Fire in the Amazon forest amidst selective logging and climatic variation

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To my grandmothers
Idalina Hinoyo Schiavon
and
Irany Cundari Machado
for being the nurturing roots of my life.

"Freedom of thought is best promoted by the gradual illumination of men's minds, which follows from the advance of science."

Charles Darwin

Thesis summary

Fires in tropical forests are strongly associated with climate, but also contingent on anthropogenic ignition sources. Tropical forests are facing increasing pressure of deforestation for agriculture, and further degradation, such as through fire and selective logging, thereby triggering detrimental impacts on biodiversity and ecosystem services. This is likely to intensify with climate change and increasing demands for agricultural goods. In this thesis, I examine how anthropogenic pressures and climatic variations relate to fire in the Brazilian Amazon. I first focused on selective logging, which is the most widespread pattern of forest degradation and has been identified as a facilitator of fire for altering microclimates through disrupting the canopy and increasing fuel loads from operational residual damage. I explored how long is required for the thermal environment of logging gaps and roads to recover, through relating canopy structure with temperature of understorey ambient and forest floor. I also investigated the extent to which damages caused to the forest structure from selective logging can alter the thermal environment of gaps and remaining surrounding forest, and how such impacts can affect forest flammability. Selective logging increases forest fire proneness through creating hotter and drier thermal environments, which accelerates desiccation of fuel loads, as well as increasing exposure to anthropogenic ignition sources. Selectively logged forests can, however, recover their thermal environment to baseline levels of a primary forest fairly rapidly (less than 5 years), and thus decrease their fire proneness as forest regenerates. In addition to smart and strategic planning of selective logging operations, it is critical that logging companies impose strong post-logging management regulations to control ignition sources during at least the first five years after harvest to prevent fires. This thesis then tackles this issue at a broader scale, where I disentangled climatic variation and anthropogenic pressures, and quantified their relative contribution in driving fire across the Brazilian Amazon. Put together, my findings demonstrate that fire is driven by a synergy between climate and anthropogenic pressures. Regulating human activities and fire use in the Amazon forest is crucial to preventing fires and preserving biodiversity and ecosystem services, especially under climate change.

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Statement of contribution

The research presented in this thesis is my own. This thesis has not been submitted for any other award at this or any other institution. In addition to myself (M.M.M.) there were several collaborators in this research: David Edwards (D.P.E.), Carlos Peres (C.A.P.), Dylan Childs (D.Z.C) and João Carreiras (J.M.B.C).

Chapter 1

Thesis introduction. M.M.M. wrote the chapter.

Chapter 2

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Chapter 4

Disentangling the contributions of climatic variation and human pressures on fire occurrence in the Brazilian Amazon.

The overall contribution of authors was as follows: M.M.M, D.P.E., D.Z.C and J.M.B.C conceived the study. M.M.M developed the methods with contributions from J.M.B.C, performed all statistical analyses with contributions from D.Z.C., and wrote the manuscript with contributions from all authors.

Chapter 5

Thesis discussion. M.M.M. wrote the chapter.

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Chapter 1

Thesis introduction

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1.1 Tropical Forests

The tropics host most of the world's biodiversity (Barlow et al., 2018), with tropical forests appearing in fifteen of a total of 25 biodiversity hotspots on the planet (Myers, Mittermeier, Mittermeier, da Fonseca, & Kent, 2000). Tropical forests are the most diverse and complex ecosystems on Earth (Laurance, 2007). Not only do they harbour the richest terrestrial biodiversity, they also provide vital ecosystem services to humanity, from moderating the global climate system, to water supply, and harbouring vast stocks of above-ground carbon (Foley et al., 2007; Gardner et al., 2009).

Forest structure and dynamics vary spatially across tropical forests, which is largely due to variations in soil fertility, geology and climatic patterns, all of which may play an important role in explaining variations in forest biomass and growth, and species diversity (Feldpausch et al., 2011; Quesada et al., 2012; Wittmann et al., 2006). Plant species adopt different strategies and responses to limitations imposed by soil structure and nutrients, which then shapes the overall forest physiognomy of each region (Emilio et al., 2014). Climatic patterns such as variation in precipitation, dry season length, and mean annual air temperature act as key drivers of variation of the relationship between tree height and diameter in tropical trees (Feldpausch et al., 2011).

Spatial patterns of wood density reflect the species composition of each area. For instance, mean stand-level wood specific gravity is 15.8% higher in forests in central and eastern Amazonia, compared with the north-western region, and such pattern is likely due to the higher diversity and abundance of taxa with high and low specific gravity values in central and eastern, and western Amazonia, respectively (Baker et al., 2004). This functional trait, along with seed size, is related to different life histories: plants with large seeds, long-lived leaves or dense wood are related to slow life histories with mean fitness (i.e., population growth rates), and more strongly influenced by survival than by growth or fecundity compared with fast life history species with small seeds, short-lived leaves, or soft wood (Adier et al., 2014).

Spatial gradients of climate and forest properties across tropical forests compose the main drivers of variation in forest structure and leaf, wood and litter properties, which are likely related to decomposition rates and fuel loads, thus influencing forest flammability.

Despite tropical forests' critical importance in buffering the effects of global crises of climate change and biodiversity loss (Butchart et al., 2010; Trumbore, Brando, & Hartmann, 2015), they are subject to pervasive stressors from rapid environmental, socio-economic and demographic change (Barlow et al., 2018), and have experienced a massive increase in rate and geographic extent of land-use and land-cover change over the past few decades (Asner, Rudel, Aide, Defries, & Emerson, 2009; Watson et al., 2016). Tropical biodiversity is disproportionally threatened (Barlow et al., 2018) as tropical forests are disappearing at alarming rates (Laurance, 2007; Pimm, Russell, Gittleman, & Brooks, 1995).

Deforestation and forest degradation

Habitat destruction through land-cover change is the greatest overall threat to terrestrial systems and the most prominent driver of biodiversity loss across the planet, with global climate change becoming increasingly important (Newbold et al., 2015; Sala et al., 2000). Tropical forests are particularly vulnerable as they face the frontier of agricultural expansion while demands for food, feed and fuel rapidly increase (Gibbs et al., 2010). It is estimated that 27% of global forest loss can be attributed to deforestation through permanent land use change for commodity production (Curtis, Slay, Harris, Tyukavina, & Hansen, 2018). Across the tropics, a devastating ~150 million hectares of forests have been converted into agricultural lands between 1980 and 2012 (Gibbs et al., 2010; Hansen et al., 2013).

In addition to the direct impacts on biodiversity, land clearing for conversion of forests into agricultural lands drastically changes the functioning and structure of ecosystems (Achard et al., 2002; Asner et al., 2005; Fearnside, 2005), and is frequently linked to wildfires (L. O. Anderson et al., 2015; Goldammer, 1988), as observed in the current severe fire season in the Amazon forest (Escobar, 2019). Alongside deforestation is forest degradation, which refers to reductions of biomass density within forests and relates to disturbances that do not completely remove the forest canopy, such as selective logging and forest fires (Barlow et al., 2016). Such disturbances can be even more widespread than deforestation (Nepstad et al., 1999). While some 20% of the humid tropical biome was designated for selective logging from 2000 – 2005, deforestation affected only 1.4% in the same period (Asner et al., 2009; Hansen et al., 2008).

While deforestation is the biggest current threat to tropical forests, forest degradation poses additional pressures that are likely to interact with land-use change and climate change, and negatively affect biodiversity and ecosystem services (Barlow et al., 2018; Gibbs et al., 2010). Carbon emissions from deforestation and degradation across the tropics averaged ~1.4 (±0.5) PgC yr^{-1} over the period 1990–2010. There is a clear need to consider the impacts of both deforestation and forest degradation on tropical forests to develop more effective conservation policies, and research must also investigate the consequences of the interaction between them, especially under future scenarios of climate change.

1.2 Fire

Fire has been a natural agent of disturbance for hundreds of millions of years (Bowman et al., 2009) as a key ecological and evolutionary driver (Bond & Keeley, 2005). Fire influences global ecosystem patterns and processes, including vegetation distribution, structure and biological diversity (Bond, Woodward, & Midgley, 2005; Govender, Trollope, & Van Wilgen, 2006), soil nutrient availability and exchange (J. S. Levine, Bobbe, Ray, Witt, & Singh, 1999), and the carbon cycle and climate system (Y. Chen et al., 2017, Nogueira et al., 2019).

In ecosystems that are dependent on natural fire regimes to maintain their structure, biodiversity and functioning, such as savannah systems, human-induced suppression of fire or changes in fire regimes can trigger drastic consequences for ecosystem functioning and composition, causing biodiversity losses and drastic changes in ecological processes (Durigan & Ratter, 2016; Probert et al., 2019). Tropical forests, however, have not evolved with frequent fires (Goldammer, 1990; Malhi et al., 2008), which has resulted in many species being ill-adapted to survive even low-intensity fires (Barlow & Peres, 2004).

Fires in tropical forests are strongly associated with human activities, either through deliberate deforestation in converting rainforests into agricultural lands or as unintended consequences of current land-use practices (Cochrane, 2003). Despite being an effective and inexpensive tool to transform natural ecosystems into agricultural lands, fire can cause severe unanticipated economic and environmental damage when it escapes the intended purpose (de Mendonça et al., 2004).

Fire and biodiversity loss

Fires in forests reduce species diversity and induce a drastic turnover in plant species composition, as forest-interior specialists are replaced by edge generalists (Barlow & Peres, 2008; Slik, Verburg, & Kessler, 2002). Common tree species suffer greater mortality, but rare species are more vulnerable to be locally extinct (Gerwing, 2002). After burning, the forest environment favours wind-borne, light demanding pioneer species and the invasion of grasses and vines, which slows the regeneration process and increases forest flammability (Brando et al., 2014; Cochrane, 2003; Holdsworth & Uhl, 1997).

Fire spread into forests is one of the greatest threats to understory forest birds (Barlow, Peres, Henriques, Stouffer, & Wunderle, 2006). Additionally, and many large frugivores and other vertebrate species are likely to decline if not disappear after recurrent burning, which can further affect ecological processes, such as seed dispersal (Barlow & Peres, 2006). Moreover, forests are less likely to regenerate with recurrent burning, as fire significantly reduces seed availability in the leaf litter and topsoil (Van Nieuwstadt & Sheil, 2005).

Recurrent fires in tropical rainforests are encouraging an ecosystem transition from high-biomass moist forests into low-biomass transitional dry and woody savannah-like forests (Barlow and Peres, 2004; N. M. Levine et al., 2016), with lower wood density trees and higher susceptibility to mortality during droughts (Brando et al., 2014). Such pressures of extensive fire-induced tree mortality and forest degradation are likely pushing tropical forests towards a tipping point, whereby they are no longer able to sustain themselves (Brando et al., 2014; Hirota, Holmgren, Van Nes, and Scheffer, 2011).

Fire and climate change

Forest fires also strongly contribute to global climate change by releasing huge amounts of greenhouse gases into the atmosphere (Y. Chen et al., 2017; Page et al., 2002). Human-induced fires in high-biomass forests are responsible for releasing huge pulses of carbon dioxide, and emissions continue at lower levels for years afterwards because of extensive delayed tree mortality (Barlow & Peres, 2004).

Net annual carbon emissions from tropical wildfires can vary greatly depending on the forest area affected, land-use history and quantity of biomass burned (Cochrane et al., 1999). During the out-of-control fires of $1997-98$, net forest fire emissions may have released carbon equivalent to 41% of worldwide fossil fuel use (Cochrane, 2003). Emission from forest fires in Southeast Asia accounted for 60% of carbon emissions anomaly, and Central and northern South America for 20% (Van Der Werf et al., 2004). In the Brazilian state of Roraima alone, a total of ~42,558 million tons of carbon were affected by fires during this period, of which, ~19,73 million were released directly from combustion, ~22,33 million from decomposition, and ~0,52 million were converted into charcoal (Barbosa & Fearnside, 1999).

Costs of carbon emissions from forest fires are summed with other impacts, such as losses of timber and non-timber products and impacts to other ecosystem services (de Mendonça et al., 2004), to quantify the economic costs of fire. In Southeast Asia, the 1997 – 1998 fires were estimated to drive a total economic loss of US$ 4.4 billion, which include direct damages from fire and consequences from haze, with some 20 million people in danger of respiratory problems (J. S. Levine et al., 1999). During the same years, 70 firefighters were killed in Mexico and 700 people died of smoke-related diseases in Brazil (Cochrane & Laurance, 2002).

Fire incidence in tropical forests is largely associated with human activities providing ignition sources (Cochrane, 2003; Malhi et al., 2008). Fire is also strongly related to climate, with the most devastating fire events having been associated with severe droughts (Alencar, Nepstad, & Vera Diaz, 2006; J. S. Levine et al., 1999). Moreover, droughts are likely to intensify the negative effects of anthropogenic deforestation and forest degradation, further increasing forest vulnerability to mortality and recurrent burning (Brando et al., 2014). Given that increasing global demands for agricultural goods are intensifying the pressure on tropical forests, there is a clear need to better understand what underpins these forest fires and how they can be mitigated.

Drivers of fire

During years of normal rainfall, undisturbed tropical rainforests hold elevated air humidity and very limited drying power with a constant damp layer of leaves, twigs and branches (Bowman, 2017). Charcoal in the soil of parts of the Amazon indicates the occurrence of four exceptionally widespread and intense fires over the past two millennia, which are associated with periods of exceptional aridity correlated with mega-Niño (occurring on the order of hundreds of years) and El Niño episodes (occurring on the order of tens of years) (Meggers, 1994).

El Niño episodes have become more frequent over the past decades, and given anthropogenic increases in greenhouse gases concentrations in the atmosphere, they are likely to intensify in frequency and severity (Li, Fu, & Dickinson, 2006; Nepstad, Tohver, Ray, Moutinho, & Cardinot, 2007; Timmerman et al., 1999). More frequent and severe El Niño episodes under climate change will likely be accompanied by severe droughts (Nepstad et al., 2004), which could drive a widespread increase in forest flammability and subsequent large-scale tropical fires (Barlow & Peres, 2008).

Fires associated with an exceptionally severe drought caused by the major El Niño event of 1997 – 1998, burned some 8 million hectares of land in Indonesia (Schweithelm & Glover, 1999), impacted over 1 million ha of previously undisturbed forests in the state of Roraima, Brazil (Barbosa & Fearnside, 1999), and left an unprecedented burned area of over 2.5 million hectares in Central America (Mutch, Lee, & Perkins, 1998).

In addition to driving forest fires, prolonged dry seasons in tropical rainforests can cause severe negative effects on net primary productivity and carbon storage (Nepstad et al., 2004). Tree mortality caused by severe droughts further increases forest flammability by augmenting fuel loads and facilitating their desiccation (Nepstad et al., 2001). Furthermore, forest fires interrupt cloud formation and reduce rainfall (Andreae et al., 2004), which is also likely to further increase the chances of wildfires. Thus, droughts and fire can interact in a positive feedback cycle and magnify fire occurrence in tropical forests.

Droughts render tropical rainforests seasonally flammable, but fire incidence is contingent on anthropogenic ignition sources (Malhi et al., 2008). Fire use for land management is nearly ubiquitous across the tropics (Beale et al., 2018; Cochrane & Laurance, 2002), and deforestation rates are closely linked to fire patterns (Escobar, 2019). Increasing human population coupled with rising global demands for agricultural goods (Gibbs et al., 2010) is increasing the availability of ignition sources across tropical forests. Concurrently, these areas are becoming more desiccated and suffering increasingly severe heat-waves as consequences of global climate change (Brodie, Post, & Laurance, 2012b). Thus, climatic and anthropogenic drivers of fire are likely to act synergistically in magnifying forest fire proneness.

1.3 Selective logging

Both deforestation and forest degradation driven by anthropogenic pressures can influence fire patterns in the tropics (Aragão et al., 2008). Selective logging is one of the most widespread drivers of tropical forest degradation (Lewis, Edwards, and Galbraith, 2015). At least one fifth of the humid tropical forest biome was affected by selective logging at some level between 2000 and 2005 (Asner et al., 2009). Even though selective logging targets only commercially valuable species typically above a minimum trunk diameter, thus leaving other species and stems unharvested (D. P. Edwards, Tobias, Sheil, Meijaard, & Laurance, 2014), it can still cause substantial residual damage on species diversity and composition (Costa & Magnusson, 2002) through increasing mortality of remnant trees, and also disrupt the forest canopy and cause soil compaction (Asner, Keller, Pereira Jr, Zweede, & Silva, 2004; Meijaard et al., 2005; Putz et al., 2012; Verissimo, Barreto, Mattos, Tarifa, & Uhl, 1992). Furthermore, extensive road networks are created to enable timber extraction, thereby facilitating further exploitation of previously inaccessible forest areas (Laurance, Goosem, & Laurance, 2009).

The extent of damage caused by selective logging can vary with harvest intensity and techniques employed (Bicknell, Struebig, Edwards, and Davies, 2014; Burivalova, Şekercioğlu, and Koh, 2014; Putz, Sist, Fredericksen, and Dykstra, 2008, Feldpausch, Jirka, Passos, Jasper, and Riha, 2005; Pereira, Zweede, Asner, and Keller, 2002). In addition to the immediate damage directly caused by each logging operation, the same forest may be re-logged several times as timber market develops or logging regulations are weakened. Multiple rounds of intensive logging create highly degraded tracts of forest with low commercial value, and therefore minimal incentive against deforestation (Van Gardingen et al., 2003). In the Amazon, the probability of deforestation for a logged forest is up to four times greater than for unlogged forests (Asner et al., 2006). In Indonesia, there has been no concerted efforts to prevent the conversion of repeatedly logged forests into oil palm and paper-pulp plantation because of their reduced biological conservation value (D. P. Edwards et al., 2011).

