain bamboo species within forest communities has been observed to significantly alter forest succession

mechanisms, due to its regeneration strategies and length of lifecycle (Gratzer et al., 1999; Abe et al., 2002; Narukawa and Yamamoto, 2002; Griscom and Ashton, 2006; Taylor, 2004).

Dieback events of *Bashania fangiiana* in the old-growth *Abies foxonian-Betula Utilis* forest of southwestern China have been observed to create a resource environment which enables the growth of specific pioneer species (Taylor, 2004), while alternatively, the presence of *Guadua weberbaueri* and *Guadua sarcocarpa* in the Brazilian Amazon has been found to arrest forest succession due to the intensive mechanical damage which the species inflict on juvenile trees (Griscom & Ashton, 2006; Carvalho et al., 2013).

The impact *M. skvortzovii* has on forest succession coincides with a forest succession mechanism model referred to as the inhibition model (Connell & Slatyer, 1977). This model states that forest succession has the potential to be governed by early colonists, by means of securing space and resources, which subsequently inhibits the growth and/or replacement of later-succession species. The mechanisms of forest succession described by this model were observed in a study performed by Lacerda and Kellermann (2017), where regeneration data collected following a dieback event from 2007 to 2014, were used to compare regeneration occurring in both *Araucaria* predominance and bamboo-dominated forest in the ERSC. It was found that *Araucaria* predominance had more diversity and a stable density, whereas bamboo-dominated forest was found to have less diversity and a decreasing density. It was determined that bamboo populations can recover following a dieback event despite the subsequent development of a dense tree canopy dominated by pioneer species, by homogeneously occupying the understorey and subsequently emerging into the canopy as pioneer populations die-off, a process mimicking the ‘inhibition’ model, that has been found to arrest forest succession.

The characterization of bamboo-dominated forest succession spectral-temporal signatures, along with the overall agreement of the hybrid model outputs assists in solidifying the correspondence between the inhibition model and bamboo-dominated forest succession. First, the 32-year hybrid model, which represents the entire lifecycle of bamboo, had an overall agreement of 85%, corroborating that the *in situ* observed perpetuated bamboo-dominance cycle is a synchronous process occurring throughout the ERSC. Additionally, *in situ* observations made in the ERSC by Lacerda and Kellermann (2017) coincide with the spectral-temporal trajectories of the dieback and pioneer regeneration lifecycle phases and based on the overall agreement of the hybrid model outputs, qualitative information regarding the canopy characteristics and species population dynamics can be inferred for each lifecycle phase. Dieback and pioneer regeneration achieved overall accuracies of 87% and 85%, respectively, which suggests that these two phases possess distinct spectral responses; dieback exhibits a distinct drop in EVI values due to the detection of the senescent bamboo population and pioneer regeneration exhibits an increase in EVI values due to the formation of a homogenous juvenile canopy. Following bamboo dieback, a very dense seedling population of *M. scabrella* establishes and quickly develops into juvenile tree populations within two to four years (2007 to 2009) (Lacerda & Kellermann, 2017), which can be observed by an increase in EVI values during this same time period. Subsequently, a self-thinning process significantly reduces *M. scabrella* populations (2009 to 2011), causing EVI values to stabilize during this time period, resulting from the detection of senescent juvenile *M. scabrella* foliage. This thinning process enables the development of the longer-lived pioneer *V. discolor* and the re-colonization of *M. skvortzovii* and is followed by the emergence of a vigorous pioneer population into the canopy

(Lacerda & Kellermann, 2017), which is spectrally depicted by an increase in EVI values from 2012 to 2015.

Although there are no field data available prior to 2006, qualitative information regarding canopy characteristics and population dynamics can also be inferred for both the pioneer predominance and mature bamboo lifecycle phases. The pioneer predominance and mature bamboo phases had the lowest overall agreement of 82% and 77%, respectively, indicating that these two phases possess heterogeneous canopies composed of senescent pioneer populations and mature bamboo. During pioneer predominance, the canopy is composed mainly of senescent *M. scabrella* and *V. discolor*, with the canopy of mature bamboo phase being increasingly composed of mature bamboo as gaps are formed due to senescent pioneer treefall. Spectral mixing is thought to be the result of non-uniform aging and dying of pioneer populations and subsequent emergence of mature bamboo into the canopy, resulting in patches of decreased and increased EVI values across the study area (Vogelmann et al., 2009). Additionally, other species (specifically the pioneer *Sapium glandulatum* (Vell.) Pax. and early successional *Ocotea puberula* (Rich.) Nees), also develop in these young forests, although in much lower abundances, which may also explain the variability observed in the classification.

The hybrid model has proven to be an effective method in observing mechanisms of bamboo-dominated forest succession, both spatially and temporally, and coincides with the findings of Lacerda and Kellermann (2017). Previous long-term studies which examined bamboo-dominated forest succession using Landsat imagery (Carvalho et.al., 2013; Nelson & Bianchini, 2005) identified similar lifecycle phases, indicating that these mechanisms are common in other bamboo-dominated forests as well. Therefore, the use of the hybrid model, or similar spectral-temporal modelling methods, would serve as an useful tool in monitoring

mechanisms of bamboo-dominated forest succession and identifying whether bamboo-populations pose a threat to adjacent plant communities.

#### *2.4.4. Spectral-temporal modelling progress and future directions*

Previous studies have been performed which use Landsat time-series to depict and characterize the lifecycle of other native invasive bamboos found in the Amazon of Brazil (Carvalho et.al., 2013; Nelson & Bianchini, 2005), but relied on manual photo interpretation and visual assessment to describe phases of bamboo-dominated forest succession, not taking advantage of spectral-temporal properties. However, consistent challenges exist when using Landsat imagery, namely its inability to be used to map plant populations <30 m in size due to its coarse resolution (Araujo et al., 2008) and availability of cloud-free imagery, especially when working with dense time-series stacks in tropical environments (Van doninck & Tuomisto, 2017). In an attempt to refine mapping and modelling techniques so as to be able to identify smaller bamboo populations, recent studies have successfully employed high resolution satellite imagery and various image segmentation algorithms to map bamboo populations (Tang et al., 2016; Ghosh & Joshi, 2014; Luz, 2009; Dlugosz et al., 2005). However, these methods rely on expensive imagery whose archives span a relatively short period of time, therefore are of limited value in observing long-term mechanisms of bamboo-dominated forest succession. Integrating both Landsat imagery with high-resolution satellite imagery, by first employing Landsat's rich archive to identify and characterize bamboo populations at a single-landscape scale and subsequently use high-resolution satellite imagery to observe fine grain spatial-temporal dynamics of bamboo populations (e.g., rate of expansion, spread pattern), from which models describing these processes can be developed and applied on a multiple-landscape scale is a potential area for future research (Gärtner et al., 2016; Krofcheck et al., 2014). Therefore, by

integrating both Landsat and finer resolution satellite imagery, it should be possible to (1) identify and characterize bamboo populations at a single-landscape scale, which will contribute to building a bamboo inventory and (2) subsequently develop models that describe bamboo expansion and spread pattern using fine grain imagery, which can then be used for forecasting on a multiple-landscape scale.

## **2.5. Conclusion**

In this paper, we identified the spectral-temporal signature of bamboo-dominated forest succession, identified four broad lifecycle phases of bamboo and developed a hybrid model, which proved to be an accurate tool for determining the synchrony of bamboo-dominated forest succession, as well as identifying regions of bamboo-dominated forest. The hybrid model was compared to both a TWDTW model and a Maximum Likelihood classifier and was found to outperform both models consistently. The hybrid model also produced results consistent with previous regeneration data collected in the same region, as well as other studies performed elsewhere (Griscom & Ashton, 2006; Budke et al., 2010; Carvalho et al., 2013), indicating that spectral-temporal modelling provides an accurate depiction of the mechanisms of bamboo-dominated forest succession.

It is thought that the hybrid model has the potential to detect *M. skvortzovii* in other fragments of Araucaria forest, which would provide valuable information regarding the health status of the remaining Araucaria forest fragments and emphasize the need for silvicultural intervention in regions impacted by bamboo. Future research could use these methods to perform a state-wide detection of *M. skvortzovii* in the remaining Araucaria forest fragments, for which it is recommended that the 15-year spectral-temporal signature (2001 to 2015) is used. It is hoped that knowledge gained from this research will assist in evaluating the state of bamboo-



dominated forests throughout the remaining Araucaria forest, enabling improved management and conservation efforts. Additionally, it is thought that the methodologies applied in this study have the potential to be used in other bamboo-dominated forest ecosystems to extrapolate information regarding the ecological processes of other bamboo species and their impact on vulnerable ecosystems.

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## Chapter Three:

### 3.0. Modelling bamboo spatial distribution within the Atlantic forest of Southern Brazil using Landsat Best-Available-Pixel image composite time-series stacks

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#### Abstract

Forest fragmentation has been found to cause taxonomic impoverishment and reduced functionality of species assemblages resulting in Biotic Homogenization. Alteration to understorey light conditions as a result of human induced forest fragmentation has enabled the invasion of bamboo, which has resulted in loss of biodiversity and arrested forest succession. Recently a semi-empirical hybrid spectral-temporal modelling approach was developed which employs Landsat time-series stacks to map single-landscape scale bamboo distribution. To explore possible anthropogenic or natural features which may influence bamboo patch distribution, the recently developed modelling approach was employed to map bamboo patch distribution throughout the critically threatened Araucaria forest, a pine-dominated subtype of the Atlantic forest. To develop a time-series stack suitable for a multiple-landscape scale analysis, it was necessary to use a Best-Available-Pixel compositing approach to create annual composites from which multiple models were derived. In this paper, we (1) perform a single-landscape scale comparison between a single-scene time-series stack and Best-Available-Pixel time-series stack to determine the effectiveness of the compositing approach in a subtropical environment, (2) map bamboo distribution throughout a portion of Araucaria forest and (3)

perform a spatial analysis of bamboo patch distribution by calculating landscape pattern indices at two scales (10-by-10 km, 25-by-25 km). The comparison between the single-scene time series stack and the Best-Available-Pixel time-series stack yielded similar accuracies (90% and 88%, respectively), indicating efficacy of the compositing method in a subtropical environment, as well as at a multiple-landscape scale. The hybrid model performed well yielding accuracies between 88% and 90% in mapping bamboo distribution. Spatial clustering of similar landscape pattern index values showed that bamboo patches which possessed the same size and shape were distributed in relation to human settlement and geographic features. It was determined that forest fragmentation is a contributing driver to bamboo distribution based on the integration of bamboo patches amongst urban and agricultural areas.