In terms of carbon stocks, selective logging can cause a range of impacts depending on techniques and harvest intensity (Blanc et al., 2009). For instance, the process of extracting ~22 t of carbon from one hectare of forest in East Malaysia can cause the conversion of 95 t of carbon of the remaining vegetation into necromass, which will subsequently be released to the atmosphere as CO_2, CO and CH_4 (Putz & Pinard, 1993). In Huang and Asner's (2010) simulations, forest carbon loss via selective logging are expected to last from two to three decades following harvest as a consequence of the delayed mortality and decomposition of the biomass damaged by logging.

Nevertheless, relative to wildfires and deforestation, selective logging has a much lower detrimental impact on forest structure and biodiversity (Gibson et al., 2011), with mammal, bird, invertebrate and plant species richness in logged forests being similar to old-growth forests, including a host of forest specialists and IUCN red-listed species (Costantini, Edwards, and Simons, 2016; D. P. Edwards et al., 2011; Putz et al., 2012). Although primary forests are irreplaceable for sustaining tropical biodiversity (Gibson et al., 2011), selectively logged forest can retain considerable conservation value (Berry, Phillips, Ong, & Hamer, 2008; D. P. Edwards et al., 2011). Maintaining their conservation value critically depends on preventing post-logging degradation and fire incursion.

However, a crucial step for the expansion of selective logging is the development of road networks, which not only facilitate further exploitation of previously inaccessible forest areas (Laurance et al., 2009), but also disrupt the canopy, which, along with the feeling of trees, create extensive forest edges that negatively impact biodiversity (F. A. Edwards et al., 2017; Pfeifer et al., 2017) and expose the forest interior to wind and heat penetration, thus affecting the forest thermal environment.

By affecting forest microclimates and increasing fuel loads from mechanized operational residual damage (Holdsworth and Uhl, 1997), selective logging has been identified as a facilitator of fire in tropical forests (Cochrane and Schulze, 1999; Nepstad et al., 1999). Furthermore, the associated effects of both fire and selective logging extend beyond their direct impacts on the forest, as they both increase the probability of fire through a positive feedback loop (Nepstad et al., 2001).

Investigating the impacts of selective logging through studying the thermal environment enables us to understand the broad effects on the habitat, which allows for multiple discussions, such as impacts on biodiversity (through spatial microclimatic availability — Chapter 2), impacts on forest structure (through canopy fractions — Chapters 2 and 3) and impacts on forest flammability (Chapter 3).

Vast expanses of tropical forest are currently slated for selective logging, which is likely to increase forests fire proneness. The extent to which selective logging impacts the forest thermal environment and how such changes may affect forest flammability, is still largely unknown. Moreover, as forests regenerate post selective logging, the thermal environment is also expected to recover, but the intricacies of these processes are yet to be explored.

1.4 Thesis rationale and overview

The overarching goal of this thesis is to determine how anthropogenic pressures and climatic variations impact the forest thermal environment and drive fire in the Amazon forest. I present four chapters addressing this theme based on existing literature, available datasets and original data collected over two field seasons during 2016 and 2017 in the Southwest Brazilian Amazon. I begin by investigating how severely selective logging can impact the forest thermal environment temporally — how much post-harvest time is required for the recovery of logging gaps and roads, and spatially — the edge-effect of logging gaps on the remaining surrounding forest. I then explore how selective logging affects forest flammability through a controlled fire experiment. Finally, I combine datasets of climate, human pressures, Protected Areas and two fire products — Burnt Area and Active Fires — to explain fire occurrence across the Brazilian Amazon. In the General Discussion I synthesise all results to provide an overall picture of how selective logging impacts forests' thermal environment and flammability, and how climate and anthropogenic pressures act synergistically in driving fire across the Amazon forest. I also discuss conservation implications, and provide recommendations for action and further research. The specific objectives of each data chapter are outlined below:

Chapter 2 — Rapid recovery of thermal environment after selective logging in the Amazon

Even though selective logging is the most widespread pattern of disturbance in tropical forests, it has a much lower detrimental impact on forest structure compared to other common disturbances, such as wildfires and conversion to farmland. Selectively logged forests harbour a substantial amount of biodiversity and ecosystem services, and likely represent the next best alternative to conserving primary forests in sustaining global biodiversity. However, the ability of these forests to rapidly recover their thermal environments will markedly influence their conservation value, particularly under mounting global climate change. The thermal environment plays a crucial role in ecosystem functioning, so a key question is how much time it takes for logged forests to recover their thermal baselines in the aftermath of selective logging. Focusing on the Brazilian Amazon, this chapter investigates how much post-harvest time is required for understorey ambient and ground surface temperatures in logging gaps and logging roads to return to unlogged primary forest levels, and how the spatial availability of surface microclimates may change considering time of recovery since logging.

Chapter 3 — Impacts of selective logging on fire risk in the Amazon

Selective logging has been extensively identified as a facilitator of fire in tropical forests for altering microclimates through canopy disturbances from felling trees and opening roads, and increasing fuel loads from operational residual damage. However, the extent to which gap edges induced by selective logging affects the forest thermal environment, and their interaction with forest flammability, had not been explored or empirically established. Thus, major uncertainties remain in understanding this relationship given the complexities in quantifying flammability in a hyper-diverse tropical environment. This chapter investigates the processes in which selective logging drives fire proneness, through studying the thermal environment and conducting a controlled fire experiment in gaps and adjacent forest in the Brazilian Amazon to tease apart and quantify the different components of flammability.

Chapter 4 — Disentangling the contributions of climatic variation and human pressures on fire occurrence in the Brazilian Amazon

Fires in tropical forests are strongly associated with droughts and anthropogenic ignition sources. Climatic and humans drivers of fire are thus likely to act synergistically in magnifying forest fire proneness, making disentangling their relative contribution to driving forest fires very challenging. This chapter utilises key climatic and anthropogenic pressures data to tease apart local climatic variation and human drivers, and explain fire occurrence across the Brazilian Amazon over the past two decades. Additionally, this chapter assesses the effectiveness of different categories of Protected Areas in inhibiting fire.

Chapter 2

Rapid recovery of thermal environment after selective logging in the Amazon

Figure 2.1: Hemispherical photograph of a logging gap one year post harvest. Jamari National Forest, Rondônia, Brazil.

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2.1 Abstract

Selective logging is one of the most widespread patterns of disturbance in tropical forests but has a much lower detrimental impact on forest structure than wildfires and conversion to farmland. Thus, logged tropical forest represents critical strongholds of global biodiversity. The ability of these forests to rapidly recover their baseline thermal environmental conditions will markedly influence their conservation value, particularly under global climate change. We investigated the impacts of commercial selective logging on the forest thermal environment in the Brazilian Amazon by relating canopy disturbance from logging to ambient understorey and ground surface temperatures. Specifically, we assessed the impact of selective logging on the forest thermal heterogeneity; how much post-harvest time is required for the thermal environment of logging gaps and logging roads return to unlogged primary forest levels; and the spatial availability of surface microclimates considering time of recovery since logging. Logging gaps following 1 year of recovery had a hotter understorey ambient than all other environments, especially during peak midday temperatures. Compared to the unlogged understorey, logging gaps after 3 years of recovery were only marginally warmer, and logging gaps after 5 years of recovery were slightly cooler. Older wide roads (5 years; 6 m) experienced very similar understorey thermal conditions to both narrow roads (3 m) after 1-5 years of recovery, and unlogged forest. Ground surface temperatures exhibited the largest discrepancies among all environments. The temperature range spanned by surface microclimates notably increased during peak midday heat in logging gaps following 1 year of recovery. Additionally, the proportion of cool area was smaller in younger logging gaps, but the average size of cool patches and their spatial aggregation was similar to that in unlogged forest. Although commercial selective logging can severely damage tropical forest structure, we found that the forest can fairly rapidly regain its thermal environment. Post-logging forest management should carefully focus on preventing fire incursions and illegal activities with special attention to those 3-5 years post-harvest. Thermal homeostasis in selectively logged tropical forests can be vital for long-term maintenance of global biodiversity under contemporary scenarios of climate change.

Keywords

Climate change, microclimate, selective logging, tropical forest

2.2 Introduction

Selective logging is one of the predominant drivers of tropical forest degradation (D. P. Edwards, Tobias, et al., 2014), and while deforestation represents the leading cause of threat, selective logging can still pose a serious risk to tropical forests and their biodiversity (Asner et al., 2006). Tropical forests are the most diverse and complex ecosystems on Earth, harbouring at least two thirds of all terrestrial biodiversity (Gardner et al., 2009; Laurance, 2007). However, over 400 million hectares of tropical forest worldwide have been designated for selective logging, with an unknown but vast area logged illegally (Blaser, Sarre, Poore, and Johnson, 2011; Michalski and Peres, 2013).

Selective logging causes substantial residual damage, increasing mortality of remnant trees, disrupting the forest canopy and causing soil compaction (Asner et al., 2004; Meijaard et al., 2005; Putz et al., 2012; Verissimo et al., 1992). Furthermore, extensive road networks are opened to enable timber extraction, thereby facilitating further exploitation of previously inaccessible forest areas (Laurance et al., 2009) creating extensive edge effects that negatively impact biodiversity (F. A. Edwards et al., 2017; Pfeifer et al., 2017).

Nevertheless, relative to wildfires and conversion to farmland, selective logging has a much lower detrimental impact on biodiversity (Gibson et al., 2011), with mammal, bird, invertebrate and plant species richness in logged forests similar to old-growth forests, including a host of forest specialists and IUCN red-listed species (Costantini et al., 2016; D. P. Edwards et al., 2011; Putz et al., 2012). Thus, selectively logged forests currently retain considerable conservation value (D. P. Edwards, Tobias, et al., 2014), but this conjecture relies on the assumption that these forests will maintain their conservation value under future climate change.

The availability and spatio-temporal distribution of microclimatic shelters in the landscape is critical for the survival of species that require and are able to track their optimal climate niche (Caillon, Suppo, Casas, Arthur Woods, and Pincebourde, 2014). Most terrestrial species experience climate at fine scales (mm to m) (Potter, Arthur Woods, and Pincebourde, 2013; Suggitt et al., 2011), especially those that thermoregulate through direct contact with the substrate surface (Kaspari, Clay, Lucas, Yanoviak, and Kay, 2015). Studies have demonstrated species strategies in avoiding suboptimal temperatures by seeking microclimatic shelters (fine scale) during macroclimatic warming (climate at coarse scales, m to ha) (Scheffers, Edwards, Diesmos, Williams, and Evans, 2014; Scheffers, Evans, Williams, and Edwards, 2014; Gonzalez del Pliego et al., 2016; Sears, Raskin, and Angilletta, 2011). The spatial variance of microclimatic shelters will therefore greatly influence the conservation value of these habitats, particularly within a logged forest landscape.

Concurrently, tropical forests are becoming more desiccated and exposed to increasingly severe heat-waves as a consequence of global climate change (Brodie, Post, and Laurance, 2012a) which poses a threat to biodiversity (I.-C. Chen, Hill, Ohlemüller, Roy, and Thomas, 2011; Esquivel-Muelbert et al., 2018; Gruner et al., 2017; Thomas et al., 2004). Over the past few decades, climate change has prompted numerous ecological responses in the phenology, abundance and distribution of plants and animals in tropical forests, including local extinctions of the most range-restricted species (I.-C. Chen et al., 2011; Parmesan, 2006; Parmesan and Yohe, 2003a). Tropical ectotherm organisms are thought to be especially vulnerable to climate change because of their adaptation to relatively stable temperature regimes, such that small changes in environmental temperature may cause large decreases in physiological performance (Logan, Cox, & Calsbeek, 2014). Changes in physiological thermal limits are, however, expected to be inadequate to match the speed and magnitude of climate change predictions (Deutsch et al., 2008; Hoffmann and Sgrò, 2011). The potentially detrimental synergism between climate change and logging disturbance can have profound unanticipated consequences on long-term biodiversity retention.

In selectively logged forests, the opening, lowering and thinning of the canopy within tree-fall gaps and roads allow a greater amount of solar radiation and wind to penetrate, creating a hotter and more desiccated thermal environment compared with undisturbed forests (Asner et al., 2004; Hardwick et al., 2015), as well as enhancing tree growth from increased light availability (Figueira et al., 2008). Over time, as logging-induced slash decomposes and tree mortality decreases, we would expect thermal conditions of forest interior to return towards those in old-growth.

After a decade of recovery, tropical forests in Borneo have similar thermal environments to unlogged primary forests, even after repeated rounds of selective logging (Senior, Hill, Benedick, and Edwards, 2017). However, much logged tropical forest is presently under a shorter recovery time (Asner et al., 2006) and we thus still need to understand how quickly the thermal environment recovers. We also still need to understand the availability of cool microclimate patches in logging gaps or roads, with Senior (2017) not focusing specifically on these core points of habitat disturbance.

Here, we focus on the thermal ambient recovery of southwestern Amazonian forests following 1 to 5 years of selective logging disturbance. Filling this knowledge gap is

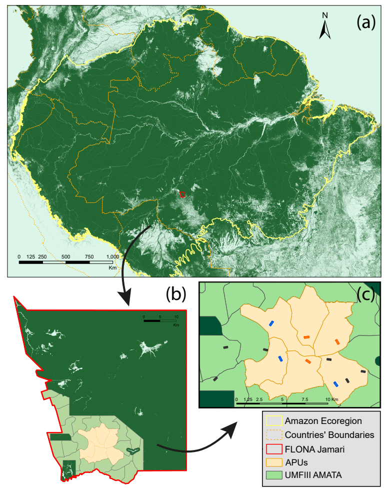

Figure 2.2: Map of the Amazon forest showing the location of FLONA Jamari (a), location of UMFIII (pale green polygons) within the FLONA (b) with differentiation of explored APUs (pale yellow polygons), and distribution of study sites (c): black rectangles indicate transects placed in unlogged and logged forests; blue and orange rectangles indicate the location of logging gaps and logging roads surveyed in this study, respectively.

particularly policy-relevant because huge tracks of forest have been selectively logged in the Brazilian Amazon over the past decades, with National Forests currently being converted into logging concessions (Brazilian Forest Service), putting their future ecosystem integrity at risk (Michalski and Peres, 2013). We assess (1) the impact of selective logging on the forest thermal environment; (2) how much time post-harvest is required for the thermal environment of logging gaps and roads to recover to unlogged (primary) forest conditions; and (3) the spatial availability of surface microclimates considering time of recovery since logging.

2.3 Material and Methods

Study Area

This study was conducted within the 2 200 km^2 Jamari National Forest (FLONA Jamari), Rondônia, Brazil, in southwest Amazonia $9^{\circ}18'S, 63^{\circ}1'W$; (Fig.2.2). Nearly half of this area (960 km^2) was set aside as a selective logging concession for commercially valuable timber tree species >40 cm in diameter at breast height (DBH) and yielding a timber harvest quota of 21.5 m^3 per hectare. A total of 460 km^2 of forest in the southern portion of FLONA Jamari, named Forest Management Unit III (UMFIII), has been managed since 2011 by the AMATA logging company, which has the responsibility of enabling post-harvest natural forest regeneration and protecting the concession from further degradation. AMATA complies with Reduced Impact Logging (RIL) techniques, such as directional felling, liana cutting and low intensity harvest. Logging operations are conducted within Annual Production Units (APUs) with an average size of 18.08 km^2 where permanent protected areas along rivers and streams are set aside, and where an average of 45.3 km of roads per APU are opened to enable operations.

This rotation system allowed us to survey commercially logged forests of similar floristic composition and climatic conditions but at different stages of natural post-logging regeneration, in a space-for-time substitution instead of a before-after study design. Control sites were sampled at the same time as the treatment, and a large number of sites with replication was used. FLONA Jamari experiences mean annual temperature of 25.8°C with modest variability and a precipitation regime ranging from 2 200 to 2 600 mm/year, which is concentrated during the wet summer season from October to April with a well-defined dry season during the austral winter months from June to September (http://en.climate-data.org/). The mature old growth forest of Jamari is widely described as Amazonian lowland open ombrophylous forest (IBGE, 2012).

Study design

Fieldwork was conducted from June to October 2016 and June to October 2017 and our sampling methods were designed to address the questions that motivated this study. Despite a strong El Niño event in 2015-2016 (Jiménez-Muñoz et al., 2016), a meteorological assessment of the region shows that our sampling periods were representative of regular climatic conditions of precipitation and air temperature observed over the last decade (Appendix Text A1, Fig. A.2).

Thermal environment in unlogged primary vs one-year logged forest

Six sites were established in 2016 within both unlogged and logged forest following 1 year of recovery, each of which consisting of three randomly located transects with 1 km of length and spaced apart by 1.5 km in each forest type. Ten plots were placed along each transect (6 sites x 10 plots = 60 plots in total) at regular 100 m intervals, within which forest structure and climatic data were sampled. Transects were placed at least

50 m from any forest edge (i.e. primary or secondary logging road), and cut without prior knowledge of forest structure in the area to reflect the overall environmental heterogeneity. Thus, unlogged and logged forests plots straddled the boundaries of several physical environmental conditions, including upland forest, narrow forest streams, and rocky sites), and in logged forests, they also intersected a variety of disturbance features, including logging gaps, skid trails, logging roads and patches of intermittently undisturbed forest canopy.

Recovery of thermal environment in logging gaps and roads

We sampled the centre of logging gaps and logging roads in APUs following 1, 3 and 5 years of recovery, in addition to primary forest controls. In 2016, we selected 30 logging gaps (10 in each of 1, 3 and 5 years since logging) and used as controls the unlogged primary forest data collected in 30 different plots for the first question (potential differences in the thermal environment in unlogged primary vs one-year logged forest). In 2017, we sampled 18 plots along logging roads of two width categories, including nine plots along 6-m wide primary roads (three in each of 1, 3 and 5 years since logging), and nine plots along 3-m wide secondary roads (three in each of 1, 3 and 5 years since logging), in addition to 10 plots in primary forest controls (28 plots in total). All plots placed along logging gaps and roads were selected prior to visiting the forest using detailed GIS spatial layers of harvest data and the entire road network, which were provided by AMATA.

Forest canopy structure

Forest structure was assessed through canopy openness data derived from hemispherical photographs (using a Canon Rebel T2i equipped with a Sigma 4.5 mm circular fisheye lens and a tripod) taken at all 118 study plots. Photographs were taken with the camera top oriented to the North and levelled with the horizon using a spirit level. Camera settings were adjusted according to the Histogram Method proposed in Beckschäfer (2013). All hemispherical photographs were binarized using the R package Caiman (available at Gaston Mauro Diaz GitHub) and a canopy openness metric was then extracted using the R package CIMES R (available at Gustaf Granath GitHub).

Forest understorey temperature

The understorey ambient air temperature was measured using iButton data loggers (model DS1921G-F5; resolution of 0.5°C) and a psychrometer (or whirling hygrometer) at all study plots. Each iButton was placed inside a re-sealable zipper storage bag and enclosed within a small metal mesh sleeve to be sheltered from water and physical damage by animals. They were then secured under plastic funnels to minimize exposure to direct solar radiation and precipitation (Gonzalez del Pliego et al., 2016) and placed at 1.5 m above ground (Scheffers et al., 2013). Although an intercomparison of sensors before and after field sampling to detect potential accuracy issues was not conducted, all of the ~180 sensors were shuffled many times among study plots in between downloading data and checking batteries over the sampling period, thereby reducing any potential bias of a particular treatment or study site. The 90 study plots sampled in 2016 had active iButtons sampling ambient air temperature at intervals of 10-min during 34 days, which amounted to approximately 440 000 temperature measurements. From these measurements, we derived the mean temperature per hour for each day in each study plot. All 28 study plots sampled in 2017 had active iButtons collecting ambient air temperature every hour for 58 days, which summed to ~25 000 temperature measurements.

Maximum ambient air temperature was calculated for each plot as the mean of values above the 90^{th}-percentile of maximum temperature during each full hour across all days. Likewise, the minimum ambient air temperature is defined as the mean of values below the 10^{th}-percentile of minimum temperature during each full hour across all days.

Forest surface temperature

To capture forest floor surface temperature we used thermal imaging technology with a FLIR-E40 Thermal Imaging Camera with a resolution of 120 x 160 pixels. At each study plot we took four photographs in four orthogonal directions (pointing North, East, South and West) while holding the camera at breast height and pointing it 45° towards the ground which captured an area of ~1m^2 per photograph (Senior, Hill, Benedick, and Edwards, 2017). Along transects and within logging gaps, each plot was visited on two different days, and within a day, each plot was sampled five times, from 04:00h to 15:00h (local time), amounting a total of 3 600 photographs (90 study points x 5 cycles within a day x 2 repetitions x 4 cardinal directions) resulting in approximately 69 million temperature samples (120 x 160 pixels x 3 600 photos). On logging roads and associated unlogged forest control plots, we sampled on two different days and during the hottest hours, from 11:00h to 15:00h, summing to approximately 2.3 million temperature samples. Additionally, measurements of light intensity using a luxmeter, and relative humidity and air temperature using a psychrometer, were obtained synchronously three metres away from each thermal photo.

The four photographs taken within each plot at each time point (visit) were then considered as one large matrix (4x120x160) that captured information in a larger area of ~4 m^2. The minimum, maximum and mean temperature values of each study plot at each repetition are the mean of values below the 5^{th}-percentile of the distribution of temperature values, the mean of values above the 95^{th}-percentile, and the mean of values between the 47.5^{th} and the 52.5^{th}-percentiles, respectively. Raw data from thermal images were extracted and converted into temperature data using the R package Thermimage (R Core Team, 2017; Tattersall, 2017). This routine allows the adjustment of several parameters, such as the object distance from the thermal camera, atmospheric temperature and relative humidity, thereby ensuring more precision in the conversion to temperature estimates. We provide an analytical procedure containing a script in R for data extraction and conversion of thermal images (Appendix Text A2).

Surface microclimate availability

We used thermal photos taken within logging gaps and primary forest in 2016 (60 study plots) to derive spatial information of microclimatic shelters on the surface of the forest floor and assess their recovery after selective logging. First, we identified spatially explicit patches of cool and warm pixels (Fig. A.4) using the Getis–Ord local statistic for each pixel within the neighbourhood of the nearest eight pixels (function 'localG' from the 'spdep' package in R) (Bivand and Piras, 2015; Getis and Ord, 1996; R Core Team, 2017). From these patches, we then calculated four variables: **(i)** thermal diversity was modelled as the range between the warmest warm patch and the coolest cool patch, which was obtained by subtracting the median temperature of the warmest warm patch by the median temperature of the coolest cool patch across the four photographs; **(ii)** average size of cool patches was obtained as the total number of cool pixels multiplied by the surface area of one pixel (0.52 cm^2) and divided by the total number of cool patches across the four photos; **(iii)** proportion of cool area was quantified as the ratio between the total number of cool pixels multiplied by the surface area of one pixel (0.52 cm^2) and the total area captured by the four photos (4 m^2); we then quantified the spatial configuration of cool pixels using the **(iv)** Aggregation Index, defined as the number of edges shared by cool pixels (inside cool patches), divided by the maximum number of edges that could be possibly shared (i.e. if all pixels were aggregated within a single patch) (He, DeZonia, and Mladenoff, 2000).

Higher Aggregation Index values of cool patches indicate increased clustering of microclimates in space (Sears et al., 2016), which represents increased difficulty for organisms to track. However, we do not think that this index alone is enough to conclude whether a surface is more or less suitable for animals' movements. The proportion of cool pixels, the average size of cool patches and the actual temperature of cool patches must also be considered alongside their spatial aggregation. The combination of these four components is much more informative of the surface suitability in providing microclimatic shelters for animals. We provide an analytical procedure containing a R script for identifying patches, calculating thermal diversity, proportion of cool and warm areas, average size of cool patches and the Aggregation Index (Appendix Text A3).

Statistical analysis

All data were analysed using mixed effect models in the "nlme" library in R (Pinheiro, Bates, DebRoy, Sarkar, and Team, 2018; R Core Team, 2017). Models were selected according to a combination of model comparisons of Akaike's Information Criterion (AIC), which is a tool for model selection where the model with the lowest AIC indicates the best model, i.e. that which offers the best fit whilst penalising for number of parameters (Akaike, 1974), and a visual interpretation of heterogeneity and normality of residuals (Zuur, Ieno, Walker, Saveliev, & Smith, 2013). To compare the understorey thermal environment between forest types, we modelled air temperature data and surface temperature data separately. All models included 'forest type' (part 1: unlogged vs logged; part 2: logging gaps with 1, 3 and 5 years of recovery vs unlogged forest; and: primary and secondary logging roads with 1, 3 and 5 years of recovery vs unlogged forest), forest structure ('canopy openness') and 'hour' as fixed explanatory variables. The availability of surface microclimatic shelters (part 3) was analysed using four microclimate response variables (thermal diversity, average size of cool patches, proportion of cool area and Aggregation Index), each of which were modelled against 'forest type' (logging gaps with 1, 3 and 5 years of recovery vs unlogged forest), forest structure ('canopy openness') and 'hour' as fixed explanatory variables. In addition, average size of cool patches, proportion of cool area and Aggregation Index were modelled using a subset of the thermal photography data spanning only hours of the day when temperature values are at their highest (10:00h to 13:00h), which comprises the period during which animals are most likely thermally constrained.

To account for spatial and temporal pseudoreplication, data were grouped with 'plot' nested within 'transect', both of which were nested within 'date'. For comparisons of maximum and minimum temperatures between forest types, models included 'plot' nested within 'transects' to account for spatial pseudoreplication, but because the calculation of maximum and minimum temperature values summarised the information into one hypothetical day, they were not nested within 'date'. Models were assessed for evidence of temporal autocorrelation of residuals (function "acf" in the "nlme" package) and a correlation structure was incorporated and adjusted according to the residuals. For investigations of thermal differences during specific parts of the day, data were divided into daytime (from 09:00h to 15:00h) and nighttime (00:00h to 06:00h). The basic structure of models used in these analysis was:

$$RV \sim Forest\ Type + Canopy\ Openness + Hour,\ + (\sim Transect \mid Plot\ ),$$
$$cor(\sim date \mid Transect\ /\ Plot\ )$$

2.4 Results

2.4.1 Thermal environment in unlogged primary vs one-year logged forest

We found a very small difference in understorey ambient temperature 1 year after selective logging, with unlogged forest on average only 0.08°C cooler than logged forest (±0.03 p<0.005; Fig.2.3). The unlogged forest understorey also experienced lower maximum temperatures per hour throughout the day (-0.34°C ±0.10 p<0.05; Fig. A.5a) but there was no difference in minimum temperatures (p=0.19; Fig. A.5b) compared to logged forest. Surface temperatures of the forest floor showed no differences between unlogged and logged forests in mean (p=0.65; Fig.2.3c), maximum (p=0.48; Fig.2.3b) and minimum temperatures (p=0.63; Fig.2.3d) per hour throughout the day.

Considering the general temperature curve across the diurnal cycle, it was evident that differences in temperature occurred during the hottest hours. To explore this, we divided the day into time periods and found that unlogged forest daytime temperatures (09:00h to 15:00h) were cooler than those in logged forests by 0.18°C in the understorey ambient (±0.07 p<0.01) and 1.26°C on the forest floor surface, albeit with greater uncertainty (±0.70 p=0.1). Unlogged and logged forest nighttime temperatures were not significantly different, both in the ambient air (p=0.17) and ground surface (p=0.63). The influence of canopy openness on temperature variation between logged and unlogged forests was notably greater during daytime, with a potential maximum increase of 9.15°C in the understorey ambient (±0.39 p<0.001) and 10.40°C on mean temperatures of ground surface (±3.07 $p\leq$ 0.001).

2.4.2 Recovery of thermal environment in logging gaps

Understorey ambient temperatures in logging gaps after 1 year of recovery were 0.23°C warmer than in unlogged forests (±0.04 p<0.001), 0.46°C warmer than in 5 year-old logging gaps (±0.04 p<0.001) and only 0.18°C warmer than in 3 year-old logging gaps (±0.04 p<0.001) throughout the day (Fig.2.4a). Logging gaps after 3 years of recovery had understorey ambient temperatures a little warmer than the unlogged forest, albeit with high uncertainty (0.04°C ±0.03 p=0.17), and, logging gaps after 5 years of recovery had understorey ambient temperatures marginally cooler than the unlogged forest (-0.23°C ±0.03 p<0.001) throughout the day (Fig.2.4a). Differences are larger when we make comparisons during daytime, with the understorey ambient of 1 year-old logging

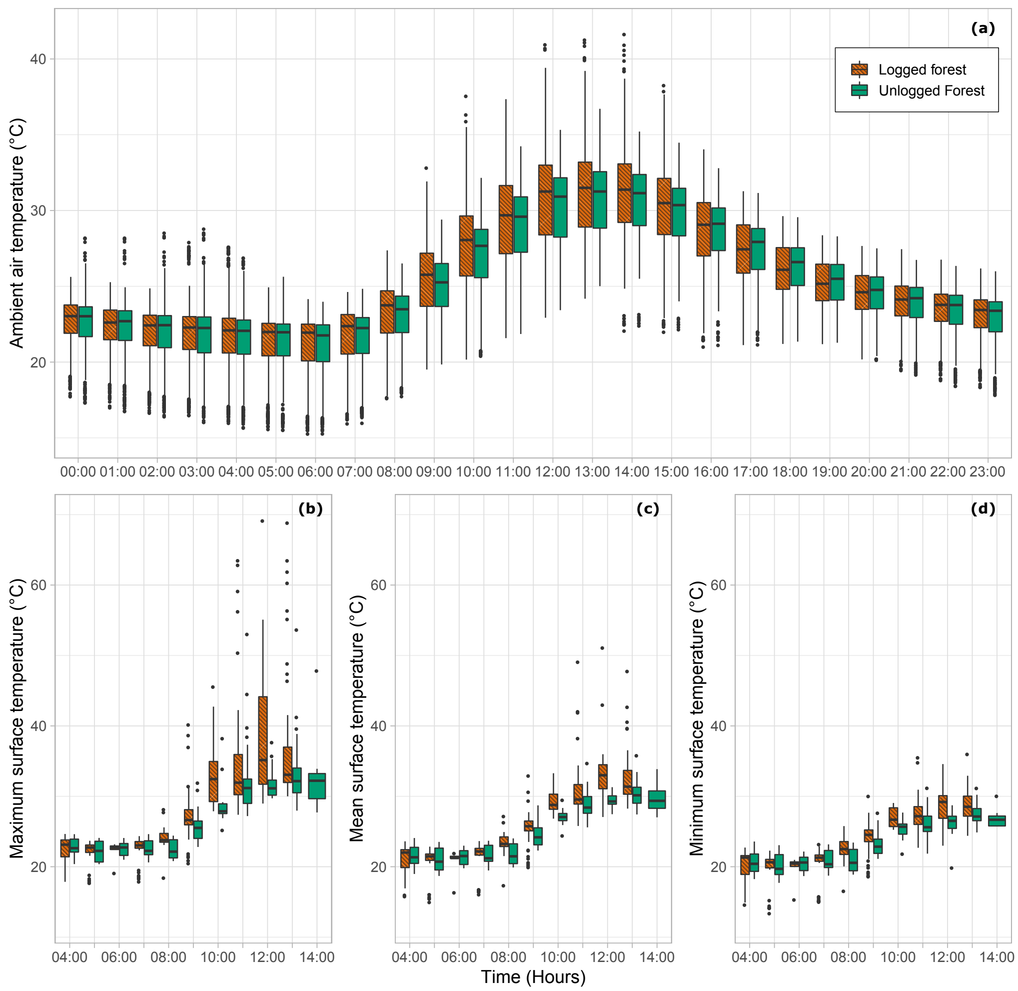

Figure 2.3: Fitted values of understorey ambient temperature throughout the (a) 24-hour diurnal cycle. Bottom row shows fitted values of (b) maximum, (c) mean and (d) minimum surface temperature for all hours for which thermal data were available (04:00h to 15:00h) in logged forest following 1 year of recovery and unlogged primary forest. Black dots represent outliers.

gaps being 0.72°C warmer than both unlogged forests and 3 year-old logging gaps (±0.09 and ±0.08 $p<0.001$), and 1.28°C warmer than 5 year-old logging gaps (±0.08 $p<0.001$). However, understorey ambient temperatures in unlogged forests were not statistically different than in 3 year-old logging gaps ($p=0.8$) and, were a little warmer than in 5-year old logging gaps (0.58°C ±0.08 $p<0.001$). During nighttime, differences were smaller among forest types, with the understorey of 1 year-old logging gaps 0.22°C warmer than unlogged forests (±0.06 $p<0.001$), 0.39°C warmer than 5 year-old logging gaps (±0.05 $p<0.001$) and only 0.11°C warmer than 3 year-old logging gaps (±0.05 $p<0.05$).

Mean forest floor surface temperatures were not different among forest types throughout the day (thermal photos available from 04:00h to 15:00h; $p>0.5$; Fig.2.4c) and during nighttime (04:00h to 06:00h; $p>0.5$). However, during daytime (09:00h to 15:00h), 1 year-old logging gaps were 4.40°C warmer than unlogged forests (±1.90 $p\leq0.05$) and 5.52°C warmer than 5 year-old logging gaps (±2.50 $p\leq0.05$), and warmer but marginally non-significantly so versus 3 year-old logging gaps (3.83°C ±2.12 $p=0.10$). Maximum surface temperatures showed much greater differences during daytime, with 1 year-old logging gaps being 7.94°C (±2.24 $p<0.05$), 12.43°C (±2.28 $p<0.001$) and 10.38°C (±2.02 $p<0.001$; Fig.2.4b) hotter than logging gaps after 3 and 5 years of recovery and unlogged forests, respectively. Minimum surfaces temperatures were more similar among forest types even during peak day temperatures (Fig.2.4d). Logging gaps after 1 year of recovery had higher minimum values of surface temperatures, and with high uncertainty, than 3 and 5 year-old logging gaps by 2.28°C (±1.70 $p=.21$) and 2.70°C (±1.97 $p=.20$) respectively, and by 3.14°C (±1.54 $p=0.07$) when compared to unlogged forests (Fig.2.4d). As with part 1 of this study, the influence of canopy openness on temperature was greater during daytime with a potential maximum increase of 3.35°C on the understorey ambient (±0.52 $p<0.001$) and of 4.56°C on mean temperatures of ground surface, albeit the latter with high uncertainty (±5.42, $p=0.4$).