### **3.1. Introduction**

Forest fragmentation has been found to promote pioneer dominance, resulting in simplification or Biotic Homogenization (BH) of the Atlantic forest (Lôbo et al., 2011), a biome which is considered the most threatened ecosystem in the world, having been reduced to 10% of its original landcover (Leal & Câmara, 2003). Fragmentation-driven BH of regional floras has been observed throughout the Atlantic forest, and is characterized by the replacement of late successional or specialist species typical of primary forest by short-lived, light-demanding generalist species (Clavel et al., 2010; Lôbo et al., 2011), which has led to taxonomic and genetic impoverishment (Taxonomic Homogenization), and reduction of ecosystem services and vitality through loss of functional traits of community composition (Functional Homogenization) (Olden, 2006; Castro & Jaksic, 2008; Clavel et al., 2010). The Subtropical Humid Forests of southern Brazil (FAO, 2005), locally known as Araucaria Forest (IBGE, 2012), is a subtype of the Atlantic Forest that has undergone significant fragmentation and now exists as a network of

minute fragments (<50 ha) scattered throughout a predominantly urban and agricultural landscape. The process of fragmentation increases edge and drastically alters canopy structure of remaining forest fragments, which enables increased solar radiation to reach the forest understorey. As bamboo growth is light driven, remaining forest fragments possess ideal environmental conditions for bamboo expansion, which has enabled the invasion of bamboo populations (Griscom, 2002; Griscom & Ashton, 2006; Lacerda & Kellermann, 2017). Within remaining fragments it has been observed that bamboo largely occupy the forest understorey of both late successional and pioneer stands, which has been found to be a contributing factor to BH (Lacerda & Kellermann, 2017; Greig et al., *Under review*). In this paper we explore how heterogeneity (e.g., anthropogenic and natural geographic features) at a multiple-landscape scale influences bamboo distribution throughout Araucaria forest, to better understand how bamboo populations contribute to BH.

*Merostachys skvortzovii* (referred to as bamboo from this point forward) is a prominent bamboo species found throughout the Araucaria forest and has a 31 to 33-year lifecycle which terminates with a monocarpic dieback event of mass seeding. Within the Araucaria forest, these dieback events act as disturbances, releasing soil nutrients and space, as well as opening the canopy (Taylor & Qin 1992; Abe et al. 2002; Taylor, 2004; Rother et al. 2009) enabling regeneration of pioneer tree species, specifically *Mimosa scabrella* and secondary species, *Vernonanthura discolor*. Following a dieback event, *M. scabrella* will initially recruit and form a homogenous canopy, followed by *V. discolor* and bamboo, which secures space in the understorey (Kellermann, 2011; Lacerda & Kellermann, 2017). Once bamboo recruits, it will continuously replace itself by clonal growth throughout its lifecycle, increasing in density as it matures and further suppressing regeneration, causing a perpetuated bamboo-dominance cycle

which has been found to arrest forest succession (Lacerda & Kellermann, 2017). The way in which the lifecycles of bamboo, *M. scabrella* and *V. discolor* overlap further contribute to the perpetuated bamboo-dominance cycle: canopy gaps resulting from treefall of aging pioneer populations increases understorey light climate, giving opportunity to existing bamboo populations to flourish and impede development of other plant species, resulting in BH.

The lifecycle of bamboo is synchronized over large areas as evidenced by state-wide dieback events of bamboo occurring from 1843 to 1876-1877, 1909-1910, 1938-1940, 1973-1975 (Pereira, 1941; Sendulsky, 1995) and 2003-2006 (Liebsch & Reginato, 2009; Kellermann, 2011). A widely accepted theory for widespread synchronized dieback events of mass seeding is predation satiation; the mass release of seeds is thought to allow for predation without decimation of the following generation (Kelly, 1994). However, at a single-landscape scale, bamboo populations have been found to gain and maintain dominance as a result of environmental conditions, specifically increased sunlight. In a primary forest setting, bamboo populations exist endemically in the understorey, but due to canopy alteration resulting from anthropogenic disturbances (e.g., agriculture, human settlement, forest extraction), increased understorey light climate has given opportunity to bamboo populations to flourish. A recent analysis by Greig et al. (*Under review*) found that multiple bamboo populations were synchronous (i.e., simultaneous dieback) and significantly impeding forest development across a single-landscape which had undergone varying degrees of past anthropogenic disturbances (Lacerda & Kellermann, 2017). Furthermore, it was found that regions within the single-landscape that had undergone intensive timber extraction in the past (i.e., increased number and size of canopy gaps), had denser bamboo populations, indicating that small-scale human disturbances influence bamboo patch distribution at a single-landscape scale. As forest

fragmentation is a widespread phenomenon throughout the Araucaria forest, it is hypothesized that the same synchronous population processes which are arresting forest succession at a single-landscape scale will be detected in other forest fragments at a multiple-landscape scale throughout Araucaria forest. Additionally, we seek to determine whether landscape heterogeneity at a multiple-landscape scale plays a role in bamboo patch distribution composition and configuration.

Bamboo ecological processes occur in the forest understorey for the majority of its lifecycle, making bamboo challenging to detect over large areas at certain lifecycle phases. By employing Landsat time-series stacks, it is possible to determine locations of bamboo-dominated forest when populations are confined to the understorey by extracting spectral-temporal signatures from known regions of bamboo due to the distinct temporal trajectory of bamboo lifecycle dynamics which can be observed in spectral space (Kennedy et al., 2007). Using these signatures, semi-empirical spatially explicit ecological process models (hybrid models) can be developed by fitting trajectories to extracted spectral-temporal signatures, which is an approach that has been found to successfully characterize lifecycle phases and model locations of bamboo at a single-landscape scale. However, this modelling approach operates on the assumption that all bamboo populations being detected will have the same lifecycle phases, therefore does not allow for detection of asynchronous processes. To determine asynchrony, deviation from the hybrid model (using RMSE values) will be used to infer asynchronous processes.

To successfully employ spectral-temporal signatures for multiple-landscape analyses, it is necessary to develop cloud-free, radiometrically consistent time-series stacks. Best-Available-Pixel (BAP) compositing is a novel, rule-based compositing approach which enables the creation of high quality annual composites (White et al., 2014; Hermosilla et al., 2015), a method which

has yet to be used in subtropical environments. By employing BAP compositing, it is possible to generate multiple-landscape scale time-series stacks, from which hybrid models can be developed, offering an opportunity for automated detection of bamboo populations at a multiple-landscape scale.

In a recent study, a hybrid model using a 15-year time-series stack (2001 to 2015) was developed, which accurately identified bamboo populations at a single-landscape scale (Greig et al., *Under review*). Using this same approach, research interest now focuses on identifying the spatial distribution of bamboo-dominated forest at a multiple-landscape scale to estimate the total amount of bamboo present throughout Araucaria Forest and explore whether certain anthropogenic or natural features influence bamboo patch pattern distribution. With the ongoing fragmentation of Araucaria forest, mapping bamboo populations will assist in identifying forest locations requiring silvicultural intervention and advise potential corridor and core regions necessary for effective conservation and adaptive management planning to reduce BH. In this paper we aim to:

1. Assess the efficacy of BAP image compositing in a subtropical environment
2. Map the spatial distribution of bamboo-dominated forest throughout Araucaria forest using a recently developed hybrid modelling approach
3. Perform a spatial analysis of mapped bamboo-dominated forest to examine the composition and configuration of bamboo distribution in relation to natural and anthropogenic features.

## 3.2. Materials and methods

### 3.2.1. Study area

The Subtropical Humid Forest of the Atlantic Forest in Southern Brazil, locally known as Araucaria forest, is composed of both temperate and tropical floras (IBGE, 2012; Leite & Klein, 1990), which occurs in subtropical highland climate (Cfb) at an altitude >700 m, characterized with high annual precipitation of approximately 1400 mm. The region is characterized by the predominance of the critically endangered late successional species, *Araucaria angustifolia* and *Ocotea porosa* (IBGE, 2012). In the past century, the majority of land conversion has occurred in Southern Brazil, the primary agriculture region and geographical range of the Araucaria forest. During the 19<sup>th</sup> and early 20<sup>th</sup> centuries, subtropical timber from this region, especially the conifer *A. angustifolia*, was Brazil's primary export product (Lacerda et al., 2012). This has resulted in the reduction of Araucaria forests to 5% primary forests and 20-25% secondary forest of the original landcover (Lacerda, 2016). Araucaria Forest originally covered an area of 216 100 km<sup>2</sup>, but now exists as a series fragments, the majority being less than 50 hectares in area, integrated into an urban and agricultural landscape throughout the states of Parana and Santa Catarina (Lacerda, 2016). The predominance of secondary forest within this region has created ideal conditions for bamboos to flourish, leaving remaining forest fragments vulnerable to bamboo invasion.

For this analysis Landsat scene WRS-2 221/79 was used, which is found at the centre of the state of Santa Catarina (Figure 3.1). Areas of the scene with an elevation >700 m were selected to distinguish regions of Araucaria forest, resulting in a range of elevation from 700 to 1815 m for the study area and a total area of 28 819 km<sup>2</sup>. For this analysis, the study area was divided into six different landcover types: bamboo-dominated forest, secondary forest, forest



plantation, agriculture, urban and wetland. Within the same Landsat scene, there is the Embrapa Research Station in Caçador (ERSC), a 1157-hectare research area located in Caçador, Santa Catarina, Brazil. This study area was used for a previous analysis and is used in this analysis to provide contextual comparison. The ERSC is one of the most well-preserved remaining fragments of Araucaria forest, having had no silvicultural intervention in the past 20 years (Lacerda et al., 2012). The study area has become a site of research interest in recent years due to its large bamboo population, which homogeneously occupies approximately one third of the study area and exists in varying intensity throughout the entirety of the understorey of the ERSC.