2.4.3 Recovery of thermal environment in logging roads

Understorey ambient air in logging roads showed greater differences between categories (primary and secondary) during daytime, with the most recently made and largest logging roads (1 year-old primary roads) being 1.42°C warmer than secondary roads with the same time of recovery, and 1.92°C warmer than unlogged forests (±0.08 $p=0.001$). While 1 and 3 year-old primary roads were over 1°C warmer than unlogged forests, secondary roads showed smaller differences, ranging around 0.5°C, and both primary

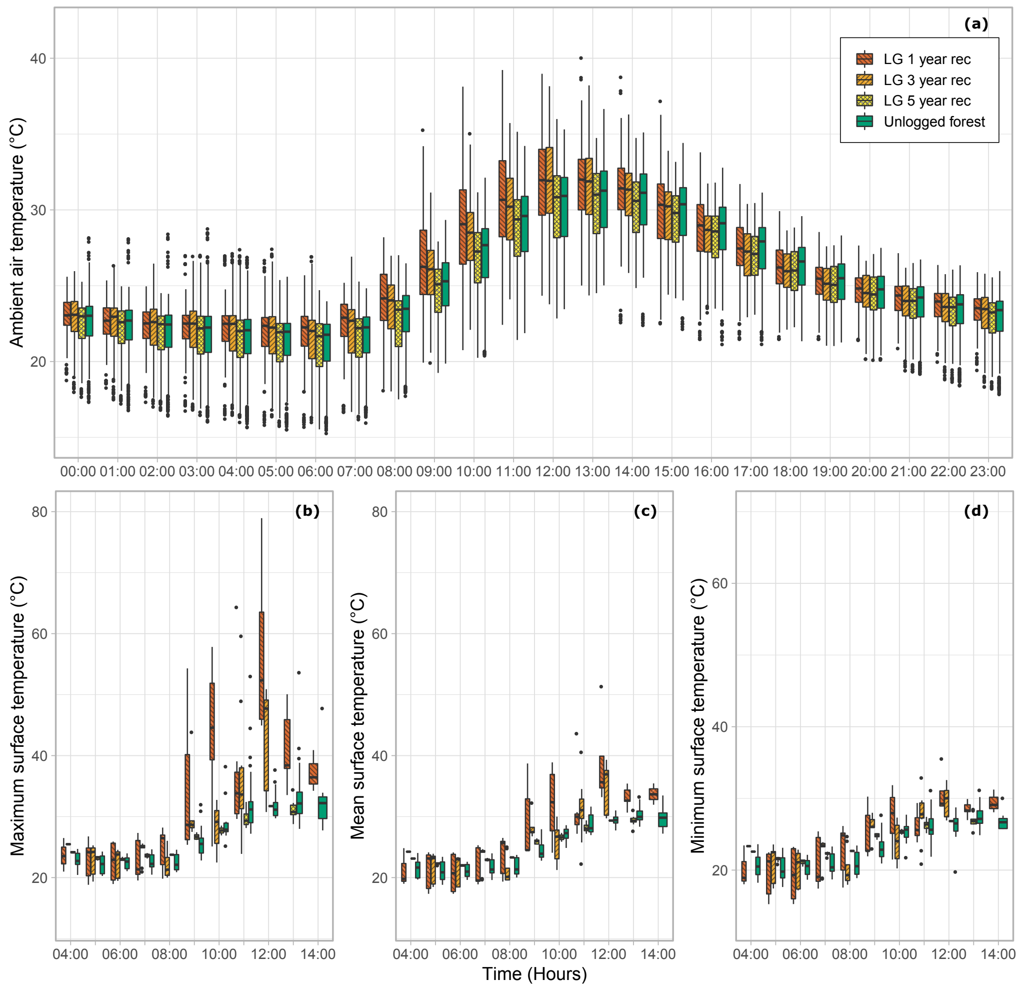

Figure 2.4: Fitted values of understorey ambient temperature throughout the (a) 24-hour diurnal cycle. Bottom row shows fitted values of (b) maximum , (c) mean and (d) minimum surface temperature for all hours for which thermal data were available (04:00h to 15:00h) in logging gaps after 1, 3 and 5 years since logging, and unlogged forests. Black dots represent outliers; LG= Logging Gap; rec= recovery.

Table 2.1: Understorey ambient temperature during all day (top table), daytime (middle table) and nighttime (bottom table) in unlogged forest and logging roads on three stages of recovery (1 year, 3 years and 5 years), and two categories, primary (PR) and secondary (SR). Values are presented ± SE and for each hour.

Type			All day												
			00:00h	p	02:00h	04:00h	06:00h	08:00h	10:00h	12:00h	14:00h	16:00h	18:00h	20:00h	22:00h
Unlogged Forest			23.34 ± 0.16	<0.001											
Logging Road	1 year	PR	23.17 ± 0.04	<0.001											
		SR	23.16 ± 0.03	<0.001											
	3 years	PR	22.82 ± 0.03	<0.001	-0.59 ± 0.03 p <0.001	-1.08 ±0.05 p <0.001	-1.40 ± 0.06 p <0.001	0.79 ± 0.09 p <0.001	5.21 ± 0.20 p <0.001	7.62 ± 0.23 p <0.001	7.53 ± 0.26 p <0.001	5.63 ± 0.21 p <0.001	3.31 ± 0.17 p <0.001	1.71 ± 0.14 p <0.001	0.75 ± 0.13 p <0.001
		SR	22.89 ± 0.04	<0.001											
	5 years	PR	22.95 ± 0.04	<0.001											
		SR	22.81 ± 0.04	<0.001											

Type			Daytime							
			09:00h	p	10:00h	11:00h	12:00h	13:00h	14:00h	15:00h
Unlogged Forest			26.12 ± 0.19	<0.001						
Logging Road	1 year	PR	28.04 ± 0.08	<0.001						
		SR	26.62 ± 0.06	<0.001						
	3 years	PR	27.23 ± 0.07	<0.001	2.22 ± 0.07 p <0.001	3.7 ± 0.11 p <0.001	4.61 ± 0.13 p <0.001	4.84 ± 0.17 p >0.001	4.50 ± 0.20 p <.001	3.73 ± 0.20 p <0.001
		SR	26.74 ± 0.08	<0.001						
	5 years	PR	25.96 ± 0.08	<0.05						
		SR	25.88 ± 0.09	<0.05						

Type			Nighttime							
			00.00h	p	01:00h	02:00h	03:00h	04:00h	05:00h	06:00h
Unlogged Forest			23.37 ± 0.16	<0.001						
Logging Road	1 year	PR	23.05 ± 0.04	<0.001						
		SR	23.11 ± 0.03	<0.001						
	3 years	PR	22.73 ± 0.04	<0.001	-0.31 ± 0.02 p <0.001	-0.59 ± 0.03 p <0.001	-0.83 ± 0.04 p <0.001	-1.07 ± 0.05 p <0.001	-1.30 ± 0.06 p <0.001	-1.39 ± 0.06 p <0.001
		SR	22.82 ± 0.04	<0.001						
	5 years	PR	22.95 ± 0.04	<0.001						
		SR	22.89 ± 0.04	<0.001						

and secondary roads after 5 years of recovery were marginally cooler than unlogged forests (-0.16°C ±0.08 p=0.05 and -0.24°C ±0.09 p<0.05). During nighttime, ambient temperature between primary and secondary roads at the same recovery stage only varied around 0.1°C between categories, and the largest difference found (of 0.64°C ±0.03) was between unlogged forests and 3 year-old primary roads (Table 2.1). Forest floor surface temperatures on logging roads of all recovery stages and categories were not different than those observed in unlogged forests (p>0.5).

2.4.4 Surface microclimate availability

All surface microclimatic metrics analysed in this study (thermal diversity; average size of cool patch; proportion of cool area and Aggregation Index) influence the ease with which organisms that are able to move and track their optimal climate niche can use surface microclimates. We found that the temperature range spanned by surface microclimates (thermal diversity) was massively increased during peak day temperatures. During the warm-hours period (09:00h to 15:00h), 1 year-old logging gaps experienced patch temperature range 9.93°C hotter than that observed in unlogged forests (±2.08 p<0.005; Fig.2.5b), while before the warm-hours period (04:00h to 09:00h) this range was only 0.91°C warmer (±0.41 p≤0.05; Fig.2.5a). Both during warm-hours and before-warm-hours, there was no significant difference of patch temperature range between 3 and 5 year-old logging gaps and unlogged forests (p>0.5). The increase in patch temperature range is consistent with the considerable increase in maximum surface temperatures followed by a more modest increase of minimum surface temperatures throughout the day observed in all forest types (Fig.2.5c, d, e and f).

The average size of cool patches was not impacted by forest type (p>0.5; Fig.2.6a). However, the proportion of cool area was larger in 5 year-old logging gaps (8.62% ±0.68) and in unlogged forests (8.02% ±0.64) than in 1 (6.46% ±1.13) and 3 year-old logging gaps (7.23% ±0.45) (Fig.2.6b). Furthermore, the aggregation of cool patches was marginally different among forest types (AI = 0.80 ±0.02; Fig.2.6c) but was overall a high Aggregation Index, which indicates increased clustering of cool patches in all forest types.

2.5 Discussion

Logged tropical forests can retain most of their ecosystem services, functions and biodiversity (D. P. Edwards, Tobias, et al., 2014), but this relies on the assumption that these forests will continue to maintain their conservation value after harvest, which can be threatened by repeated rounds of logging (Asner et al., 2006), clear-cuts and wildfires (Cochrane, 2003), all of which may be aggravated by unanticipated extreme climatic events (Aragão et al., 2007). The El Niño event of 2015-2016 caused not only record breaking heat but also an unusual wet-dry spatial distribution pattern in the Amazon (Jiménez-Muñoz et al., 2016).

Even though our study was conducted partially at the end of the 2015-2016 El Niño event, we found no evidence that our results on the forest's thermal environment were directly affected due to climatic conditions during our sampling matching the precipitation and air temperature over the last decade (Appendix Text A1, Fig. A.2). Still, severe droughts and heat waves may interact synergistically with logging in magnifying each other's impacts and threatening tropical biodiversity (Brodie et al., 2012a). Thus, the impact of logging on the forest thermal environment and the rate with which it returns to the baseline levels of a primary forest is crucial in dictating the potential of logged forests to cope with extreme climatic events and maintain their long-term conservation value.

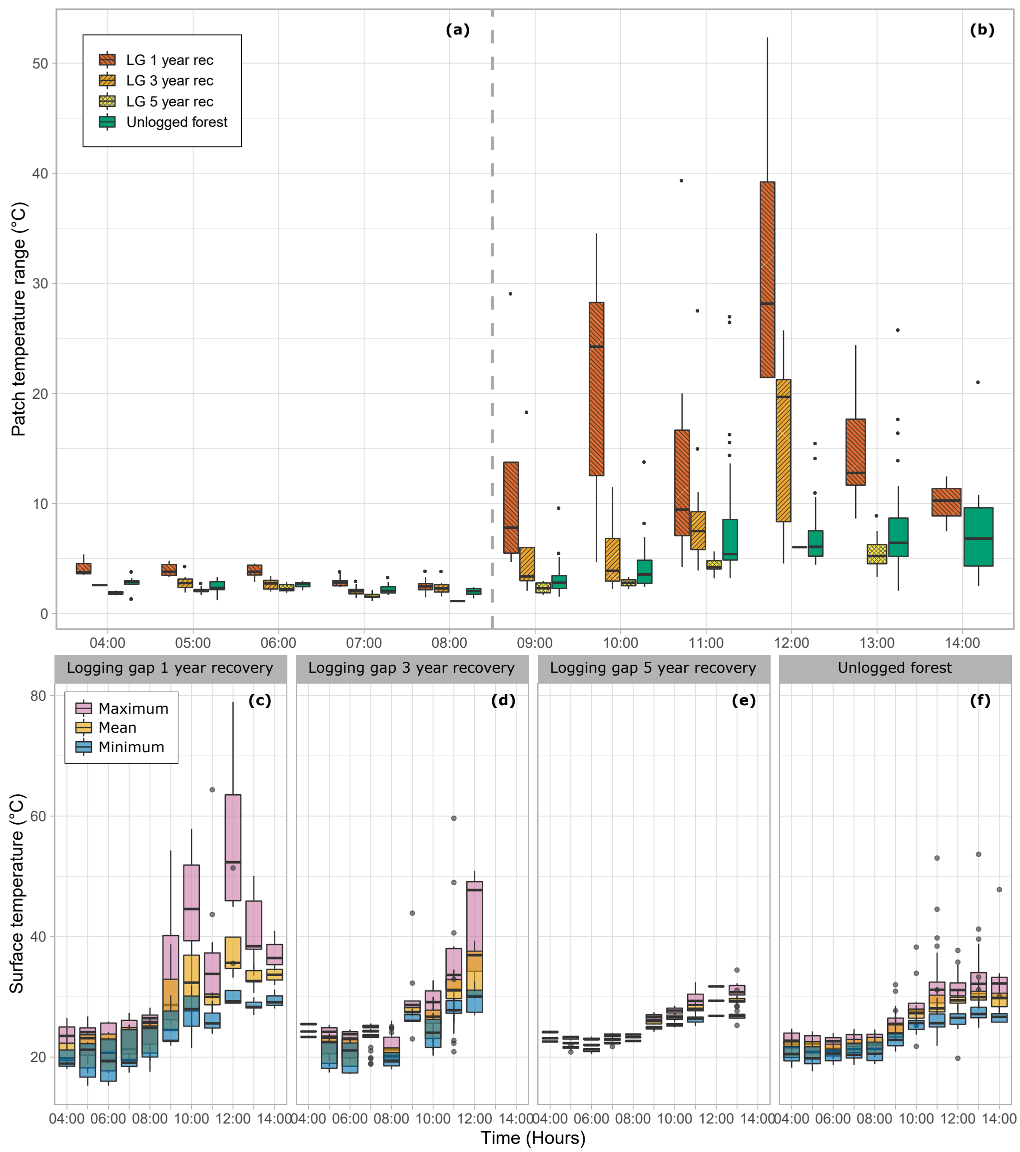

Figure 2.5: Fitted values of patch temperature range from the warmest warm patch to the coolest cool patch across before-warm-hours (a) and warm-hours (b) in logging gaps after 1, 3 and 5 years since logging, and unlogged forests. Bottom row shows maximum, mean and minimum surface temperatures for all hours for which thermal data were available (04:00h to 15:00h) in logging gaps after 1 (c), 3 (d) and 5 years (e) since logging, and unlogged forests (f). Black dots represent outliers; LG= Logging Gap; rec= recovery.

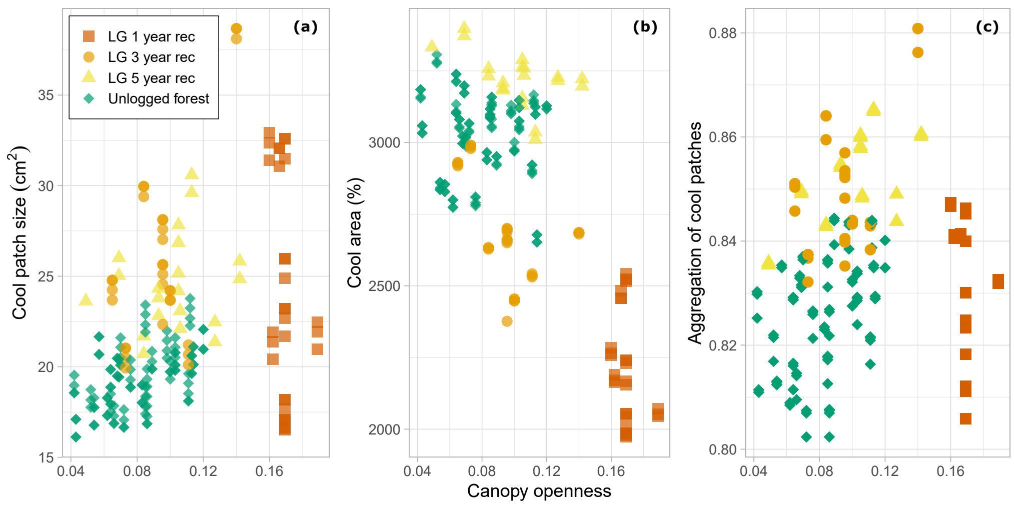

Figure 2.6: Influence of forest canopy structure (measured as canopy openness) and forest type: logging gaps after 1, 3 and 5 years since logging, and unlogged forests on microclimatic availability, which includes: (a) average surface area of cool patches, (b) proportion of cool temperatures and (c) aggregation of cool patches. LG= Logging Gap; rec= recovery.

2.5.1 Thermal environment in unlogged primary vs one-year logged forest

Focusing on the southwestern Brazilian Amazon, we found that after just one year since logging, the forest thermal environment becomes largely similar to that of unlogged forest considering the whole landscape and its natural heterogeneity. This is an important finding for forest management and tropical conservation because it indicates that low intensity harvest combined with reduced-impact logging techniques can enable rapid recovery trajectories of the thermal environment, thereby not being the reason for selectively logged forests not to maintain biodiversity.

Despite the negative impacts associated with selective logging in tropical forests (Asner et al., 2006), our study uniquely shows that the post-harvest vegetation regrowth can allow the thermal environment to recover fairly rapidly. Given these findings, we emphasize the importance of protecting forest integrity over the years following selective logging with focus on the thermal environment and its implications for biodiversity conservation retention and recovery.

2.5.2 Recovery of thermal environment in logging gaps

Understorey ambient air in logging gaps after 3 years of recovery was only marginally warmer than that in unlogged forest. Such rapid recovery of the understorey thermal environment is evidence of ecosystem resilience, and represents good news for biodiversity retention and decreased post-logging fire risk (Asner et al., 2006; Cochrane et al., 1999). In logging gaps after 5 years of recovery, the understorey was even slightly cooler than in unlogged forest, which could be related to variations in forest structure given that natural tree fall gaps also occur and are thus randomly encountered in primary forest. Moreover, we emphasize that although statistically different, this variation is not biologically very meaningful.

While understorey ambient air temperatures were only around 1°C warmer in 1 year-old logging gaps compared to the unlogged forest, surface temperatures on the forest floor were on average ~5°C warmer and ~10°C hotter in terms of daytime mean and maximum temperatures, respectively. These values likely result from a combination of effects, but most importantly, it is the open canopy structure that allows solar radiation to strike directly the forest floor creating sunflecks that can linger for long periods of time. Such elevated ground surface temperatures in logging gaps likely exceed the critical thermal maximum of many species and represent an obstacle for species tracking suitable microclimatic conditions, such as leaf-litter invertebrates and herpetofauna (Kaspari et al., 2015; Vitt, Sartorius, Avila-Pires, Zani, and Espósito, 2005). Still, minimum surface temperatures showed a much smaller discrepancy among logging gaps in different stages of recovery, even during peak day temperatures. Such cool patches on the forest floor can potentially serve as thermal corridors for species that can move and track their optimal climate niches (Gonzalez del Pliego et al., 2016).

2.5.3 Surface microclimate availability

Species options in responding to changes in their thermal environment are limited by their own ability to track optimal climates combined with the thermal landscape configuration on their surroundings (Sears et al., 2016; Sears et al., 2011). We have shown that the thermal spectrum of surface microclimates is largely affected by logging gaps during the heat of the day which accentuates the importance of microclimatic shelters for the persistence of thermally constrained organisms, specially under global warming scenarios (Sinervo et al., 2010). Furthermore, the proportion of cool microclimates on the surface of the forest floor was lower in recently formed logging gaps, which, in combination with highly clustered cool patches, represents a more challenging landscape in which organisms can operate (Sears et al., 2016). The average size of cool patches was, however, not affected by logging, which is in agreement with a logged forest in Borneo following a decade of recovery (Senior, Hill, Benedick, and Edwards, 2017).

2.5.4 Recovery of thermal environment in logging roads

Microclimatic alterations caused by canopy damage from logging road networks have been highlighted as a strong determinant in ecological changes in small mammal (Malcolm and Ray, 2000) and insect populations (Hosaka et al., 2014). We found that the thermal environments of both narrow secondary roads under all stages of recovery (1, 3 and 5 years) and wider but older primary roads after 5 years of recovery were very similar to that in unlogged forest, even during daytime when differences in temperature become more noticeable. Wider and more recent roads, however, had warmer understorey environments, which emphasises the imperative of strategic road design in production forests to more effectively preserve biodiversity and retain ecological functions (F. A. Edwards et al., 2017; Hosaka et al., 2014).

Ground surface temperatures of logging roads were not different among all forest types. One possible explanation of why our thermal imagery approach missed capturing temperature variation of logging roads, is likely related to leaf litter properties and quantities, which vary according to the road's stage of recovery after harvest. In addition, the centre of logging roads is likely to have a much less dense leaf litter layer, if any, than the forest interior, which could have influenced the degree to which ground temperatures were captured by thermal imagery.

Another caveat regarding our sampling of logging roads is the lack of consideration of these linear features orientation in respect to solar angles, which could lead to a misinterpretation of the thermal environment properties and recovery rates (Forman et al., 2003). Clearings parallel to the solar track are more exposed to solar radiation than perpendicular ones, are thus are more likely to have their thermal environment impacted (Laurance et al., 2009). Even though roads are linear features along which the sun path could linger for longer periods depending on their orientation and time of year, they can equally exist underneath the undisturbed upper canopy and therefore never receive direct solar radiation, aside from sunflecks. In contrast, logging gaps are not long linear features like roads, and only allow shorter time periods of direct sunlight exposure. Nevertheless, logging gaps nearly always disrupt the upper canopy allowing direct sunlight to penetrate the forest interior. Additionally, our study did not have soil compaction data, although all roads were created by the same bulldozer which likely created similar levels of soil compaction.

2.5.5 Forest canopy structure

The thermal environment is greatly dependent on the forest structure. Instead of having a binary classification of 'Gap/Non-Gap', which does not reliably reflect the diversity of recovery trajectories after a treefall, our study used the quantitative variable 'canopy openness' which is able to capture a broader range of canopy structures. Canopy damage, rather than stem damage, is the most suitable measure of logging damage (Malcolm and Ray, 2000). The degree of canopy disruption is related to the methods implemented (e.g. reduced impact logging vs conventional logging) (Bicknell et al., 2014) and the intensity of selective logging (Burivalova et al., 2014), which in our study were reduced impact logging areas that had experienced low intensity harvest (maximum of ~16m^3/ha). Thus, it is likely that a higher level of canopy disturbance caused by higher intensity offtakes would promote a longer-lasting impact on the thermal environment. However, after multiple rounds of selective logging summing 145 m^3/ha harvested in Borneo, thermal recovery was complete within ~10 years (Senior, Hill, Benedick, and Edwards, 2017). Furthermore, within individual logging gaps, we would expect the size of trees felled, rather than the harvest intensity to have an effect, suggesting that even in higher intensely logged forests, many gaps could still return to thermal parity with a primary forest within 5 years.

2.5.6 Conclusions

The ability of selectively logged forests to cope with increasingly severe climate change will directly dictate their capacity to protect species and retain biodiversity. This study suggests that rapid thermal recovery of the forest understorey is achievable given a low-intensity harvest guided by reduced-impact logging techniques. While we acknowledge that primary forests are unparalleled for sustaining tropical biodiversity (Gibson et al., 2011), selectively logged forests in the tropics are becoming increasingly ubiquitous and likely represent the next best alternative to sustaining biodiversity and ecosystem services and preventing more destructive land-use change (D. P. Edwards, Gilroy, et al., 2014). Therefore, we highlight the importance of enforcing smart and strategic planning of selective logging operations that include intensity limits, reduced-impact logging techniques, efficient design of road networks and ensure post-harvest protection from wildfires and illegal activities during at least the first five years after harvest.

Acknowledgements

We thank all staff members at the AMATA logging company for logistical support at FLONA Jamari and all field assistants for data acquisition. M.M.M. was funded by the Brazilian Council for Scientific and Technological Development (CNPq) through the Science Without Borders scholarship program, and the Rufford Foundation. We also thank Felix Lim, Marcelo Mollinari and Renato Rodrigues for analytical support. Declarations of interest: none.

Chapter 3

Impacts of selective logging on fire risk in the Amazon

Figure 3.1: Tent structure set up for the controlled fire experiment in this study. Jamari National Forest, Rondônia, Brazil.

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Mollinari MM, Peres CA, Edwards DP. **Impact of logging gaps on fire risk in the Amazon.**

3.1 Abstract

Vast expanses of tropical forest worldwide are currently slated for selective logging, and while these forests can still harbour a substantial amount of biodiversity and carbon, maintaining their future conservation value relies heavily on preventing post-logging fire. Selective logging facilitates tropical forest fires by altering microclimates through canopy disturbances from felling trees and opening roads, and by increasing fuel loads from residual damage. However, the extent to which forest edges induced by selective logging affect the forest thermal environment and flammability have not been empirically established. Focusing on a selectively logged forest in the Brazilian Amazon one year post-harvest and at peak temperature hours in the dry season, we investigated how selective logging affected: **(i)** the thermal environment of gaps and adjacent forest using dataloggers for understorey ambient and thermal images for ground surface temperatures; and **(ii)** forest flammability, using a controlled fire experiment.

Logging gaps were hotter and drier than the surrounding forest, causing a steep leaf-litter desiccation rate and increased fire intensity, especially at larger logging gaps. However, the ease with which fuel catches fire when exposed to an ignition source and the ability to sustain that fire did not vary from gaps to forest after simulated rainfall. Furthermore, even at saturated moisture content, leaf litter still had a 10% chance of igniting when exposed to an ignition source for at least 3 seconds. Our study thus shows that logging gaps have a direct influence on forest vulnerability to fire by accelerating leaf-litter desiccation and increasing fire intensity, but the entire landscape is equally able to catch and sustain fire. Given that fire proneness also depends strongly on exposure to ignition sources, strategic and careful planning to limit logging gap size, as well as stricter control of ignition sources in concessions and post-logging management, are both required to prevent fire incursions and preserve the structure of selectively logged forests.

Keywords

Edge effect, flammability, forest management, microclimate, selective logging, thermal camera.

3.2 Introduction

Selective logging is a major driver of tropical forest degradation and continues to expand globally (Lewis et al., 2015). At least one fifth of the humid tropical forest biome was affected by selective logging at some level between 2000 and 2005 (Asner et al., 2009). Beyond impacting vegetation structure and composition (Costa & Magnusson, 2002) and damaging soils (Feldpausch et al., 2010), selective logging affects forest microclimates by disrupting the canopy through gaps and roads (Mollinari, Peres, & Edwards, 2019), and increasing fuel loads from mechanized operational residual damage (Holdsworth and Uhl, 1997). Selective logging has therefore been extensively identified as a facilitator of fire in tropical forests (Cochrane and Schulze, 1999; Nepstad et al., 1999). However, major uncertainties remain in understanding this relationship given the complexities in quantifying flammability in a hyper-diverse tropical environment.

Fire in tropical rainforests has been a rare agent of disturbance with natural return intervals of hundreds or thousands of years (Goldammer, 1990; Saldarriaga and West, 1986). Recently, however, anthropogenic pressures, such as land-use and climate change, have increased fire frequency in the Amazon into an annual process (Aragão et al., 2008; Malhi et al., 2008; Robinne et al., 2018). Forest susceptibility to fire depends on the availability of ignition sources, and on local climatic and fuel conditions (Gill and Zylstra, 2005), all of which are likely altered in selectively logged forests. Determining flammability of a hyper-diverse tropical forest is a challenging task (Pausas, Keeley, and Schwilk, 2017), since a mixture of species with different chemical and physical properties composing the fuel load can create a multitude of flammability responses. Given that logged tropical forests are widespread across the tropics (Laurance, Sayer, and Cassman, 2014), failing to properly account for the impacts of selective logging on forest flammability can severely underestimate fire risk.

Although neither logging nor surface fires kill all trees, many individuals and species are killed, severely damaging forests (Nepstad et al., 1999) and increasing forest vulnerability to future burning (Cochrane and Schulze, 1999; Uhl and Kauffman, 1990). Tropical wildfires alter species composition and reduce species richness (Barlow and Peres, 2008), promote local extinctions (Pausas, 2015), release huge amounts of carbon to the atmosphere (Y. Chen et al., 2017), induce human health problems, and degrade the forest economic value (Gaveau et al., 2014). To preserve the forest structure after selective logging, it is paramount to focus on preventing fire incursion through a combination of strategic landscape planning and protection measures (Cochrane, 2002).

Historically, widespread fires in the tropics were associated with severe droughts (Meggers, 1994; Swaine, 1992), the most extreme of which are associated with the occurrence of El Niño episodes (Y. Chen et al., 2017; Cochrane and Laurance, 2008; J. S. Levine et al., 1999), which have become more frequent over the past few decades and will likely become more frequent and intense under future scenarios of climate change (Malhi et al., 2008; Timmerman et al., 1999). On average, reductions in precipitation and terrestrial water storage increased fire emissions in pan-tropical forests by 133% during and following El Niõo as compared with La Niña (Y. Chen et al., 2017). The combination of more frequent and intense El Niño episodes, which would further impact forests' biomass productivity (Feldpausch et al., 2016), with potentially drier forests following selective logging, could interact synergistically in magnifying fire proneness. Thus, considering that more extreme climatic events are predicted (Brodie et al., 2012b) and that logging continues to expand into undisturbed primary forests, it is critical that we unravel this relationship to better inform logging management focusing on fire prevention.

Undisturbed closed-canopy tropical rainforests hold elevated air humidity, which renders wildfires very unlikely to be sustained (Bowman, 2017; Uhl, 1998). However, the selective harvest of commercially valuable species perforates the forest, damaging its structure and creating edges, which exposes the forest interior to wind and heat penetration (Laurance et al., 2002; Pohlman, Turton, and Goosem, 2009). Edge effects have been recognized as pervasive and deleterious processes in tropical forests (Gascon, Williamson, and da Fonseca, 2000; Pfeifer et al., 2017). They can alter forest dynamics by changing vegetation structure and species richness, increase rates of tree mortality leading to elevated carbon emissions, and facilitate species invasions (Armenteras, González, and Retana, 2013; Cochrane, 2003; Laurance and Useche, 2009). However, the extent to which gap edges induced by selective logging affects the forest thermal environment, and their interaction with forest flammability, have not been explored or empirically established.

The key question addressed here is whether selective logging alters the thermal environment of the remaining forest stand and increases its susceptibility to fire. We focus on a selectively logged forest in southwest Amazonia one year post-harvest and at peak temperature hours during the dry season. We determine: **(i)** to what extent selective logging affects the thermal environment of gaps and adjacent forest; and **(ii)** how selective logging impacts fire risk by examining leaf-litter moisture content and three main components of flammability – ignitability (how well fuel ignites), combustibility (fire intensity) and sustainability (maintenance of burn over time).

3.3 Materials and Methods

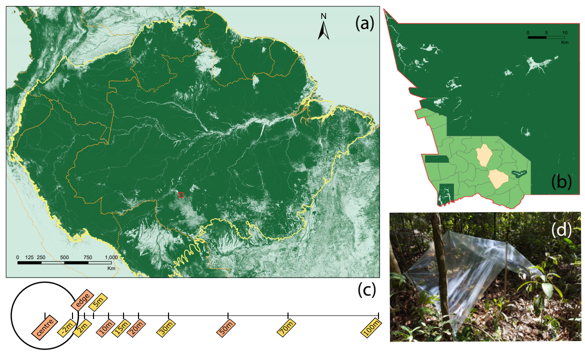

Figure 3.2: Map of the Amazon forest with FLONA Jamari delimited in red (a), and detailed in (b): area managed by the logging company AMATA S/A in pale green polygons and the two Annual Production Units (APUs) with one year following harvest, where this study was conducted, in pale yellow; a total of 50 sites (logging gaps) were used for the thermal study — 32 transects with 12 study points in 2016 (c) and 18 transects with 5 study points in 2017 (orange boxes at gat centre, edge, 10 m, 20 m and 50 m from edge). Leaf-litter samples for the fire experiment were collected from study points on all 18 transects in 2017 (orange boxes); and a photograph of the plastic roof structure covering an experimental quadrat used to prevent leaf litter and rainfall from reaching the samples used on our fire experiment (d).

Study area

This study was conducted within a 960-km^2 selective logging concession within the Jamari National Forest (FLONA Jamari), Rondônia, Brazil, in southwest Amazonia $9°18'S, 63°1'W$). Nearly half of this area (460 km^2) has been managed since 2011 by the logging company AMATA S/A, which complies with Reduced Impact Logging (RIL) techniques, such as directional felling, liana cutting and low-intensity harvest, and ensures post-harvest natural forest regeneration and protection of the area from further degradation. Logging operations are conducted within Annual Production Units (APUs) with an average size of 18.08 km^2, where permanent protected areas along streams and rivers are set aside. FLONA Jamari experiences mean annual temperatures of 25.8°C with modest variability and a precipitation regime ranging from 2,200 to 2,600 mm/year, which is concentrated during the wet season from October to April with a well-defined dry season between June and September (http://en.climate-data.org/). The mature primary forest of Jamari is widely described as Amazonian lowland open ombrophylous forest (IBGE, 2012).

Study design

Fieldwork was conducted from June to October 2016 and 2017. Our methods were designed to investigate the edge effect of logging gaps on the thermal environment of the surrounding forest during peak temperature hours and to relate this to forest flammability one year after harvest. Focusing on the thermal environment, we related local canopy structure (from hemispherical photographs) to understorey ambient temperature (using iButton data loggers) and ground surface temperature (using thermal imaging technology) from 11:00h to 15:00h. Additionally, we designed an experiment to investigate the main forest flammability components (ignitability, combustibility and sustainability, as per H. E. Anderson, 1970 and Simpson et al., 2015) using leaf-litter samples collected in and around logging gaps over 72 days after rain.

Edge effects on the thermal environment

In 2016, we selected 32 logging gaps, in each of which we set up 12 study points, starting at gap centre, then at 2 m from gap edge, at gap edge, and away from gap edge at 2 m, 5 m, 10 m, 15 m, 20 m, 30 m, 50 m, 70 m and 100 m towards the forest interior. In 2017, we selected 18 logging gaps and set up 5 study points at each, at the gap centre, edge, and 10 m, 20 m and 50 m towards the forest interior. Thus, the logged-forest dataset had 50 different logging gap sites, amounting to 474 study points (32 repetitions with 12 distance-points in 2016; 18 repetitions with 5 distance-points in 2017). As a control, we set up four 1-km long transects (3 in 2016, 1 in 2017) that were randomly located in different areas of unlogged primary forest within the same concession, with 10 points evenly spaced along each. All sites were selected using detailed GIS spatial layers of harvest data provided by AMATA and an in-situ inspection conducted in the surroundings of each potential study location to ensure that the transect did not cross neighbouring logging disturbances, such as logging gaps or roads, and that they were also surrounded by a 100 m buffer of undisturbed forest, such that any edge effect could be attributed to the study gap.

Forest structure and logging gap area

Forest structure was quantified using canopy openness values derived from hemispherical photographs at all study points. All photos were taken with a Canon Rebel T2i equipped with a Sigma 4.5 mm circular fisheye lens and a tripod. The camera was oriented to the North, levelled with the horizon and settings were adjusted according to the Histogram Method proposed in Beckschäfer, Seidel, Kleinn, and Xu (2013; Mollinari et al., 2019). All hemispherical photographs were processed in R (R Core Team, 2017) using the packages Caiman and CimesR (available at Gaston Mauro Diaz GitHub and Gustaf Granath GitHub).

Logging gap boundaries and size were quantified from polygons in ArcMap 10.4.1 (ESRI), which were drawn using values collected in-situ of angle and distance between trees >20 cm DBH that shaped each logging gap in this study.

Understorey air temperature

Understorey ambient air data were collected using iButton data loggers (model DS1921G-F5; resolution of 0.5°C) and a psychrometer at all study points. Each iButton was enclosed in a re-sealable zipper storage bag, metal mesh sleeve and placed under a plastic funnel at 1.5 m above ground (Gonzalez del Pliego et al., 2016; Mollinari et al., 2019; Scheffers et al., 2013).