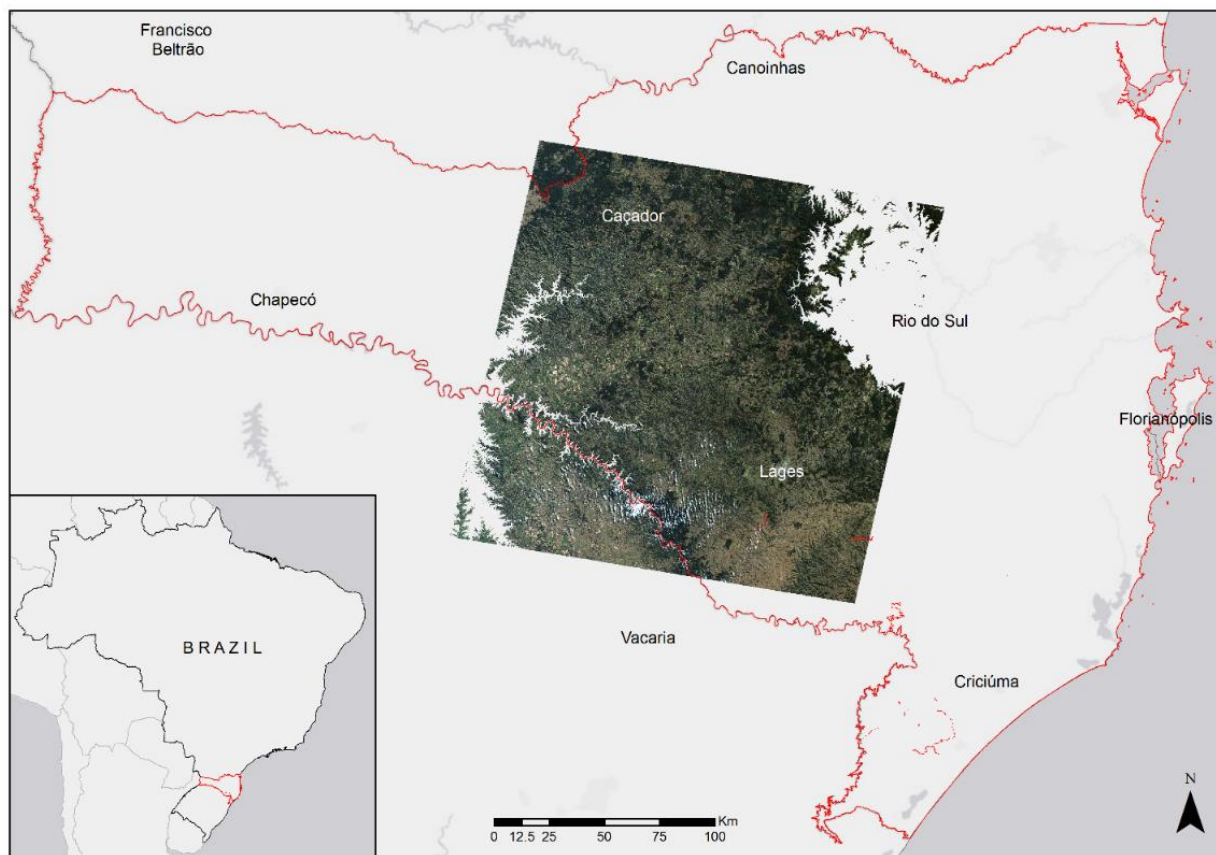


Figure 3.1: Remaining Araucaria forest (>700 m elevation) in the centre of the state of Santa Catarina, Brazil. Landsat 5 WRS-2 221/79 scene from 2001.

### *3.2.2. Imagery and processing*

Using Landsat 5 TM, Landsat 7 ETM and Landsat 8 OLI Surface Reflectance Collection 1 Level-2 products, 69 Landsat WRS-2 221/79 scenes were selected to create a 17-year annual composite time-series stack from 2001 to 2017, based on the previous analysis performed using a 15-year (2001 to 2015) time-series stack (Greig et al., *Under review*). Composites for 2016 and 2017 were included so as to provide up-to-date results. Scenes with <50% cloud cover and acquisition dates between the months of May and September were selected to reduce aerosol contamination and spectral variation caused by seasonality.

#### *Best-Available-Pixel (BAP) compositing*

BAP compositing, a rule-based compositing approach, was used to generate the 17 annual composites. Each pixel of an image was scored based on four rules: sensor score, day-of-year score, distance to cloud or cloud shadow score, and opacity score. The following methodological description is based on White et al. (2014) using equations from Griffiths et al., (2013).

#### *Sensor score*

Sensor score was calculated at the image level, meaning all pixels within this image received the same score. To give preference to both Landsat 5 TM and Landsat 8 OLI images, pixels from these images were given a score of 1 and pixels from Landsat 7 ETM images, after 2002, were given a score of 0.5 to mitigate the issue of the dropped scan-line of the Landsat 7 ETM sensor.

### *Day of year score*

Day of year score was also calculated at the image level. Pixels were assigned a score based on the image acquisition date relative to the defined target date to ensure temporal consistency. The score was calculated using the following equation (Griffiths et al., 2013):

$$Score_{DOY} = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x_i - \mu}{\sigma}\right)^2} \quad (1)$$

Where  $\mu$  and  $\sigma$  represent the mean and standard deviation, respectively, of all the image dates and  $x_i$  is the date for the image under assessment. For this analysis, July 15<sup>th</sup> (Julian day 197) was used as the mean (target date), and 77 was the standard deviation so as to include all images from May 1<sup>st</sup> to September 30<sup>th</sup>, a time range which has been found to reduce seasonality while allowing a large enough timeframe to ensure image availability. The score is subsequently scaled to a value between 0 and 1.

### *Distance to cloud or cloud shadow score*

Using the Pixel QA band, cloud and cloud shadow pixels were assigned a “no data” value. Any pixel located at a distance >50 pixels from cloud or cloud shadow pixels were given a score of 1, and any pixels located at a distance <50 pixels from pixels identified as cloud or cloud shadow, were given a score between 0 and 1 using the following equation (Griffiths et al., 2013):

$$Score_{CloudDistance} = \frac{1}{1 + e^{(-0.2\left(\min(D_i, D_{req}) - \left(\frac{D_{req} - D_{min}}{2}\right)\right))}} \quad (2)$$

Where  $D_i$  is the pixel’s distance to cloud or cloud shadow,  $D_{req}$  is the minimum required pixels and  $D_{min}$  is the minimum distance of the given pixel observations. For this analysis, 50 pixels (i.e., 1500 m) was the  $D_{req}$  and 0 was the  $D_{min}$ .

### Opacity score

As aerosol contamination has been found to reduce image composite quality, an opacity score was calculated for each pixel using the atmospheric opacity band from Landsat 5 TM and Landsat 7 ETM+ surface reflectance products and the aerosol QA band from the Landsat 8 OLI surface reflectance products. Pixel values from the atmospheric opacity band indicate level of aerosol contamination, with values  $<0.1$  considered to be clear,  $0.1$  to  $0.3$  considered average opacity and  $>0.3$  considered hazy (Masek et al., 2006). The aerosol QA band has attributes which describe the level of aerosol contamination, which include low, medium and high, and for this analysis were assigned numeric values  $0.1$ ,  $0.2$  and  $0.3$ , respectively. To calculate the opacity score, pixels with an opacity value  $<0.2$  were assigned a score of  $1$  and pixels with an opacity value  $>0.3$  were assigned as “no data” value. Using the equation from Griffiths et al., (2013), pixels with opacity values  $\geq 0.2$  and  $<0.3$  were given a score between  $0$  and  $1$ .

$$\text{Score}_{\text{Opacity}} = 1 - \left( \frac{1}{1 + e^{\left( -0.2 \left( \min(O_i, O_{max}) - \left( \frac{O_{max} - O_{min}}{2} \right) \right) \right)}} \right) \quad (3)$$

Where  $O_i$  is the pixel’s opacity value,  $O_{max}$  is the maximum opacity value ( $0.3$ ) and  $O_{min}$  is the minimum opacity value ( $0.2$ ).

Scores were then summed for each pixel. Given a set of Landsat scenes from a WRS-2 path/row, the pixel with the highest total score at each pixel location was used in the annual composite. Enhanced vegetation index (EVI) was subsequently calculated over the time-series stack, and a Savitzky-Golay smoothing filter (Savitzky & Golay, 1964) was applied to the time-series stack to reduce year-to-year noise (Tuanmu et al., 2010).

### *3.2.3. Overview of hybrid spectral-temporal modelling (hybrid modelling)*

Hybrid modelling is a process-based modelling approach which has been used to determine synchrony of bamboo-dominated forest succession and identify bamboo populations within the ERSC. Developing a hybrid model is a multi-step process based on the work of Kennedy et al. (2007, 2010). First, a spectral-temporal pattern or signature is extracted from a time-series stack of EVI values. In this paper, spectral-temporal pattern refers to a spectral time-series extracted at a pixel location, and spectral-temporal signature refers to a singular signature which is created by averaging together annual spectral values of multiple spectral-temporal patterns. Change point analysis is then performed on the spectral-temporal pattern or signature. Using identified change points as vertices, trajectories are fit to each segment using linear regression. Based on slope of each modelled segment, phases of bamboo-dominated forest succession can be determined. The modelled segments are then combined to create a hybrid model representative of a defined time period (e.g. 15-year time-series from 2001 to 2015) of bamboo-dominated forest succession, which is then compared to a time-series of EVI values. Root-mean square error (RMSE) is computed and summarized using the hybrid model and the time-series stack of EVI values, creating a raster output of RMSE values. The RMSE rasters can then be used to perform a cluster analysis (e.g., Getis-Ord  $G_i^*$ ) or a defined threshold (e.g., lower quartile, median, upper quartile values derived from boxplots) can be used to identify regions of bamboo-dominated forest.

### *3.2.4. BAP composite comparison*

BAP compositing is a new method which has yet to be used in Subtropical environments. We wanted to compare a BAP time-series stack to a single scene (SS) time-series stack to

determine whether there were any noticeable changes in annual scene pixel values as a result of using a compositing approach, as opposed to a single annual scene. To do this, we performed a classification in the ERSC, a single-landscape study area, using the hybrid model developed by Greig et al. (*Under review*). The hybrid model was compared to both a BAP and SS time-series stack by calculating RMSE. Using the RMSE output rasters from both time-series stacks, boxplots were created to compare RMSE value distribution. A Getis-Ord Gi cluster analysis was then performed on both RMSE output rasters to classify regions of bamboo-dominated forest in the ERSC for both time-series stacks. An accuracy assessment was performed using field sample points collected from the ERSC for both SS and BAP maps, and accuracies were compared.

### *3.2.5. Multiple-landscape scale mapping and modelling of bamboo-dominated forest distribution*

Here we map bamboo spatial distribution using a hybrid modelling approach, thus testing the hypothesis that bamboo ecological processes are synchronized across multiple-landscapes. Greig et al. (*Under review*) found that a singular 15-year hybrid model achieved the highest accuracy among five other hybrid models, which included a 32-year hybrid model representing an entire bamboo lifecycle, and a model for each of the four lifecycle phases (i.e., pioneer predominance, mature bamboo, dieback and pioneer regeneration). However, due to varying canopy cover throughout Araucaria forest, as a result of varying natural and anthropogenic influences, the hybrid model previously developed may only be applicable to certain single-landscapes of generally undisturbed/unmanaged forest systems, such as the ERSC. Therefore, it was necessary to develop multiple hybrid models that describe bamboo-dominated regions with varying canopy cover to accurately perform a multiple-landscape scale analysis.

Using a subsetting region of continuous forest and high resolution RapidEye imagery, spectral-temporal patterns were extracted from 19 pixel locations using a 17-year smoothed EVI time-series stack. The temporal trajectory of each pattern was visually examined to ensure consistency among patterns; the aim was to select patterns which possessed the same temporal trajectory, but varied in spectral value range. Using previously defined changepoints as vertices from Greig et al., (*Under review*) (Table 3.1), trajectories were fit for each of the sample patterns, resulting in 19 hybrid models, each possessing 17 modelled annual values.

Table 3.1: Three segments defined by Greig et al. (*Under review*) used as vertices to fit model trajectories.