All 414 study points from 2016 (32 logging gaps with 12 study points each + 30 control points) had active iButtons sampling ambient air temperature at 10-min intervals over 30 days, which amounted to over ~2 million temperature measurements. From these values, we derived the mean temperature per hour for each day at each study point. All 100 study points from 2017 (18 logging gaps with 5 study points + 10 control points) had active iButtons collecting ambient air temperature every hour for ~100 days which amounted to ~450,000 temperature measurements. All measurements of dry and wet bulb temperatures using a psychrometer were collected alongside thermal photographs and then used to derive local relative air humidity.

Ground surface temperature

Ground surface temperature data were collected using a FLIR-E40 Thermal Imaging Camera, following Scheffers et al. (2017). At each visit across all study points, we took four photographs in each orthogonal directions (pointing North, East, South and

West) holding the camera at breast height pointed at 45° towards the ground (Mollinari et al., 2019; Scheffers et al., 2017; Senior, Hill, Benedick, and Edwards, 2017). Each photograph captured an area of approximately 1-m^2 with a resolution of 120 × 160 pixels. The four photos taken during each visit were then considered as one large matrix (4 × 120 × 160) that captured information within a larger ~4-m^2 area. The minimum, maximum and mean temperature values of each study point at each repetition are the mean of values below the 5^{th} percentile of the distribution of temperature values, the mean of values above the 95^{th} percentile, and the mean of values above the 47.5^{th} and below the 52.5^{th} percentiles, respectively (Mollinari et al., 2019). Raw data from thermal images were processed using the *Thermimage* R package (Tattersall, 2017).

Along transects in primary forest and logging gaps in 2016, each point was visited on two and three different days, respectively. In 2017, however, all logging gaps and primary forest points were visited less regularly, with visits varying from 1 to 11 repetitions depending on the site. Such imbalance was accounted for in the analysis. All thermal photographs were taken from 11:00h to 15:00h to capture surface temperature variation during the hottest hours of the day. This dataset comprises about 7,840 thermal photographs, representing approximately 150 million temperature values (120 × 160 pixels × 7,840 photos). Measurements of light intensity using a luxmeter, and relative air humidity and air temperature using a psychrometer, were obtained simultaneously to each thermal photo.

Flammability experiment

We conducted the flammability experiment at all study points used for the thermal study in 2017 (see above). The experiment started soon after the rain season ended (early June). At each point, we set up the borders of a 1.2 × 1.2 m quadrat on the ground, which was covered by a 2 × 2 m plastic roof structure standing 1 m above ground to exclude rainfall and leaves reaching the forest floor (Fig. 3.2d). Each 1.2 × 1.2 m quadrat was subdivided into sixteen 30 × 30 cm squares, from which samples of leaf litter were taken. All quadrats were then evenly watered with 10L of fresh water to ensure maximum saturation of leaf litter and soil. Transects (logging gaps) were not all watered and sampled on the same days because of field logistics and laboratory oven space limitations.

The experiment started along each transect immediately after watering, which represented ‘Day 0’ of desiccation, and one 30 × 30 cm sample was collected from each quadrat to represent maximum leaf-litter moisture content. Sampling across sites was conducted in a way that allowed sufficient replicates spanning 72 desiccation days. To prevent moisture loss, samples were stored inside resealable plastic bags until the moment they were processed. Each sample was equally divided into two sub-samples, one of which used to determine fuel moisture content, which was accomplished through desiccation in a laboratory oven, and the other burned under controlled laboratory conditions with data collected for each flammability component — ignitability (how well fuel ignites), combustibility (how well fuel burns, which relates to fire intensity) and sustainability (maintenance of burn over time).

Fuel moisture content

Samples were placed inside paper bags with their identification (study point and collection date), and wet weighed. They were then placed inside a laboratory oven at constant 70°C temperature for 48 hours, after which they were removed and dry weighed.

Ignitability, combustibility and sustainability

We constructed a flammability arena using a 60 × 85 cm metal barrel cut in half lengthways. Each half was partially filled with clean sand and placed in an area shielded from wind. At each new burn, a single sample bag was weighed and then emptied into the arena. A controlled flame from a gas blowtorch (Carbografite 190 g) was held on each sample's top right corner for 3 sec while timed by a second observer using a stopwatch to measure: **i)** delay time to flame – how long until the sample ignited a flame without aid of the blowtorch ('Ignitability'); **ii)** flaming time – how long a flame was sustained – which was used to divide the initial sample weight to determine the average leaf-litter combustion rate (g s^{-1}) ('Combustibility'); and **iii)** burn duration – how long any sign of burning (flame or ember) was sustained ('Sustainability'), and which had a 10-min burning limit (reached on 0.61% of occasions). The blowtorch flame was held a total of 5 times per sample, for 3 sec each time, starting at the top right corner, followed by the bottom right corner, bottom left corner, top left corner and ending at the centre. All the above metrics were recorded on each occasion.

Statistical analysis

Edge effects on the thermal environment

All thermal and flammability data were analysed using mixed effect models with the *nlme* and *lme4* packages in R (Bates, Mächler, Bolker, and Walker, 2015; Pinheiro et al., 2018; R Core Team, 2017). Data were log-transformed to meet residuals assumptions where necessary. Models were selected according to a combination of model comparisons of Akaike's Information Criterion (AIC), which is a tool for model selection where the model with the lowest AIC indicates the best model, i.e. that which offers the best fit whilst penalising for number of parameters (Akaike, 1974), and a visual interpretation of heterogeneity and normality of residuals (Zuur et al., 2013).

To investigate a potential edge effect on the understorey thermal environment around logging gaps, we modelled air and surface temperature data separately. Understorey air temperature was modelled against the distance from logging gaps ('study point') interacting with logging 'gap size'. We accounted for forest structure at every point with 'canopy openness', transect 'direction', 'hour' of day, and 'volume' of harvested tree, and used the study point 'centre' as reference. To account for spatial and temporal pseudoreplication, data were grouped with 'study point' nested within 'site' (i.e. each unique logging gap) for each 'date' of data collection.

Surface temperature data and relative air humidity were modelled separately for each response variable (i.e. Minimum, Mean and Maximum temperatures and Air Humidity) against distance from logging gap ('study point'), logging 'gap size', forest structure at every point ('canopy openness'), transect 'direction' and 'volume' of trees harvested from each logging gap, using the study point 'centre' as reference. To account for spatial and temporal pseudoreplication, data were grouped with 'site' (i.e. each unique logging gap) nested within each 'date' of data collection.

To compare the thermal environment around logging gaps with that in undisturbed primary forest, we modelled each response variable against forest structure at every point ('canopy openness') and accounted for spatial and temporal pseudoreplication by grouping data with 'study point' nested within 'site' (i.e. each unique logging gap) nested within each 'date' of data collection.

To further explore the interaction between distance from gap and gap size on the thermal environment, all logging gaps were categorized into three size classes, each of which containing one third of the data: 'small' – logging gaps smaller than 329 m^2;

'medium' – gaps between 329 m^2 and 688 m^2; and 'large' – gaps larger than 688 m^2. A 'size category' co-variable was then added to each full model, and each response variable was modelled within each 'size category' subset.

To investigate the effect of logging gap size on the understorey thermal environment in the 'centre' and 'edge' of logging gaps, we modelled each response variable separately against logging gap size ('gap area') for each subset of the data containing either only point 'centre' or only point 'edge'.

Flammability experiment

Moisture Content

Leaf-litter moisture content was modelled against log-transformed 'desiccation', represented by the number of consecutive days after the last rain event, interacting with distance from logging gap ('study point'). We accounted for forest structure at each study point ('canopy openness'), for thermal environment conditions at the time of sampling ('air temperature') and for logging 'gap size', using the study point 'centre' as reference. To account for spatial and temporal pseudoreplication, data were grouped with 'study point' nested within 'site' (i.e. each unique logging gap) nested within each 'date' of sampling.

Ignitability

The probability of samples igniting a flame was calculated through modelling the proportion of ignition success over all burning attempts (5 times per sample) against leaf-litter 'moisture content'. Proportion of ignition was modelled using binomial Generalised Linear Mixed Modelling (GLMM), in which 1 means that all 5 attempts of ignition were successful and 0 means that the sample never ignited a flame across all 5 attempts, against leaf-litter 'moisture content' and with 'study point' nested within 'site' (i.e. each unique logging gap).

Ignitability was represented by the variable 'delay time to ignition' (DT) which was built from a combination of the flammability metrics collected: if the sample ignited a flame, the value recorded for 'delay time to flame' became 'delay time to ignition' (DT). If, however, the sample never ignited a flame during any 3 sec of assisted blowtorch flame, but ignited an ember (with therefore an associated 'burn time'), DT was considered equal to 3 sec. In cases where neither a flame nor an ember were observed, DT was considered equal to 5 sec, which is an arbitrary value outside of our experimental time frame (3 sec) that aims to represent that the sample would probably ignite at some point with prolonged exposure to an ignition source and therefore this value is not equal to zero or a missing value. We tried modelling these data using higher values of 30 and 60 sec to represent longer hypothetical exposure to an ignition source. The increased distance between these higher values and the experimental data values (<3 sec) changed the scale of the response variable and caused errors in the analyses and interpretation of results. The final DT variable represents the mean DT value of all 5 burning attempts made per sample. DT was modelled against log-transformed ‘desiccation’ (number of days after rain), ‘study point’ (distance from logging gap), leaf-litter ‘moisture content’, understorey ambient ‘air temperature’ and forest structure at each study point (‘canopy openness’). To account for spatial pseudoreplication, data were grouped with ‘study point’ nested within ‘site’ (i.e. each unique logging gap).

Combustibility

Combustibility of fuel was derived as the average leaf-litter combustion rate, i.e. initial sample weight divided by flaming time (g s^{-1}), which is defined as the time sum of sustained flames considering all 5 burning attempts per sample. Combustibility was modelled with log-transformed mean combustion rate against logging ‘gap size’ interacting with distance from logging gap (‘study point’). We accounted for leaf-litter ‘moisture content’ and understorey ambient ‘air temperature’.

Sustainability

Sustainability was represented by the ‘burn time’ (BT) variable which corresponds to the sum of time any sign of flame or ember was observed on each sample. The analysis of this metric followed the same protocol as that of ignitability.

A gap ‘size category’ co-variable was added, and models were adjusted for leaf-litter moisture content, ignitability and sustainability of fire. Models of both thermal and flammability trials were assessed for evidence of temporal autocorrelation of residuals (using function “acf” in the *nlme* package) and their random structures were adjusted accordingly.

3.4 Results

3.4.1 Edge effects on the thermal environment

Air temperature

During the heat of the day (11:00h to 15:00h), understorey ambient air at the centre of logging gaps was warmer than at other points in the surrounding forest by an average of 0.80°C. Canopy openness was an important feature in altering understorey ambient air temperatures, and showed a potential maximum influence of 12.06°C among points (± 0.37 Std. Error, p<0.001).

Logging gap size ('area') had a positive effect on understorey ambient air temperatures both at the centre and edge of logging gaps of 0.1°C for 100 m^2 of area increased (± 0.00, p<0.001; Fig. 3.4a and 3.4b). Within the subset of 'small' logging gaps, there was no clear pattern of understorey air temperature change between logging gap centre and points in the surrounding forest (Fig. 3.3a). In the centre of 'medium' logging gaps, however, understorey air temperature was 7.90°C warmer than at 10 m from gap edge (± 2.45, p<0.01), and 14.73°C warmer than at 50 m from gap edge (± 2.45, p<0.001; Fig. 3.3b). At 'large' logging gaps, the difference range was even greater, with understorey air temperatures at gap centres 22.59°C hotter than along gap edge (± 1.97, p<0.01), 19.95°C hotter than at 10 m from gap edge (± 1.96, p<0.001), and 18.06°C hotter than at 50 m from gap edge (± 1.93, p<0.01; Fig. 3.3c). Furthermore, canopy openness had a much greater influence in understorey ambient air temperatures in 'large' logging gaps, with a potential maximum value of 12.67°C (± 0.56 p<0.001), than in 'medium' (potential maximum of 7.66°C ± 0.85 p<0.001), and 'small' (potential maximum of 0.98°C ± 0.52 p=0.06).

Understorey ambient air along transects facing SE was consistently warmer than along transects facing the other three cardinal directions, with the maximum temperature difference occurring in 'large' logging gaps of 1.13°C between SE and NW (± 0.07, p<0.001). The understorey of primary forest was cooler than all the other study points by an average of 0.48°C.

Surface temperature

Centre of logging gaps recorded higher mean and maximum surface temperatures than the surrounding points. Mean surface temperature at the centre was 0.38°C warmer than at the gap edge (± 0.09, p<0.001), 1.17°C warmer than at 10 m (± 0.10, p<0.001), 1.65°C warmer than at 50 m (± 0.10, p<0.001) and 1.38°C warmer than at 100 m from gap edge (± 0.12, p<0.001). Maximum surface temperature showed greater differences between centre and surrounding points. Gap centres were 4.20°C warmer than at 10 m (± 0.32, p<0.001), 4.89°C warmer than at 50 m (± 0.32, p<0.001) and 4.41°C warmer than at 100 m from the gap edge (± 0.37, p<0.001). There was little difference in minimum surface temperature between centre and points up to 5 m into the forest

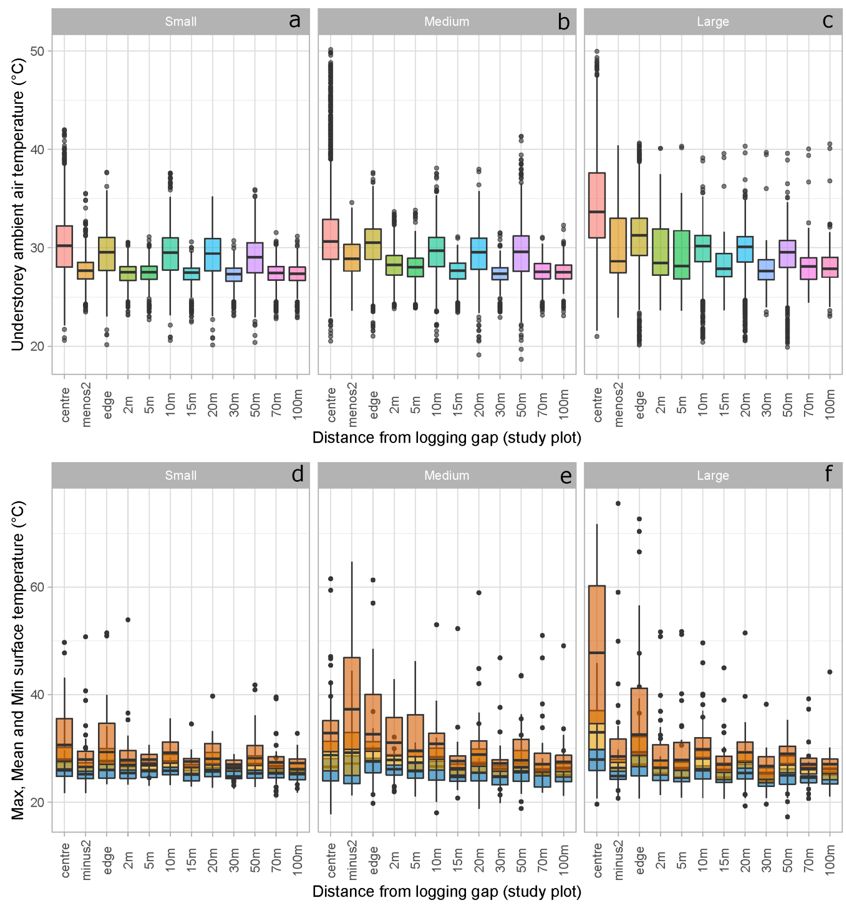

Figure 3.3: Fitted values of understorey ambient air temperature in 'small' (a), 'medium' (b) and 'large' logging gaps (c); and Maximum (red), Mean (orange) and Minimum (blue) surface temperatures in 'small' (d), 'medium' (e) and 'large' logging gaps (f) against 'study point', which represents distance from gap edge.

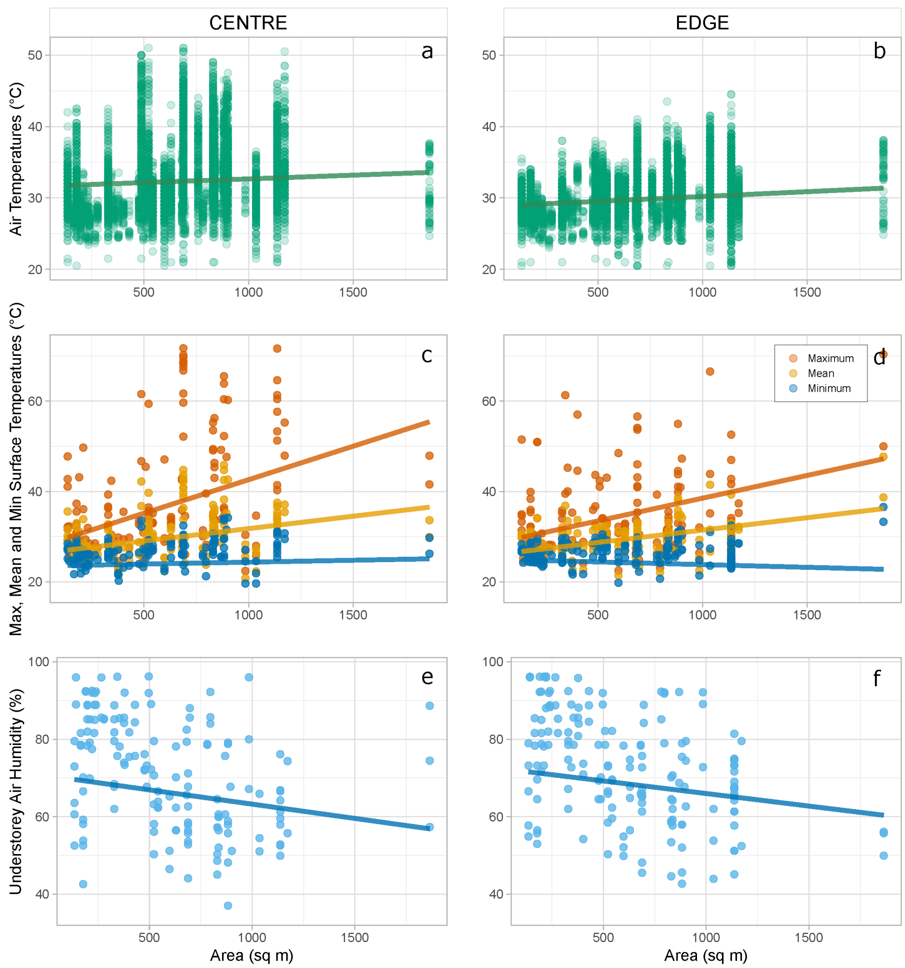

Figure 3.4: Understorey ambient air temperature (°C) in logging gap centre (a) and edge (b); Maximum (red), mean (orange) and minimum (blue) surface temperatures (°C) in logging gap centre (c) and edge (d); and understorey relative air humidity (%) in logging gap centre (e) and edge (f), all against logging gap size (area sq m).

(+ 0.03°C at 5 m, p=0.77). Further into forest interior, however, minimum surface temperatures were lower. Centre was 0.39°C warmer than at 10 m (± 0.07, p<0.001), 0.88°C warmer than at 50 m (± 0.08, p<0.001) and 0.63°C warmer than at 100 m (± 0.09, p<0.001).

Volume of harvested trees and transect direction only had an effect on maximum surface temperatures, with transects facing SE showing higher maximum surface temperatures than all other cardinal directions and a maximum difference of 5.86°C between SE and SW (± 1.39, p<0.001). Canopy openness is an important component of the understorey thermal environment, and had greater influence in maximum surface temperatures by a potential maximum of 31.24°C (± 2.65, p<0.001) in contrast with 10.82°C in mean (± 0.86, p<0.001) and 5.25°C in minimum surface floor temperatures (± 0.61, p<0.001).

Maximum surface temperature at the centre of 'small' logging gaps was warmer than in surrounding points by 2.09°C (± 0.25, p<0.001) and 2.43°C (± 0.26, p<0.001) compared to 50 m and 100 m from gap edge, respectively (Fig. 3.3d). At the centre of 'medium' logging gaps, maximum surface temperature was warmer than in surrounding points by a larger difference, with 3.89°C warmer than at 50 m (± 0.65, p<0.001) and 3.91°C warmer than at 100 m from gap edge (± 0.77, p<0.001) (Fig. 3.3e). In 'large' logging gaps, the difference was even greater, with gap centres recording maximum surface temperatures 17.47°C hotter than at 50 m (± 0.90, p<0.001) and 13.03°C hotter than at 100 m from gap edge (± 1.09, p<0.001) (Fig. 3.3f).

Mean surface temperatures followed the same pattern observed on maximum surface temperatures, with the difference between gap centre and surrounding points increasing from 'small' to 'medium' to 'large' logging gaps. At the centre of 'small' logging gaps, mean surface temperature was warmer than in surrounding points only by 0.93°C (± 0.09, p<0.001) and 0.71°C (± 0.10, p<0.001) compared to 50 m and 100 m from gap edge (Fig. 3.3d). In 'medium' logging gaps, mean surface temperature was 1.34°C (± 0.20, p<0.001) and 1.56°C (± 0.22, p<0.001) warmer than at 50 m and 100 m from gap edge, respectively (Fig. 3.3e). Finally, mean surface temperature at the centre of 'large' logging gaps was 5.12°C (± 0.27, p<0.001) and 3.49°C (± 0.32, p<0.001) hotter than at 50 m and 100 m from gap edge (Fig. 3.3f).

Minimum surface temperature also increased from 'small' to 'medium' to 'large' logging gaps, but with a smaller difference range in all gap size classes. The centre of 'small' logging gaps was only 0.61°C (± 0.09, p<0.001) and 0.39°C (± 0.10, p<0.001) warmer than points 50 m and 100 m, respectively (Fig. 3.3d). Minimum surface temperature in the centre of 'medium' logging gaps was 0.63°C (± 0.14, p<0.001) and 0.87°C (± 0.16,

$p<0.001$) warmer than at 50 m and 100 m from gap edge (Fig. 3.3e). In 'large' logging gaps, the centre had minimum surface temperatures 3.07°C (± 0.19, $p<0.001$) and 2.15°C (± 0.22, $p<0.001$) warmer than at 50 m and 100 m from gap edge (Fig. 3.3f). Logging gap size ('area') had a positive effect of 1°C on maximum surface temperature (± 0.00, $p<0.01$) and of 0.5°C on mean surface temperature (± 0.00, $p<0.01$) for 100 m^2 of area increased both at logging gap centre and edge, but very little effect on minimum surface temperature of the forest floor (≤0.001°C, $p>0.5$; Fig. 3.4c and 3.4d).

Air humidity

During peak temperature hours, understorey relative air humidity at the centre and the edge of logging gaps was lower than in all other points in the surrounding forest. Study points as close as 2 m from gap edge had 1.61% higher relative air humidity than at centre and edge (± 0.33, $p<0.001$), and points at 20 m, 50 m and 100 m from gap edge had 2.62% (± 0.25, $p<0.001$), 3.26% (± 0.27, $p<0.001$) and 3.10% (± 0.30, $p<0.001$) higher relative air humidity, respectively. Canopy openness had a negative effect on understorey relative air humidity with a potential maximum of 13.06% (± 1.79, $p<0.001$). Tree offtake volume and logging gap area had very little, but negative, impact on understorey relative air humidity around logging gaps (-0.15% ± 0.09, $p=0.09$, and -0.003% ± 0.001, $p=0.03$, respectively). The centre of 'small', 'medium' and 'large' logging gaps had 1.86% (± 0.43, $p<0.001$), 3.70% (± 0.49, $p<0.001$), and 8.29% (± 0.68, $p<0.001$) less relative air humidity than at 50 m from gap edge, respectively. Logging gap size had a negative effect on relative air humidity at logging gap centre of -0.7% (± 0.00, $p=0.05$) and -0.6% (± 0.00, $p\leq0.01$) at gap edge for each 100 m^2 of area increase (Fig. 3.4e and 3.4f).

3.4.2 Flammability experiment

Fuel moisture content

All study points around logging gaps had a drier leaf-litter than those at gap centre on zero days of desiccation (-3.05% ± 0.79 at 10 m and -5.07% ± 0.81 at 50 m from gap edge, $p<0.001$; Fig. 3.5). The rate of moisture content loss at logging gap centre was -4.82% per log-transformed day since rain (± 0.28) and was the steepest drop compared to study points surrounding logging gaps (-3.98% ± 0.27 at 10 m and -3.74% ± 0.27 at 50 m from gap edge, $p<0.001$). Primary forest had 5.11% (± 2.88) higher moisture content than logging gap centre at zero days of desiccation, and an even steeper drop-down rate than that at gap centres (-6.64% ± 0.96), albeit both with higher uncertainty

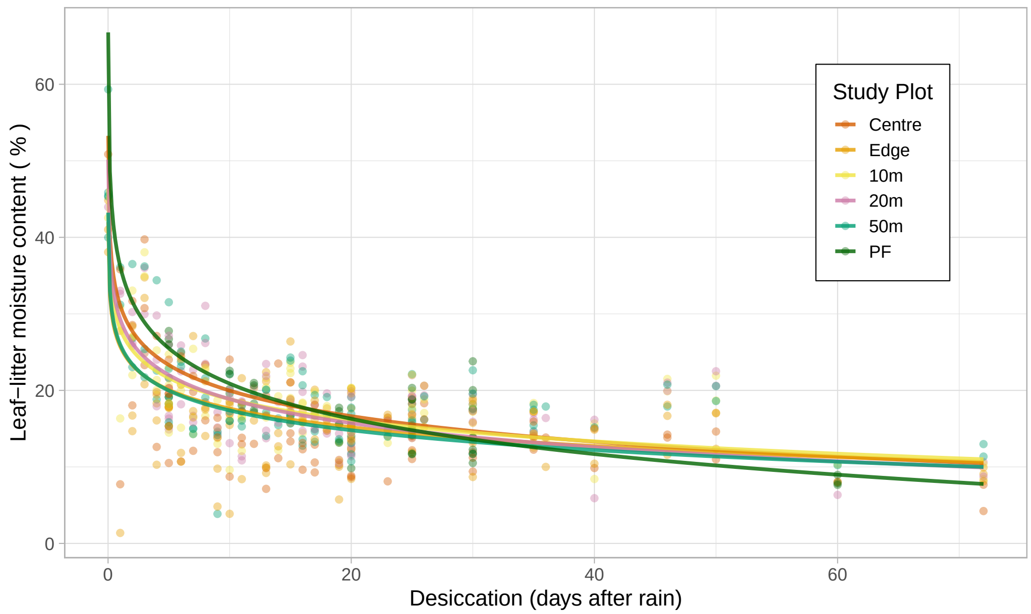

Figure 3.5: Leaf-litter moisture content (%) against desiccation (days after rain) in logging gap centre (red), edge (orange), 10 m (yellow), 20 m (pink) and 50 m (green) from gap edge, and in unlogged primary forest (dark green).

(p=0.08 and p=0.06). Understorey ambient air temperature had a negative effect of -0.68% (± 0.06, p<0.001) on moisture content for 1°C increased. Forest structure also had a negative influence on moisture content with -5.51% drop (± 2.46, p<0.05) for each unit of canopy openness. There was no noticeable difference in moisture content loss across logging gap size classes (p>0.20).

Ignitability

A 50% chance of ignition was predicted for 34.32% of leaf-litter moisture content, and a 10% probability of ignition for 50% leaf-litter moisture content, which represents near saturation conditions (Fig. 3.6a).

The drop-down rate of delay time to ignition was -0.17 sec (± 0.02, p<0.001) for all study points per log-transformed day since rain (Fig. 3.6b). Leaf-litter moisture content had a positive effect of 0.02 sec (± 0.00, p<0.001) on delay time to ignition for 1% of moisture increase. Understorey ambient air temperature had a negative influence of -0.04 seconds (± 0.01, p<0.001) for 1°C increase. There was no noticeable difference in delay time to ignition across logging gap size classes (p>0.70).

Sustainability

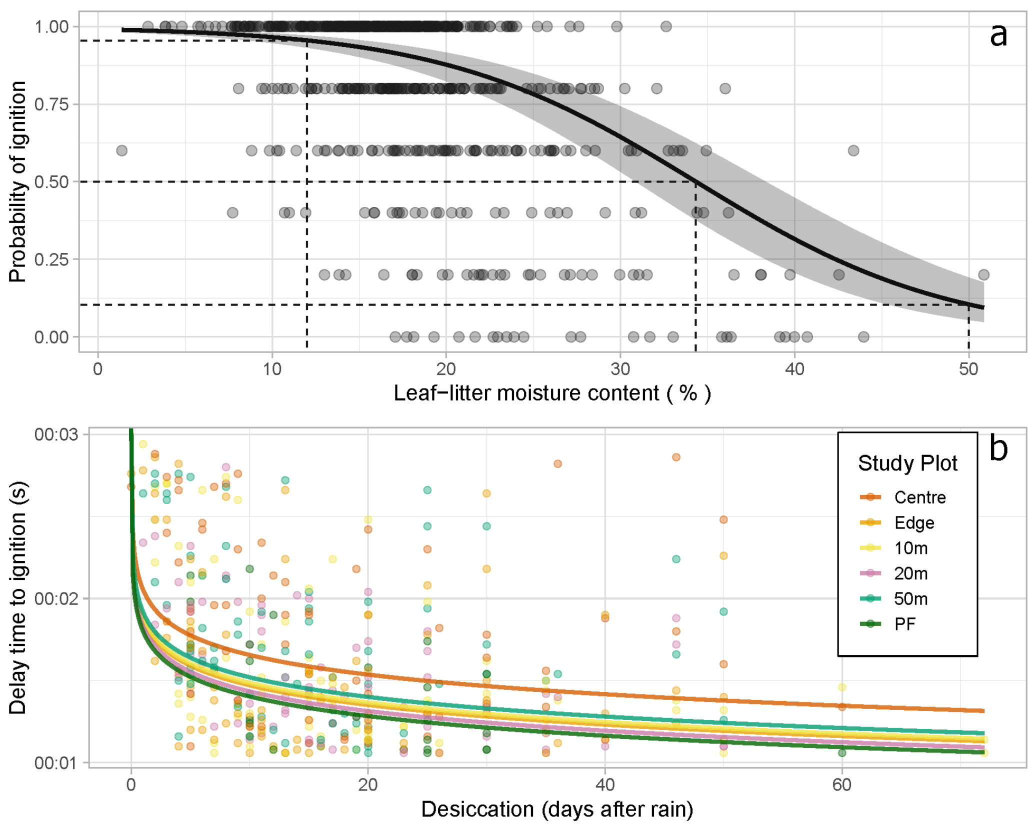

Figure 3.6: Probability of ignition against leaf-litter moisture content (%) (a); and Ignitability: Ignition delay (seconds) against desiccation (days after rain) in logging gap centre, edge, 10 m, 20 m and 50 m from gap edge, and in unlogged primary forest (b).

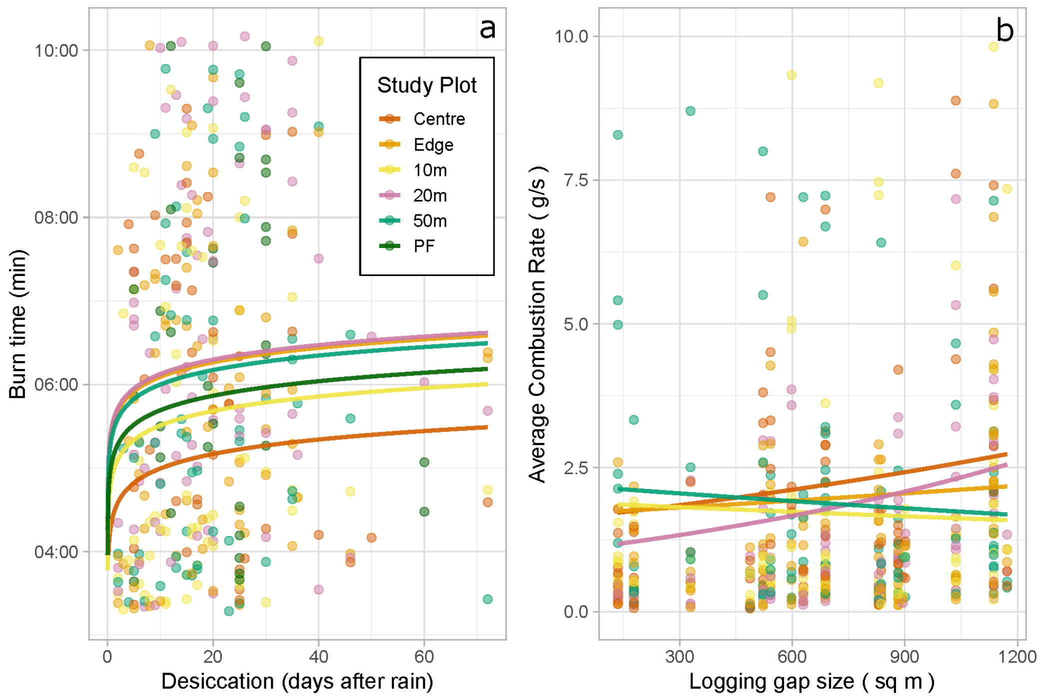

Figure 3.7: Sustainability of fire (a): burn time (min) against desiccation (days after rain) in logging gap centre (red), edge (orange), 10 m (yellow), 20 m (pink) and 50 m (green) from gap edge, and in unlogged primary forest (dark green); and combustibility (b): average combustion rate (g/s) against logging gap size (m^2) in logging gap centre (red), edge (orange), 10 m (yellow), 20 m (pink) and 50 m (green) from gap edge.

The increase rate in burn time was 15.02 sec (± 6.00, p<0.01) per log-transformed day since rain for all study points (Fig. 3.7a). Leaf-litter moisture content had a negative effect of -7.23 sec (± 1.08, p<0.001) of burn duration for 1% of moisture increase. Understorey ambient air temperature had a positive effect of 9.30 sec (± 2.52, p<0.001) for 1°C increase. There was no noticeable difference of sustainability of fire across logging gap size classes (p>0.50).

Combustibility

The effect of logging gap size on fire intensity was greater at the centre than across all other study points (Fig. 3.7b). The log-transformed average combustion rate at logging gap centres increased 1 g/s for each square metre of logging gap size increase. Since there is no value of 'logging gap size' for study points in primary forest, they were not included in this analysis.

3.5 Discussion

Selective logging has been extensively identified as a facilitator of fire in tropical forests due to altered microclimates induced by canopy disturbance from logging roads and tree falls, and increased fuel loads from woody slash after harvest activities (Cochrane and Schulze, 1999; Nepstad et al., 1998). In this study, we empirically investigated this relationship to better understand the processes in which selective logging drives fire proneness in tropical forests. We found that selective logging has a direct influence on forest vulnerability to fire by accelerating leaf-litter desiccation, thereby raising the probability of ignition, and increasing fire intensity, especially in larger logging gaps. The delay to ignition and the ability to sustain fire over time following rain, however, did not differ across the landscape. Thus, beyond the direct influence of selective logging on forest flammability, increased fire-proneness of logged forests is also likely driven by greater exposure to ignition sources, which are invariably more available in a production forest landscape.