Changepoint	Year
(1)	2004
(2)	2008
(3)	2011

Each of the 19 hybrid models were converted into a 17-year hybrid model raster time-series stack, which was then compared to the 17-year Landsat time-series of smoothed EVI values by calculating RMSE, creating raster outputs of RMSE values for each hybrid model. Using the 19 RMSE rasters, a composite of lowest RMSE values in the study area was generated. In a previous analysis, boxplots were used to show RMSE value distribution within bamboo-dominated regions, thus the first quartile, median and third quartile values were employed as thresholds to define regions bamboo-dominated forest (Table 3.2).

Table 3.2: Thresholds determined by Greig et al. (*Under review*) used to classify regions of bamboo-dominated forest at a regional-scale.

Summary number	EVI value
Lower quartile	0.04989414
Median	0.06015783
Upper quartile	0.07138422

However, the hybrid model operates on the assumption that all bamboo population dieback events are synchronous, therefore does not account for potential asynchronous processes; the most recent dieback event was recorded between the years of 2003 and 2006, suggesting dieback timing may vary spatially. To better understand whether there are asynchronous processes occurring, clustering of hybrid model output RMSE values will be visually examined and interpreted as an indication of potential asynchrony.

### *3.2.6. Multiple-landscape spatial analysis*

Landscape patterns and processes are influenced by scale; patch distribution may be explained by one variable at a single-landscape scale, but at a multiple-landscape scale, patch distribution may be explained by another variable (Turner, 1989). For example, Meentemeyer (1978, 1984) studied variance in litter decomposition at both a single and multiple-landscape scale, and it was found that at a single-landscape scale, decomposition variance was primarily explained by litter properties and present decomposer communities, whereas at a regional-scale, climatic variables were the main driver of variance.

The remaining Araucaria forest, much like the entire Atlantic forest, has undergone significant forest fragmentation. Due to alteration of canopy structure, it is hypothesized that many of these remaining fragments will be composed of bamboo populations existing in varying intensities. Greig et al. (*Under review*) performed a study which classified patches of bamboo-dominated forests within a single-landscape forest fragment, and it was determined that a series of small patches were found throughout the fragment. Based on these finding, we wanted to explore whether other forest fragments at a multiple-landscape scale shared a similar bamboo



patch pattern as found in the ERSC and identify whether certain natural or anthropogenic features influenced bamboo patch composition and configuration throughout Araucaria forest.

To perform a multiple-landscape spatial analysis, landscape pattern indices were calculated and visually interpreted. Landscape pattern indices are numerical metrics developed to quantify map patterns, which primarily focus on landscape composition and configuration. There is a suite of algorithms that compute spatial characteristics of a single patch, class of patches or entire landscapes. For this analysis we focus on class metrics which represent the quantity and spatial distribution of one patch type (bamboo) and are generally interpreted as indices of fragmentation (McGarigal et al., 1995). Composition refers to the proportion of patches (e.g., type, richness, evenness, diversity) within a landscape, but does not provide spatial characteristics, pattern structure or location of patches within the landscape (McGarigal et al., 1995). Composition metrics must be interpreted in relation to configuration metrics to understand the spatial structure/pattern of the patch mosaic. Configuration metrics quantify the spatial character and arrangement of patches within a class or a landscape (McGarigal et al., 1995). The calculated index is a single value representative of the aggregation of all individual patch characteristics within a class or landscape (McGarigal et al., 1995). By combining composition and configuration indices, the user can infer the landscape patch pattern, based on configuration, and the proportion of the landscape which is composed of the patch pattern.

Landscape pattern indices used to determine patch composition and configuration included proportion landscape (PLAND), number of patches (NP), edge density (ED) and largest patch index (LPI). As Araucaria forest is known to be very heterogeneous in structure, existing within an urban and agricultural matrix, the four indices were selected to interpret class (i.e., bamboo) patch fragmentation across multiple-landscapes and varying scales, working under the

assumption that bamboo patches are subsections of forest fragments. *PLAND* measures the relative percent of the landscape (i.e., composition) that is occupied by the class under investigation, which enables comparison of landscape pattern across multiple scales. To characterize the patch pattern and spatial structure (i.e., configuration), *NP* was selected to provide information regarding the size of patches within the landscape, and *ED* was selected to provide information regarding the shape of patches present in the landscape, as *ED* describes the total perimeter of all patches within the landscape. *NP* is important to interpret the size of patches in the landscape, for example: if *PLAND* is a high value and *NP* is a low value, it can be determined that patches present in the landscape are large. *ED* is important to describe shape of patches within a landscape and must be interpreted with *PLAND* and *NP*, for example: if a landscape is characterized by a high *PLAND*, low *NP* and high *ED* value, it can be deduced that patches within the landscape are large with a high amount of edge. Additionally, edge metrics are valuable for landscape ecological investigations as edge effects influence environmental conditions and expose organisms to further natural or anthropogenic disturbances, which could potentially influence or drive organism ecological processes (McGarigal et al., 1995). In this case, edge is explored primarily as a configuration metric, but may be of value in the development of forest management strategies or further investigation of bamboo patch relative to other classes (e.g., forest). *LPI* is another configuration metric and provides absolute information regarding patch size within each landscape.

Each metric is calculated with a specific formula, which were acquired from the work of McGarigal et al. (1995). *PLAND* is calculated using the following equation (McGarigal et al., 1995):

$$PLAND = \frac{\sum_{j=1}^n a_{ij}}{A} (100) \quad (4)$$

where  $a_{ij}$  is the sum of the areas of all patches belonging to the specified class and A is the total landscape area, which is then converted into a percentage by multiplying by 100. NP is the number of patches of the specified class present within the landscape, therefore is calculated based on a patch count. ED is the total amount of edge (m) per hectare. ED is calculated using the following equation (McGarigal et al., 1995):

$$ED = \frac{E}{A}(10000) \quad (5)$$

where E is the total length of patch edge for a specified class within the landscape and A is the total area of the landscape, which is then converted to hectares by multiplying by 10000 to render units in m/ha to allow comparison between varying landscapes. LPI is an index that identifies the proportion of the landscape which the largest patch within that landscape occupies. LPI is calculated using the following equation (McGarigal et al., 1995):

$$LPI = \frac{\max(a_{ij})}{A}(100) \quad (6)$$

where  $a_{ij}$  is the area of the largest patch within the landscape and A is the total area of the landscape, which is then converted to a percentage. Using both 10-by-10 km and 25-by-25 km gridcells, the four indices were mapped for the study area and global summary statistics were calculated.

### 3.2.7. Validation

The spatial extent of the state of Santa Catarina makes data collection an arduous and expensive task, therefore field sampling could not be carried out. As an alternative remote approach, seven RapidEye images were used to perform gridded random sampling to ensure sufficient spatial coverage, as well as representation of different landcover types. As the

objective of this study was to identify regions of bamboo, RapidEye images were selected based on forest coverage. For each of the 7 images, a three by three fishnet was created, and of those nine gridcells, two gridcells were selected that were predominantly forested. The two forested gridcells were then divided into quadrants. This partitioning resulted in 15 gridcells, and within each of the gridcells, two random points were plotted, resulting in 30 random sample points per image, amounting to a total of 210 reference points (Figure 3.2). The reference point dataset was comprised of six different landcover types, which included 48 bamboo-dominated forest points, 65 forest points, 54 forest plantation points, 40 agriculture points, 2 urban points and 1 wetland point. The reference point dataset was determined by two photo interpreters, who had an initial agreement of 79%. For the 21% disagreement, boxplots were created to show distribution of error values specific to class exchange (e.g., bamboo and forest, bamboo and forest plantation, bamboo and agriculture, etc.). The disagreeing reference points were collaboratively re-interpreted. For the accuracy assessment, all landcovers types, excluding bamboo-dominated forest were combined to create an “other” category, which was used to determine presence/absence of bamboo.

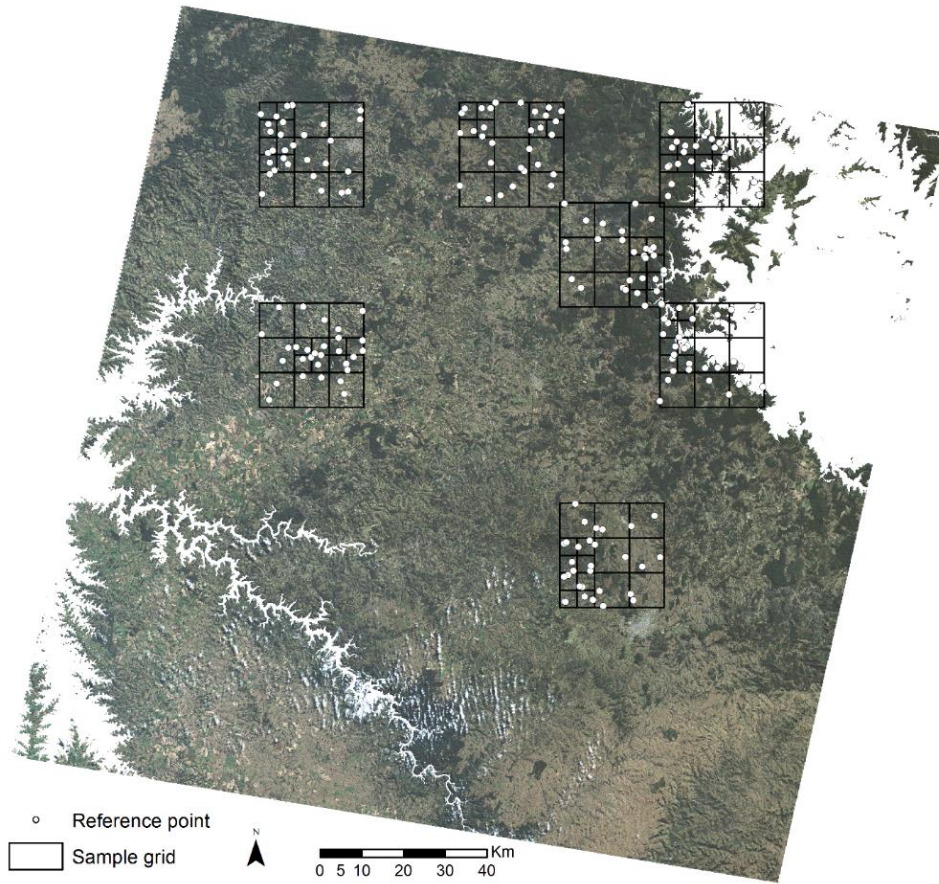


Figure 3.2: Gridded random sampling procedure used to develop reference point dataset (n=210). Landsat 5 WRS-2 221/79 scene from 2001.

Overall agreement and allocation and quantity disagreement were calculated using a method developed by Pontius and Millones (2011). This accuracy assessment predominantly differs from other approaches by (1) assuming data is a perfect match as opposed to complete spatial randomness and (2) mathematically converts sample error matrices into estimated unbiased population matrices (Pontius & Millones, 2011). Quantity disagreement refers to the number of misclassified pixels between categories (e.g., bamboo-dominated forest and other), and allocation disagreement refers to the omission and commission of pixels between categories (e.g., bamboo-dominated forest and other). Total disagreement is the sum of quantity disagreement and allocation disagreement, and overall agreement is calculated by subtracting total disagreement from 100.

### 3.3. Results

#### 3.3.1. BAP comparison

Boxplots showed that within the ERSC the BAP time-series had slightly higher RMSE values than the SS time-series stack for all summary statistics (Figure 3.3). The most notable difference was the number of outliers; the BAP time-series had two outliers, whereas the SS time-series had a total of five outliers.

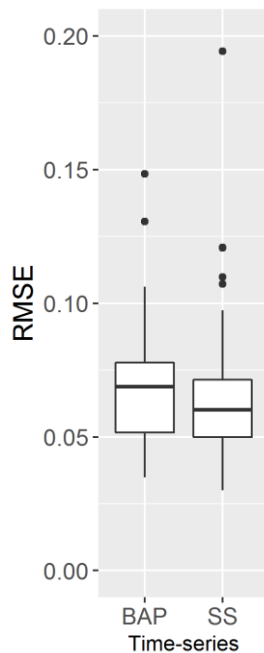


Figure 3.3: Boxplots comparing RMSE value distribution of SS (single-scene) time-series stack and BAP (Best-Available-Pixel) time-series stack from the ERSC.

An accuracy assessment showed that the BAP time-series yielded a lower overall accuracy of 88%, compared to the SS time-series which obtained a 90% accuracy. Quantity disagreement was 8% for both time-series, whereas for allocation disagreement, BAP time-series had a 5% disagreement compared to a 3% disagreement for the SS time-series (Figure 3.4) (Table 3.3).

Table 3.3: Accuracy statistics comparing SS (single-scene) time-series stack and BAP (Best-Available-Pixel) time-series stack from classification performed in the ERSC.

Time-series	Overall Agreement (%)	Quantity Disagreement (%)	Allocation Disagreement (%)	Estimated Area (ha)
BAP	88	8	5	228
SS	90	8	3	172

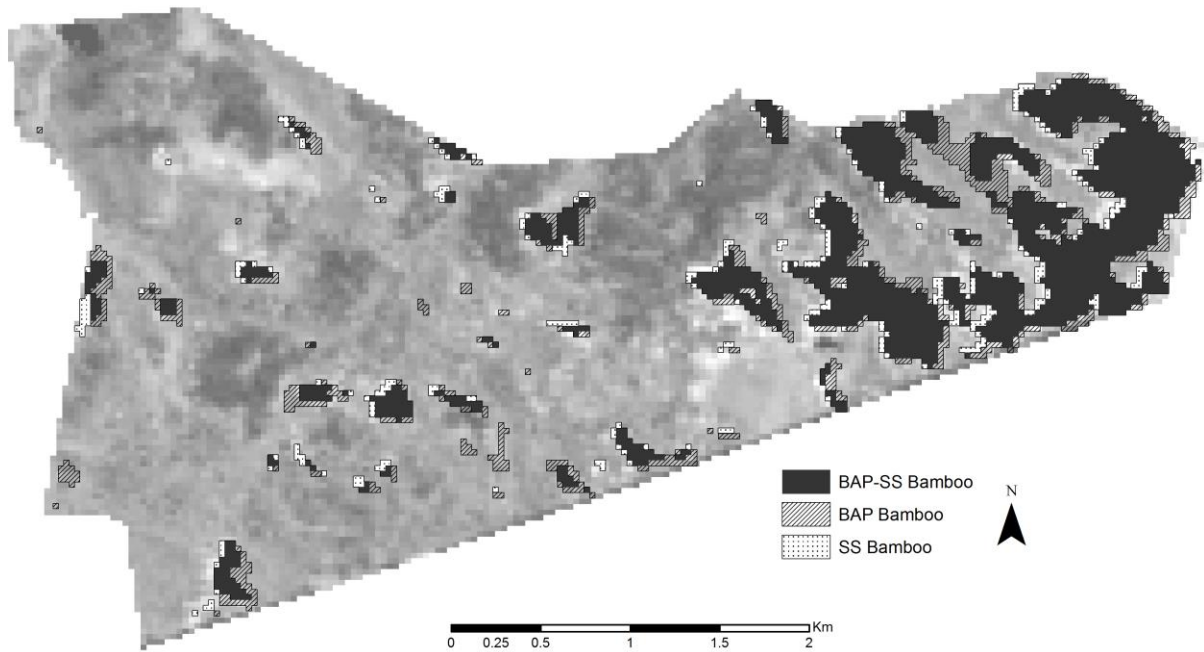


Figure 3.4: Map of bamboo-dominated forest created using both the SS (single-scene) time-series and the BAP (Best-Available-Pixel) time-series within the ERSC. BAP-SS Bamboo denotes classification agreement between both time-series; BAP Bamboo and SS Bamboo show classification disagreement.

### 3.3.2. Regional-scale mapping and modelling bamboo-dominated forest distribution

Boxplots were generated to examine RMSE value distribution for each of the landcover types, excluding urban and wetland, as there were few reference points for these two landcover types (Figure 3.5). Boxplots generated indicated that bamboo-dominated forest had the lowest median value, strongest central-tendency, smallest value range and smallest value spread

between the first and third quartile, compared to other landcover types. Also, the second and third quartile groups of bamboo-dominated forest did not overlap with the second and third quartile groups of any other landcover types. It can be observed that there is overlap between the entire bamboo RMSE value distribution and the first and second quartile groups of forest RMSE value distribution. It is also worth noting that there is some overlap between the first quartile group of forest plantation and the third and fourth quartile group of bamboo-dominated forest. Agriculture had the least amount of overlap with bamboo-dominated forest, with only the first quartile group overlapping with the fourth quartile group of bamboo-dominated forest.

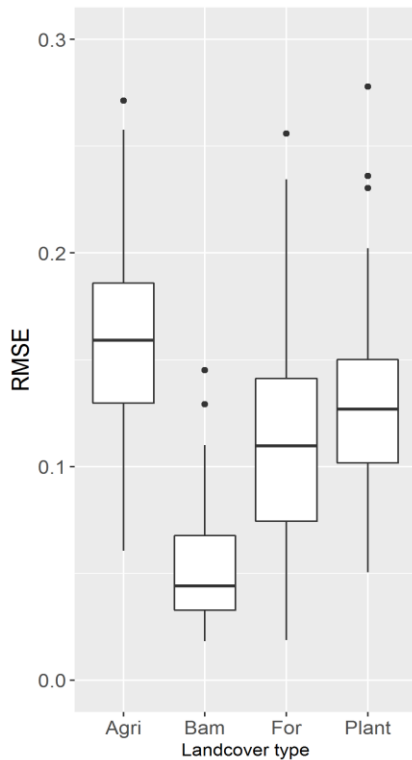


Figure 3.5: Boxplots showing RMSE value distribution of each landcover type. Values extracted using reference point dataset (n=210).

For the reference point interpretation, there was disagreement amongst 43 points, with class exchange occurring between bamboo-dominated forest and forest (BF, n=19), bamboo-dominated forest and forest plantation (BP, n=2), forest and agriculture (FA, n=5), forest and



forest plantation (FP, n=10) and forest plantation and agriculture (PA, n=7). Boxplots show that the RMSE value distribution for BF exchange had the lowest median value, and no second and third quartile group overlap with other exchange pairs (Figure 3.6). Worth mentioning is the slight overlap between BF third and fourth quartile groups and FP first to third quartile groups, as well as the overlap between the BF second to fourth quartile groups and PA first quartile group.

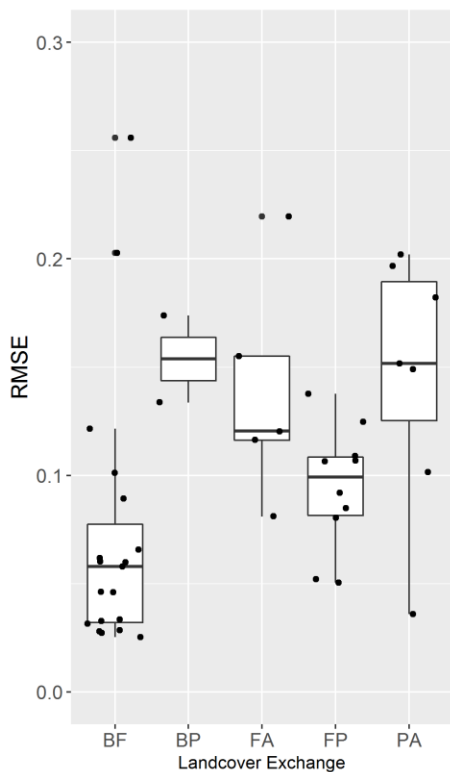


Figure 3.6: Boxplots and jitter points showing RMSE value distribution and sample size (n) for landcover class exchange. BF is bamboo-dominated forest and forest (n=19), BP is bamboo-dominated forest and forest plantation (n=2), FA is forest and agriculture (n=5), FP is forest and forest plantation (n=10) and PA is forest plantation and agriculture (n=7)

The ERSC values from the previous analysis performed in the ERSC were used as thresholds to define regions of bamboo, all of which yielded high accuracies (Table 3.4) (Figure 3.7). The lower quartile threshold received an overall agreement of 88%, with the majority of error being due to quantity disagreement, and had a total estimated area of 100 198 ha. Both the

median and upper quartile thresholds achieved an overall agreement of 90%, although quantity disagreement was the main source of error for the median threshold and alternatively, allocation disagreement was the main cause of error for the upper quartile threshold. The median threshold and upper quartile threshold had total estimated areas of 164 149 ha and 249 006 ha, respectively. Additionally, when the three outputs were layered, it was observed that within certain patches there was an outward proliferation of progressively higher RMSE values (Figure 3.8). Further explanation of this pattern will be provided in the discussion (section 3.4.1).

Table 3.4: Overall agreement, quantity disagreement, allocation disagreement and estimated area for lower, median and upper quartile thresholds.

Threshold	Overall Agreement (%)	Quantity Disagreement (%)	Allocation Disagreement (%)	Estimated Area (ha)
Lower quartile	88	11	2	100 198
Median	90	7	4	164 149
Upper quartile	90	3	6	249 006

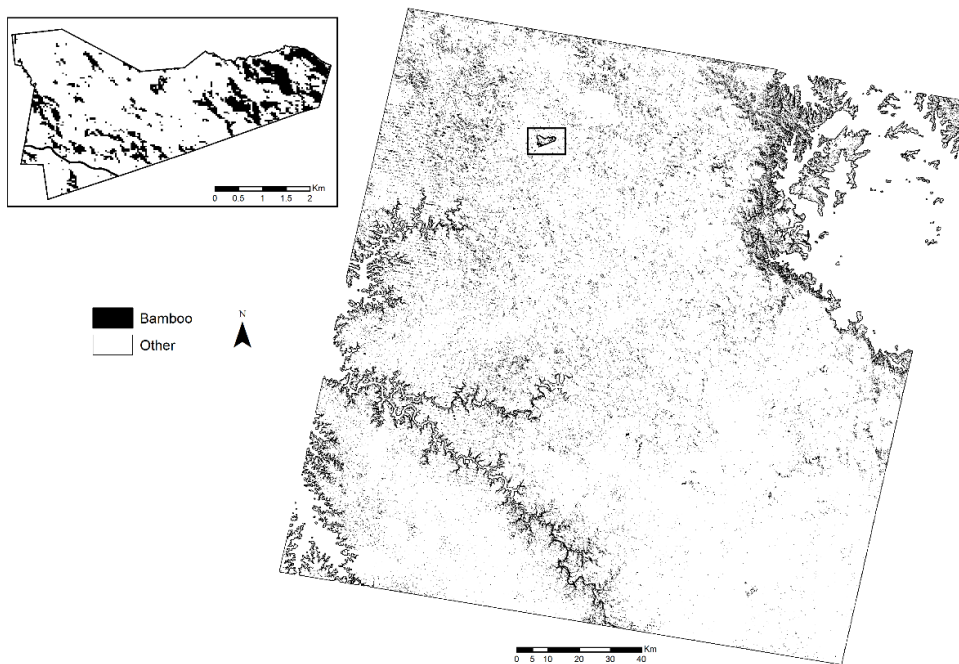


Figure 3.7: Regional-scale map of bamboo-dominated forest patches throughout Araucaria forest. The inset is showing a local-scale map of bamboo-dominated forest within the ERSC. The median threshold was used to create this map.

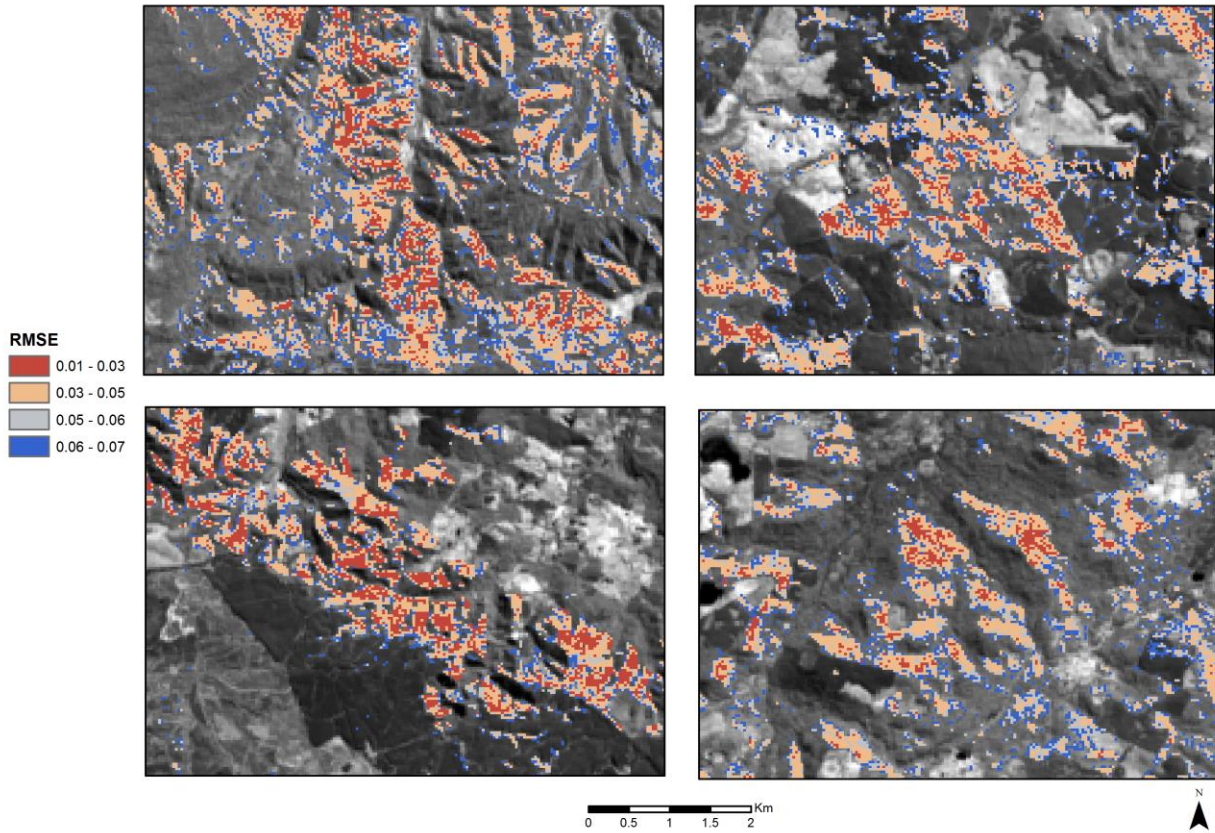


Figure 3.8: Four examples of bamboo patches showing error value 'proliferation'.

By using a threshold, the classification was rendered as presence/absence, and because of this, it was possible to determine which landcover types were commissioned as bamboo, but the classification of omitted bamboo reference points could not be determined. Based on the omission of the five other landcover types, it was determined that the majority of forest reference points were commissioned as bamboo, with forest plantations being the second highest contributor (Table 3.5).

Table 3.5: Landcover types commissioned as bamboo for each of the three output maps.

Threshold	Total bamboo commission	Forest omission	Forest plantation omission	Agriculture omission	Urban omission	Wetland omission
Lower quartile	9	9	0	0	0	0
Median	15	13	1	0	1	0
Upper quartile	22	16	4	1	1	0

### 3.3.3. Multiple-landscape spatial analysis

Global summary statistics show that both mean and standard deviation of PLAND and ED are very similar at both scales: 10-by-10 km PLAND mean 5.69 and standard deviation 5.99, ED mean 28.11 and standard deviation 22.84; 25-by-25 km PLAND 5.69 and standard deviation 4.87, ED mean 28.03 and standard deviation 19.18 (Table 3.6). These metrics are standardized, therefore are ideal for comparison across scales. NP mean and standard deviation increases relative to change in landscape area, that is the 25-by-25 km landscape is 6.25 times larger than the 10-by-10 km landscape, meaning the 25-by-25 km landscape NP mean is almost 6.25 times larger (i.e.  $530.86 \times 6.25 = 3317.875$  patches) than the 10-by-10 km landscape, which is also the same case for standard deviation (i.e.  $272.18 \times 6.25 = 1701.125$  patches). LPI mean and standard deviation decreases in relation to change in landscape size as well, although not as a function of landscape area change.

Table 3.6: Global summary statistics for four landscape pattern indices for a 10-by-10 km multiple-landscape and 25-by-25 km multiple landscape. Indices were chosen to describe bamboo patch composition and configuration.

Scale	Index	Mean	Standard Deviation
10 x 10	PLAND	5.69	5.99
	NP	530.86	272.18
	ED	28.11	22.84
	LPI	0.52	1.03
25 x 25	PLAND	5.69	4.87
	NP	3114.88	1523.71
	ED	28.03	19.18
	LPI	0.22	0.40

Based on the mapped indices pattern (Figure 3.9), it is evident that the majority of the scene (interior and North-West) of the study area is composed of many patches, but cumulatively represent a very small proportion of the landscape, based on high NP values and low PLAND values. Low ED values indicate that patches in the same region are generally small and compact.

The East edge has the highest PLAND values, indicating high occupancy of bamboo-dominated forest, and it can be determined that patches are generally larger and less compact based on NP and ED values, as NP values are similar to the interior region, but ED values are much higher than that of the interior region. The South-East area has low values for PLAND, NP and ED, indicating that the area consists of very few small, compact patches of bamboo. LPI shows that the entirety of the study area is predominantly composed of very small patches, with exception to the North-East edge.

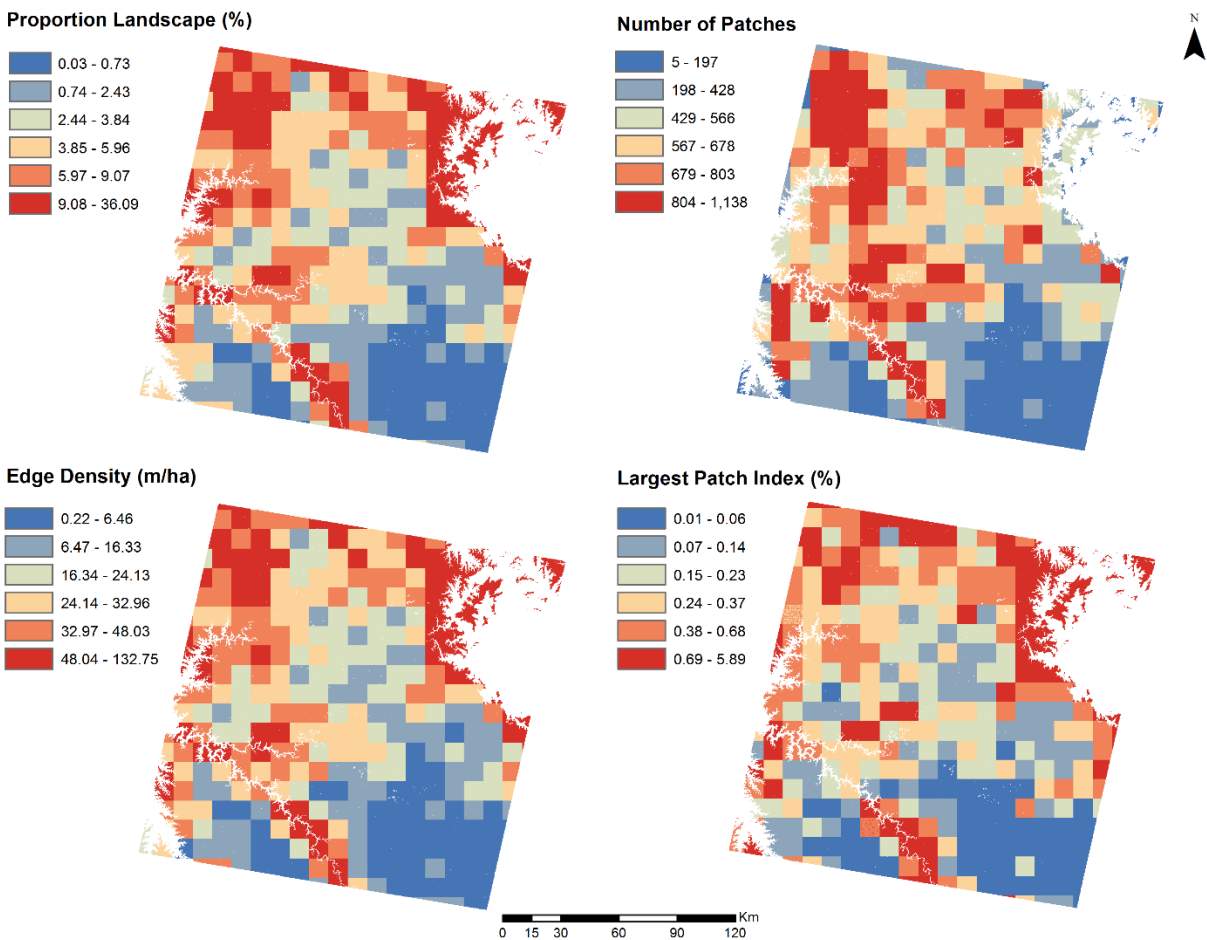


Figure 3.9: Maps of the four landscape pattern indices (PLAND, NP, ED, LPI) used at a 10-by-10 km scale showing bamboo patch composition and configuration across multiple landscapes.

### 3.4. Discussion

#### 3.4.1. Hybrid Model and BAP performance for multiple-landscape scale classification

In this paper we developed a BAP annual composite time-series stack from which multiple hybrid models were derived and used to map regions of bamboo-dominated forest throughout a portion of Araucaria forest. The hybrid modelling approach proved to be effective in determining regions of bamboo dominated forest; using lower quartile, median and upper quartile thresholds determined at a single-landscape scale, three maps were created, which received overall agreements of 88%, 90% and 90%, respectively. Although accuracies are similar, there is a substantial change in total area among the three outputs. This variation in values can (1) be the result of misclassification, (2) interpreted as confidence levels for estimating total area of bamboo and (3) provide insight to asynchronous processes.

In the case of misclassification, there was substantial class exchange between bamboo-dominated forest and forest, and to a lesser degree, forest plantation. Boxplots showed that there was some overlap between the first quartile group of forest and the first to third quartile group of bamboo-dominated forest, which is attributed to error in reference point interpretation, as bamboo is often confined to the understorey making visual interpretation difficult. Similarly, visual inspection showed that forest plantations harvested around the same time as dieback were misclassified as bamboo due to the similar drop in EVI values which is characteristic to a dieback and harvest event.

In terms of total area estimates and asynchronous processes of bamboo, when the three model outputs were layered (Figure 3.8), error values show patch proliferation, with low error values typically being at the centre of bamboo patches, with progressively higher adjacent error

values expanding outward. When quantifying total area occupied by bamboo, this pattern gives confidence to both the low and high total area estimates; patch generation could be attributed to misclassification, whereas patch expansion would suggest pixel membership of the existing bamboo population. Patch proliferation could also be an indicator of asynchrony; as the lower values indicate an inferior model fit, the wave-like proliferation pattern could suggest that the model is one to two years out of synch. Further analysis which test this hypothesis must be undertaken in order to verify population asynchrony and potentially improve understanding of dieback pattern across multiple-landscapes.

The comparison between the BAP composite time-series stack and the SS time-series stack indicate that BAP compositing is an effective method for developing time-series stacks which can be used in subtropical environments, and integral for performing multiple-landscape scale spatial analysis. However, there is banding in the output maps in certain regions in the West and South of the study area, which is a result of the BAP compositing. For this study, a minimum of three images with <50% cloud coverage were used for each annual composite due to time constraints, as generating each composite was computationally intensive (i.e., 90 minutes/scene; CPU 2.60 GHz; 64 GB ram). As a result, banding from the dropped scanline of Landsat 7 impacted the final RMSE output raster, potentially resulting in misclassification. There were also issues of 'no data', where pixels did not meet the criteria required to be included in the final composite. In the case of this study, only small patches of pixels were missing which were easily filled by performing linear interpolation from year to year. However, if larger gaps existed, which might be the case in a more cloud-covered tropical environment, alternative approaches to dealing with missing data would be required which implement proxy values. White et al. (2014) discuss that it is possible to use proxy values to create a multiyear composite,

which is useful when single-scenes are required for analysis, but are less-so when annual composites are required for time-series analysis. Additionally, it is suggested that observing temporal trajectories is an important component for determining missing values, but at this point superior methods to account for missing data are still being developed.

Evidently, as a standalone classification approach, hybrid modelling for mapping bamboo-dominated forest has its short-comings; it is limited in that it can only capture bamboos which possess the same spectral-temporal signature (i.e., lifecycle) and similarly, it is difficult to distinguish between different disturbance events which occurred in 2006 (e.g., forest or forest plantation harvest). Additionally, hybrid modelling is pixel-based, therefore ignores spatial structure; by incorporating spatial information (e.g., neighbouring pixel values, patch shape or size) in the hybrid model, it is thought that classification would be improved.

Despite the shortcomings of hybrid modelling, error metrics derived from hybrid modelling have the potential to be used as inputs for multi-criteria modelling, which would improve classification accuracies for both forest and bamboo-dominated forest. Alternative modelling approaches (e.g., classification and regression tree (CART), entropy models (Maxent), etc.), and object-oriented classification approaches employ multiple environmental and anthropogenic variables, and indices and metrics derived from satellite imagery to accurately map landcover types. A recent classification developed by Brazilian National Forest Inventory (NFI-BR) employs a hybrid approach which integrates object-oriented analysis and pixel based multi-data to perform state-wide classifications (Batista de Luz et al., 2015). Currently, forest classification within Araucaria forest does not include bamboo-dominated forest as a forest subtype, although during state-wide forest inventories notes regarding bamboo presence are often recorded, indicating widespread presence of bamboos in the forest understorey (Vibrans et al.,



2013). It is thought that the incorporation of pixel-based error metrics derived from hybrid modelling into current Araucaria forest classification methods would (1) improve forest classification by distinguishing between forest and bamboo-dominated forest and (2) provide valuable information regarding the health status of remaining forest fragments based on their composition of bamboo populations.

#### *3.4.2. Multiple-landscape pattern analysis*

Araucaria forest has been reduced to a series of fragments, integrated amongst a predominantly agricultural and urban landscape. Understanding the impact bamboo has on remaining forest fragments based on bamboo patch distribution will assist in informing policy so as to include bamboo focused silvicultural intervention practices into forest management plans (Lacerda, 2016; Lacerda & Kellermann, 2017). As a recent analysis of bamboo-dominated forest distribution had been performed at a single-landscape scale, we wanted to determine whether the same bamboo patch distribution and synchronous ecological processes could be observed across multiple-landscapes, as well as at varying scales, and explore whether landscape heterogeneity influenced patch distribution. Based on the multiple-landscape pattern analysis, spatially it can be determined that bamboo patch composition and configuration coincides with natural and anthropogenic landscape features throughout the study area. The North-West and interior region is composed of fairly flatland, which has been converted to agricultural land and urban areas, and therefore has many small bamboo patches which exist as subsections of remaining forest fragments and account for a very small proportion of land. The North-East edge of the study area consist of mountainous terrain, which is not conducive to human settlement, therefore has been left as forest which has been selectively logged and left to naturally regenerate, enabling the development of large patches of bamboo within that specific area. The South-East region also

consist of flatland, and based on landscape pattern indices, it is evident that this region has been heavily altered for agricultural practices, which is evidenced by very few, small bamboo patches.

Based on the similarity of global statistics for both the 10-by-10 and 25-by-25 gridcells, it is evident that bamboo patch composition and configuration is the same at coarse multiple-landscape scales, indicating that landscape heterogeneity in relation to human settlement and geographic features is a contributing factor to patch spatial arrangement. Based on the findings of Greig et al. (*Under review*), it can be understood that locally bamboo patch composition and configuration can be explained by small-scale anthropogenic disturbances, and at a regional scale, geographic features that influence human settlement explain bamboo patch arrangement. Understanding local and regional drivers of bamboo ecological processes has important implications for both local and state-wide conservation programs. In recent years, to conserve biodiversity and improve genetic flow, Brazil has developed legal regulations (Brazilian Protected Areas System Act; Brasil, 2000) and significantly expanded the country's protected areas (Bertzky et al., 2012) as a signatory of the Convention on Biological Diversity (CBD) by the United Nations Environment Programme (Dudley, 2008; Stolton et al., 2013). However, these protection efforts are concentrated on the Amazon region, leaving other biomes, such as Araucaria forest underrepresented. Current conservation efforts of Araucaria forest centres on several protected areas consisting of large fragments composed of predominantly original forest, often with *A. angustifolia* serving as a flagship species for conservation (Lacerda, 2016).

Lacerda (2016) performed an analysis examining difference in diversity of different forest types found within the ERSC (i.e., *A. angustifolia*-dominated and non-*A. angustifolia*) and smaller fragments surrounding the exterior of the reserve. Although it was found that the ERSC was significantly more diverse, 19 % of recorded species were exclusive to smaller fragments,

with 38% of species exclusive to the reserve. Furthermore, it was found that *A. angustifolia*-dominated forest was consistently less diverse than other forests types, which is thought to be in part due to bamboo impacting species composition and diversity in the understorey (Lacerda et al., 2012). This suggests that both large and small forest fragments are important for maintenance of species diversity and are necessary to increase connectivity throughout Araucaria forest to enable genetic flow, and also raises the question of whether the current designated protected areas are also impacted by bamboo populations. Therefore, to identify forest fragments ideal for protection, it is important to determine the proportion of forest patch impacted by bamboo populations to optimize connectivity and increase diversity and develop management strategies which target bamboo-dominated forest in order to increase functionality of bamboo impacted forest fragments as potential corridors. Additionally, based on the findings of Lacerda (2016), it can be assumed that similar trends in diversity in relation to forest fragment size and presence/absence of *A. angustifolia* can be observed at a multiple-landscape scale.

Although this analysis does not compare bamboo patch distribution to forest patch distribution, this is a necessary task to be undertaken; understanding the proportion of forest fragments impacted by bamboo is an indicator of species diversity, and consequently BH. BH as an index encompasses both Taxonomic Homogenization (TH) and Functional Homogenization; TH describes the taxonomic impoverishment of local species and FH describes the reduction in functional traits belonging to local plant communities (Clavel et al., 2011). TH is argued to be less indicative of overall ecosystem health as the index does not account for replacement of local specialist species by widespread or exotic generalist species (Clavel et al, 2011), whereas FH has been found to be a greater indicator of ecosystem health as it examines functional traits amongst communities (e.g., response to disturbance events) (Clavel et al., 2011).

Fragmentation-driven BH has been determined to operate at a regional scale through the rearrangement of native floras (Lôbo et al., 2011) and the replacement of local species by more widespread, generalist species (Clavel et al., 2011) (e.g., pioneer and bamboo species). The process of forest fragmentation increases light at exposed edges, enabling pioneer regeneration (Lôbo et al., 2011) and proliferation of bamboo populations which may result in arrested forest succession due to lifecycle characteristics of bamboo (Lacerda & Kellermann, 2017), further contributing to BH. In an undisturbed forest, pioneers represent 2-3% of tree species richness (Swaine and Whitmore, 1988), but can represent over 80% of all species in edge-affected habitats (Oliveira et al., 2004; Aguiar & Tabarelli, 2010). Decline in specialist species as a result of the proliferation of short-lived, generalist species has led to reduced species richness at multiple spatial scales (i.e., TH) (Laurance et al., 2006), partitioning of tree groupings that impact pollination systems and other functional tree assemblages based on reproductive traits (i.e., FH) (Girão et al., 2007; Lopes et al., 2009) and biological convergence of tree species across edge-affected habitats (Tabarelli et al., 2008; Aguiar & Tabarelli, 2010).

### *3.4.3. Agroforestry as a strategy for conservation*

Based on composition and configuration of bamboo patch distribution throughout Araucaria forest, it is evident that many of the remaining forest fragments are impacted by bamboo populations. As remaining Araucaria forest is heavily fragmented due to agricultural landuse, the majority of remaining forest fragments fall on the property of private landowners. In an attempt to preserve remaining Araucaria forest fragments, current state and federal legislation requires that a minimum of 20% of rural properties be forest covered, with strict restrictions being placed on forest use, with some allowance for agroforestry activities (Lacerda et al., 2012). Agroforestry for sustainable forest management is increasingly being adopted as an

approach to improve forest health while simultaneously supporting small-scale rural economic development (Lacerda et al., 2012) and has been found to be an effective buffer for forest fragments to reduce edge effects (Tabarelli & Gascon, 2005). As many of the mapped bamboo patches occur on private landowner's property, a suggested approach for bamboo management is the implementation of agroforestry systems, which would give opportunity to small-scale farmers to profit from sustainably yielded forest products, while simultaneously improving forest health. By employing agroforestry as a form of bamboo management, forests in a state of arrested succession can be revitalized into functioning ecosystems with increased diversity, enabling these fragments to serve as corridors to create connectivity amongst remaining forest fragments, consequently improving genetic flow. As hybrid modelling has proven to be functional for mapping bamboo at a single and multiple-landscape scale, it is thought that the tool would assist in developing both local and state-wide sustainable management initiatives and stewardship programs that focus on reclamation of bamboo impacted forest fragments through implementation of agroforestry systems to manage bamboo populations that fall on private landowner property.

### **3.5. Conclusion**

In this paper we used a recently developed hybrid model derived from a BAP time-series to map a prominent bamboo species throughout Araucaria forest. A multiple-landscape pattern analysis was then performed using the mapped bamboo-dominated forest, and landscape pattern indices were calculated and mapped at two different scales. It was determined that bamboo patch distribution is similar at multiple scales and composition and configuration of patch distribution is governed by anthropogenic features, such as agricultural areas and human

settlement. Although bamboo patch distribution has not be compared relative to forest fragment distribution, it is assumed that bamboo populations exist as subsections of forest fragments, suggesting that remaining forest fragments have less species diversity than previously thought, and may be in a state of arrested succession, resulting in BH. A suggested remedy to increase biodiversity, improve forest health and assist in rural economic development, it to use agroforestry as an approach to manage bamboo populations.

Hybrid modelling coupled with BAP compositing has proven to be effective in mapping regions of bamboo-dominated forest at multiple scales, therefore is thought to be a useful tool to inform both local and/or state-wide forest management and conservation programs. Additionally, it is advised that metrics derived from hybrid modelling are used in other mutli-criteria based classification approaches to improve current forest classification efforts within Araucaria forest; by using these metrics bamboo-dominated forest can be distinguished from other forest types, thus providing valuable information regarding forest health. It is recommended that bamboo patch distribution is examined in relation to forest fragment distribution to determine the total amount of remaining Araucaria forest that is or is not impacted by bamboo. In doing so, insight will be gained regarding the overall health of the remaining forest fragments which will help in determining appropriate conservation and management actions to be made to manage bamboo populations so as to increase forest fragment connectivity and improve overall forest health.

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## Chapter Four:

### 4.0. Summary and conclusions

The first chapter aimed to describe the ecological processes of a pervasive bamboo species (*Merostachys skvortzovii*) throughout Araucaria forest by developing a hybrid model, a new semi-empirical spatially explicit ecological process model developed using extracted spectral-temporal signatures from Landsat time-series stacks. The hybrid model was initially used on a single-landscape scale to identify lifecycle phases of bamboo-dominated forest succession and to test the hypothesis that community-level ecological processes were a synchronized phenomenon which occurred across the single-landscape. A TWDTW classification approach was also used to test the same hypothesis; if bamboo-dominated forest succession were an asynchronous process, the TWDTW model would presumably achieve a higher accuracy. Using the hybrid model, it was determined that bamboo lifecycle has four broad phases, pioneer predominance, mature bamboo, dieback and pioneer regeneration, and is a synchronous process occurring at a single-landscape scale based on hybrid model accuracies which ranged from 77% to 90% overall agreement. Alternatively, the TWDTW approach yielded lower accuracies which ranged from 68% to 82%.

The objective of the second paper was to perform a multiple-landscape analysis to explore bamboo patch pattern within a predominantly agricultural and urban matrix. To do this, we created a time-series stack using a BAP compositing approach from which multiple hybrid models were derived to map bamboo spatial distribution throughout Araucaria forest at a multiple-landscape scale. Additionally, we did a comparison using a single-landscape (ERSC) between a SS time-series stack and a BAP time-series stack to explore the radiometric similarity between the two time-series stacks. Using the resulting bamboo map from the hybrid model,

landscape pattern indices (i.e., PLAND, NP, ED, LPI) were calculated, and bamboo patch composition and configuration was explored in relation to natural and anthropogenic features throughout Araucaria forest. The comparison between the SS and BAP time-series achieved similar accuracies (i.e., 90% and 88%, respectively), thus indicating the functionality of the compositing approach in a subtropical environment and for its use at a multiple-landscape scale. The hybrid modelling approach performed well achieving between 88% and 90%, giving strong confidence to perform the multiple-landscape spatial analysis with the mapped outputs. The multiple-landscape analysis showed that patch composition and configuration was generally linked to human settlement and geographic features; bamboo patches tended to be small and compact surrounding urban and agricultural areas, which is characteristic of flat terrain, whereas mountainous regions with less human development had larger patches with high edge density.

Although the hybrid modelling approach has yielded fairly accurate results, there are limitations to using this method to map bamboo distribution, and other landcover types more generally. The current hybrid model spectral-temporal template is specific to *M. skvortzovii* therefore cannot identify other bamboo species and also causes circular reasoning, as the model does not allow for any asynchronous processes of *M. skvortzovii* to be identified. Additionally, the model cannot distinguish between other forest disturbance events if they occurred in the same year as dieback (e.g., forest plantation harvest). To rectify this issue, it is thought that the incorporation of spatial structure (e.g., patch shape, size), would assist in distinguishing between other disturbance events.

#### **4.1. Research contributions**

Although spatially explicit ecological process models have been increasingly used in the past decade, this research employs this modelling approach in a novel subtropical environment to

explore a biological invasion which is not widely known as an ecological issue; due to the ubiquitous presence of bamboo throughout tropical and subtropical forests of Brazil, their impact on native floras is often overlooked, therefore, it was the aim of this research to shed light on this issue through the application of novel geospatial methods. As an ecological project, this project served to characterize the lifecycle phases of a prominent bamboo species throughout the Araucaria forest and determined that bamboo lifecycle is a synchronous phenomenon which is causing arrested succession. Additionally, an exploratory spatial analysis was performed which identified bamboo patch distribution composition and configuration throughout a portion of Araucaria forest. The analysis strongly indicates that human induced forest fragmentation contributes to bamboo population proliferation and demonstrates the potential impact that bamboo populations are posing on remaining forest fragments based on patch pattern's relationship to human settlement and geographic features.

As a methodological contribution, the hybrid model serves to be a useful mapping tool as an initial attempt at mapping bamboo populations. Although the incorporation of space would assist immensely with improving classification accuracies, for the time being, derived error metrics can be used in other multi-criteria modelling approaches which already incorporate spatial information. Additionally, one of the major challenges with mapping bamboo populations is that they are confined to the forest understorey for the majority of its lifecycle. By incorporating these metrics in existing models, it is possible to map bamboo that is confined to the forest understorey.



## **4.2. Research opportunities**

This research is the commencement of many further analyses to come. By developing a basic tool to map bamboo, multiple-landscape analyses can subsequently be performed that look at bamboo patch distribution to forest patch distribution. This specific analysis would have strong implications for forest management and conservation, as knowledge regarding bamboo ecological processes and their impact on biodiversity gained from this research would strongly depict the need for bamboo management. Subsequent research could be carried out which uses mapped bamboo as a tool to develop local and state-wide initiatives to develop forest management plans which include bamboo management.

The current hybrid modelling approach can also be improved by incorporating spatial information, as well as developing growth models for other known bamboo species, so as to enable mapping of other prominent bamboo species and increase knowledge of individual species' ecological processes. This seminal research has opened the door to many novel and interesting analyses which can be performed at a single or multiple-landscape scale; the community-level ecological processes of other pervasive bamboo species can be examined; further multiple-landscape analyses can be performed which give insight into the current health of remaining forest fragments; and further development of the hybrid modelling approach to incorporate spatial structure will improve bamboo classification at all scales and have the potential to be used in many other degraded subtropical and tropical forests throughout the world.

## **4.3. Implications for conservation**

Current Araucaria forest conservation efforts are focused on the protection of large forest fragments which are predominantly occupied by *A. angustifolia*, based on the assumption that

presence of *A. angustifolia* is indicative of old-growth, species-rich forest (Klein, 1960; 1984), and because of the cultural symbolism that the species holds (Carvalho, 2012). However, this reasoning is flawed, as fragments with large populations of *A. angustifolia* have been found to be less diverse (Lacerda, 2016) than previously recorded (Reitz et al., 1979; Vibrans et al., 2012, 2013). It is apparent that forest fragments predominantly occupied by *A. angustifolia* have undergone substantial anthropogenic disturbances, leaving fragments vulnerable to additional disturbances (e.g., fire, understorey clearing, biological invasion), which has altered forest structure and diversity immensely (Lacerda et al., 2016). Evidently, focusing on *A. angustifolia* as a flagship species for environmental protection is problematic, as this approach does not consider recent findings in regard to biodiversity (Lacerda, 2016), nor does it acknowledge bamboo as an invasive species.

This research provides evidence that bamboo within the Araucaria forest is a widespread biological invasion impacting many remaining forest fragments and contributing to biotic homogenization, which necessitates management and should be considered a high priority when developing forest management plans. With this knowledge, it is necessary for current forest management policies to be re-evaluated, with new policies being developed based on empirical evidence and adaptive management strategies. Additionally, management practices surrounding bamboo management present an opportunity for socio-economic growth through the development of stewardship programs centered on sustainable forest management. A suggested approach for bamboo management is through local engagement of small-scale landowners, which could involve the implementation of agroforestry systems as a method to control bamboo populations and re-introduce native species, while simultaneously promoting sustainable forest management and rural-economic development (Lacerda et al., 2012; Lacerda, 2016).

It is anticipated that evidence from this research will assist in developing forest management plans which include bamboo management strategies. Additionally, it is hoped that hybrid modelling will serve as an effective tool for synoptic mapping and monitoring of forest health in general, and bamboo in particular, and will enable more evidence-based decision-making surrounding forest management practices.

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