3.5.1 Edge effects on the thermal environment

Previous studies have shown that the thermal environment in selectively logged forest can recover to baseline levels found in primary forest, within a decade in Borneo (Senior, Hill, Benedick, and Edwards, 2017) and five years in the Brazilian Amazon (Mollinari et al., 2019). However, these studies have not focused on the spatial configuration of such impacts from logging gap to forest interior shortly after timber harvest activities. Our study at one year post-harvest, demonstrates that selective logging negatively affects the forest thermal environment, not only at the centre of logging gaps but also in the surrounding forest, especially at larger gaps. The hotter and drier thermal environment is likely to affect the availability of favourable fine-scale microclimates, which will negatively impact biodiversity. Such microclimates are critical for the persistence of forest species that track their optimal climate niche during macroclimatic warming (climate at coarser scales, m to ha), particularly during heat-waves and severe droughts (Caillon et al., 2014; Scheffers, Evans, et al., 2014).

Vegetation structure plays a major role on the thermal environment (Senior, Hill, González del Pliego, Goode, & Edwards, 2017), which explains why logging gap centre and edge had more severely impacted thermal environments than the surrounding forest, where canopy had not been directly disturbed by tree felling and roundlog removal. This indicates that the degree of influence and severity of the edge effect on thermal environment is related to both logging intensity (volume of timber harvested) and management practices, because these directly determine canopy gap size (Burivalova et al., 2014, Pereira et al., 2002).

3.5.2 Leaf-litter moisture content

Despite the higher leaf-litter moisture content at logging gap centres immediately after rain, the steeper drop-down rate means that the drier and hotter environment directly promotes fuel-load desiccation. Environmental conditions typically triggered by strong El Niño events, such as prolonged droughts and excessive heat (Y. Chen et al., 2017), could accelerate fuel desiccation even more in these environments, which supports the idea that severe droughts act synergistically with selective logging to increase forest vulnerability to future burning (Cochrane and Laurance, 2008; Laurance and Williamson, 2001).

The higher leaf-litter moisture content at gap centres compared to their surroundings is likely due to the higher proportion of twigs and branches from the crown of felled tree left after harvest being able to store more water than the typical leaf litter in a random forested area (Uhl and Kauffman, 1990). Moreover, despite the overall steeper desiccation rate in primary forest compared to gap centre, the higher initial leaf-litter moisture content and the gentler initial drop off, could be due to a more intact vegetation structure. Still, the lack of data on leaf-litter characterization, such as type, size and arrangement of debris, is a limitation in this study.

3.5.3 Probability of ignition

At saturated moisture content (~50%), leaf litter had a 10% chance of igniting when exposed to an ignition source for at least 3 sec, even in primary forest. Our findings thus suggest that forests of parts of the south-western Amazon that naturally exhibit a more fractured upper canopy are likely to be more vulnerable to fire than closed-canopy eastern Amazon forests, which create microclimates that are virtually immune to wildfires (Uhl and Kauffman, 1990). Moreover, thresholds of 12% and 15% fuel-load moisture content, below which fuel could ignite and fire could spread, were quantified for eastern Amazon forests (Holdsworth and Uhl, 1997; Uhl and Kauffman, 1990). For these thresholds, we predict a 95% and 93% chance of ignition, respectively, in the south-western Amazon whenever fuel is exposed to an ignition source for at least 3 sec, which indicates that they do not represent safe limits of fire risk for this region.

3.5.4 Ignitability, Combustibility and Sustainability

Despite the accelerated leaf-litter desiccation at gap centres compared to the surrounding forest, delay time to ignition and the ability of fuel to sustain fire did not vary from gap centre to forest interior across days after rain. Nevertheless, fire intensity increased with logging gap size, more markedly so at gap centres. Thus, even though logging gaps are the focal points for fire susceptibility and could intensify a wildfire (Cochrane, 2003; Holdsworth and Uhl, 1997), areas outside tree-fall gaps in logged forests are equally able to catch and sustain fire, suggesting that, suppressing ignition sources in and around production forests is crucial to manage their vulnerability to burning.

3.5.5 Conservation implications

Connecting the various aspects influencing fire susceptibility and spread is crucial to develop policies against forest fires (Cochrane, 2002). Harvest planning should account for gap size and proximity between gaps to avoid creating a landscape that could, in the case of a wildfire, ensure contagion of interstitial forest areas between large and closely distributed logging gaps. Furthermore, although we can infer that smaller logging gaps would be beneficial in terms of controlling fire intensity, the creation of more numerous smaller gaps would require opening more logging roads, which could potentially exacerbate canopy disturbances further augmenting forest flammability and fire incidence (Kleinschroth and Healey, 2017).

Given that even the largest logging gaps in this study were created by a company that employs several Reduced Impacts Logging (RIL) techniques and complies with timber volume offtake quota set by law, it seems likely that our study area does not reflect the worst possible impacts of selective logging. Other areas in the Amazon are logged illegally or via unplanned and unregulated activities (Bicknell et al., 2014; Burivalova et al., 2014), and could potentially result in more impacted thermal environments and higher vulnerability to burning. Additionally, the 3-sec blowtorch flame we used in our fire experiment is likely to be rather conservative, given that ground fires in Amazon forests typically have higher residence time through slow moving flames that burn at low intensity (Holdsworth and Uhl, 1997). Longer exposure to an ignition source would likely increase the probability of fuel ignition by flames directly accelerating fuel-load desiccation.

Selectively logged ecosystems represent a unique fire environment in the Amazon, with increased fuel loads, modified microclimates promoting fuel desiccation and increased likelihood of ignition sources from anthropogenic activities (Cochrane and Schulze, 1999; Uhl and Kauffman, 1990). Logging companies should be compelled to maintain fire brigades with trained personnel ready to act on fire spots, not only inside the concession, but also in the surrounding forest, especially during severe droughts. Additionally, they should allocate efforts to teaching local communities about the risks of uncontrolled fires and prevention actions. Finally, they must prevent ignition sources in the forest by controlling the use of logging roads by local communities, and ensuring their closure and protection post-logging activities.

The ability of logged forests to retain their conservation value critically depends on avoiding fire after logging (Nepstad et al., 1999). Our study shows that the increased fire proneness of selective logged forests is likely driven by a synergy between accelerated desiccation of fuel-loads from altered microclimates and greater exposure to ignition sources. Thus, strategic and careful harvest planning, as well as strong regulations to control ignition sources should be management priorities to prevent fire incursion and preserve the structure and species composition of selectively logged forests.

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Chapter 4

Disentangling the contributions of climatic variation and human pressures on fire occurrence in the Brazilian Amazon

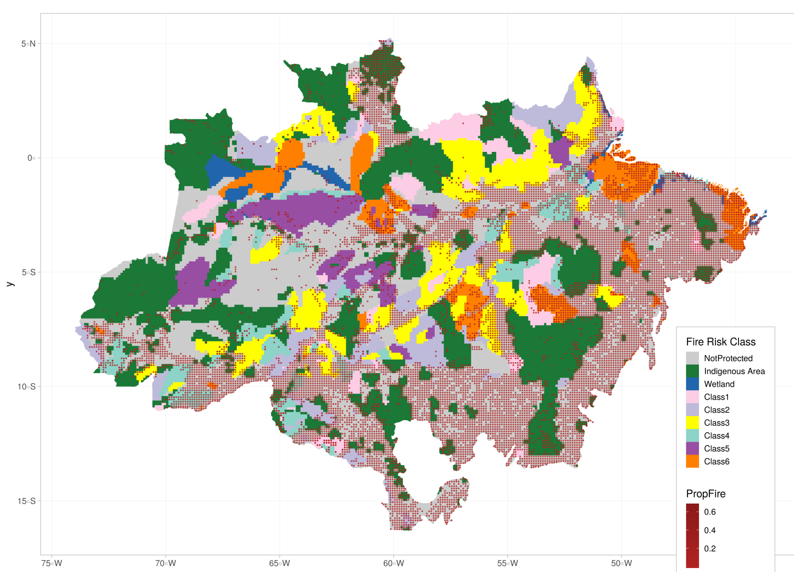

Figure 4.1: Proportion of active fires in 2015 across the Brazilian Amazon.

4.1 Abstract

Fires in tropical forests are strongly associated with climate, as droughts render rainforests seasonally flammable. Fire incidence, however, is contingent on anthropogenic ignition sources, which are widespread across the tropics given fire use for land management is nearly ubiquitous. Of particular concern, increasing deforestation rates and accessibility are intensifying the pressure upon protected areas (PAs), which represent powerhouses of biodiversity and ecosystem services. Climatic and anthropogenic drivers of fire are thus likely to act synergistically in magnifying forest fire proneness, making disentangling their relative contribution to driving forest fires very challenging. Using maps of key climatic and anthropogenic pressures, we disentangled local climatic variation and human drivers to explain fire occurrence across the Brazilian Amazon over the past two decades. Additionally, we assessed the effectiveness of different categories of PAs in inhibiting fire. We found that Vapour Pressure Deficit (VPD) had a stronger effect on fire occurrence than the Human Footprint (HFP), suggesting that local climate is a stronger predictor of fire than anthropogenic pressures. Additionally, our results revealed a higher proportion of active fires in indigenous lands compared to all other classes of PAs, but not the highest proportion of burnt area, which indicates good fire management. The highest proportion of burnt area was observed in Class 6 PAs, which allows for agricultural and industrial activities, and is the most permissive protection level. These results likely indicate higher incidences of deforestation and should therefore be closely monitored. Moreover, we found that drought severity magnifies fire occurrence where human pressures are increased, which reinforces that fire in the Amazon is driven by a synergy between climate and anthropogenic ignition sources. Regulating human activities and fire-use in the Amazon forest amidst more frequent and severe droughts under climate change is critical to prevent wildfires that will reinforce this cycle.

Keywords

Active fires, burnt area, drought, protected areas, tropical forests

4.2 Introduction

Fires in tropical forests are strongly related to climate conditions, and forests become particularly vulnerable to burning during severe droughts (Alencar et al., 2006). They are, however, also largely associated with human presence, either through deliberate burning via slash-and-burn in converting rainforests into agricultural lands or as unintended consequences of current land-use practices (Cochrane, 2003). Given the difficulties in disentangling climatic and anthropogenic pressures, major uncertainties remain in quantifying their respective contribution to forest fires and properly understanding the temporal variability in active fires and burnt area in tropical forests.

Fire in tropical rainforests has historically been a rare agent of disturbance and thus a weak evolutionary selective force (Goldammer, 1990; Malhi et al., 2008), resulting in many species being ill-adapted to survive even low-intensity fires (Barlow and Peres, 2004, Brando et al., 2012). Fires induce a drastic turnover in plant species composition as forest-interior specialists are replaced by edge generalists (Barlow and Peres, 2008; Slik et al., 2002). Additionally, forest fires contribute to global climate change by releasing huge amounts of greenhouse gases into the atmosphere (Y. Chen et al., 2017; Page et al., 2002). During the extreme drought associated with the major El Niño - Southern Oscillation (ENSO) event of 1997 – 1998, out-of-control fires burned more than 20 million hectares within Southeast Asia and Latin America (C. V. Barber and Schweithelm, 2000; Nepstad et al., 1999), resulting in an estimated ~1.7 ± 0.79 Pg (1 Pg $= 10^9$ tons) of carbon emissions anomaly (Van Der Werf et al., 2004). Moreover, beyond the impact on atmospheric composition, forest fires also interrupt cloud formation and reduce rainfall (Andreae et al., 2004), further increasing forest fire proneness.

During years of normal rainfall, undisturbed rainforests hold elevated air humidity and a damp layer of leaves, twigs and branches, and thus are naturally not very flammable (Bowman, 2017). Droughts, however, create the required conditions to enable forest fires to be sustained and spread (Aragão et al., 2007), which nonetheless mainly occur because of anthropogenic ignition sources (Malhi et al., 2008). Fire use for land management and advancing deforestation is nearly ubiquitous in rural areas across the tropics (Cochrane, Kull, and Laris, 2009; Goldammer, 1988; Malhi et al., 2008). Concurrently, more frequent and severe droughts and heat-waves are expected under future scenarios of climate change (Lewis, Brando, Phillips, Van Der Heijden, and Nepstad, 2011). The combination of severe drought events with increasingly widespread anthropogenic ignition sources, are likely exacerbating ecosystem transitions from high-biomass moist forests to transitional dry and woody savannah-like forests (N. M. Levine et al., 2016, Esquivel-Muelbert et al., 2018), and pushing tropical forests towards a tipping point, whereby the forest is no longer able to sustain itself, through extensive fire-induced tree mortality and forest degradation (Brando et al., 2014; Hirota et al., 2011), which intensifies the importance of Protected Areas and their mitigating effects (Barber, Cochrane, Souza, and Laurance, 2014; Nolte and Agrawal, 2013).

Protected Areas (PAs) are an effective global strategy for preserving biodiversity through regulating human presence and activities (Nolte and Agrawal, 2013). Additionally, they are an essential component of strategies for mitigating climate change (Soares-Filho et al., 2010), and have demonstrated effectiveness in inhibiting fire and deforestation (Adeney, Christensen, and Pimm, 2009; Andam, Ferraro, Pfaff, Sanchez-Azofeifa, and Robalino, 2008; Nepstad et al., 2006). In the Brazilian Amazon, which is the largest tropical rainforest in the world (Alencar et al., 2006), PAs shelter 54% of the remaining forests (Soares-Filho et al., 2010), and face increasing pressure from illegal activities, including agricultural expansion, selective logging and mining (Blaser et al., 2011).

The Brazilian government has recently announced an eminent review of PAs categories aiming at softening protection levels and facilitating their use through agriculture and forest production (OECO, 2019). Currently, PAs in the Brazilian Amazon are categorized under three major groups: strictly protected and sustainable use, in addition to indigenous lands (MMA - SNUC, 2016). They are then subdivided in 11 management categories that allow for six levels of human activities, such as low-impact agriculture and forest production (MMA), which then introduces different types and intensities of anthropogenic pressures and ignition sources. Downgrading protection levels amidst the prospect of more frequent and severe droughts, and increasingly widespread ignition sources, further increases the vulnerability of PAs to deforestation and degradation. This poses a serious threat to biodiversity conservation and ecosystem services provision (Fonseca et al., 2019; Laurance et al., 2012; Soares-Filho et al., 2010). Thus, properly understanding how local climatic variation interacts with anthropogenic activities is crucial to improve fire-risk prediction models, and advance with strategic management and conservation of PAs in the Amazon.

In this study, we attempt to tease apart and quantify the contribution of seasonal climatic variation and anthropogenic pressures in driving fire in the Brazilian Amazon. Furthermore, given the increasing pressure on protected areas, we assess the effectiveness of different categories of PAs and wilderness areas in the Brazilian Amazon in inhibiting fire. We integrated key climatic and anthropogenic variables with landscape information and fire occurrence data registered over the past two decades in the Brazilian Amazon to: (1) quantify the role of climate and key anthropogenic pressures in driving fire occurrence; and (2) assess the effectiveness of different levels of protection in PAs and wilderness areas in inhibiting fire.

4.3 Methods

Study area

Our study region encompasses the Brazilian Amazon — the ~4.2 million km^2 of moist, tropical forest biome (Olson et al., 2001). Dense and open tropical rain forests are the most representative vegetation cover of the Brazilian Amazon, which is roughly 30% of global tropical rain forests (FAO, 2001). The region experiences mean annual temperatures ranging from 24°C to 26°C with modest seasonal variability, and a mean precipitation regime of approximately 2 300 mm · $year^{-1}$, with some areas in the southwest experiencing drought (i.e. rainfall below 100 mm · $month^{-1}$) for up to 5 months, generally from June to November, and others in central regions having no water deficit throughout the year (de Moura et al., 2015). In addition to the variability in length of dry season, the time period in which it occurs also varies in space, with the North region experiencing water deficit mainly between January and March (de Moura et al., 2015).

Data collection

Climatic data

Vapour pressure deficit — VPD and Palmer Drought Severity Index — PDSI

Vapour pressure deficit (VPD) integrates air temperature and relative humidity as a measure of atmosphere evaporative demand (Zhang, Wu, Yan, Zhu, and Feng, 2014). VPD is an important variable related to evapotranspiration and is frequently applied to ecosystem models in simulating fluxes and states of water and carbon (Wang and Dickinson, 2012), as well as in fire modelling (Silvestrini et al., 2011). The Palmer Drought Severity Index (PDSI) is a standardized index generally ranging from − 10 (dry) to + 10 (wet) that integrates air temperature and precipitation data to estimate relative dryness, and is one of the most widely used regional indices of drought (Alley, 1984).

We obtained monthly layers of VPD and PDSI at a spatial resolution of ~500 m with Terra Climate, which is a dataset of high-spatial resolution monthly climatic variables, from 2001 to 2018 (Abatzoglou, Dobrowski, Parks, and Hegewisch, 2018). VPD and PDSI were employed separately as climatic explanatory variables of fire occurrence in our models, better detailed in *Data analysis*.

Landscape data

Wilderness

Wilderness areas are defined as biologically and ecologically largely intact landscapes that are mostly free of human disturbances (Watson et al., 2016). We obtained temporally inter-comparable maps of global terrestrial wilderness areas of 1993 and 2009 at a spatial resolution of ~1 km (Allan, Venter, and Watson, 2017) that were then combined to determine three distinct classes: areas that have been cleared before 1993, wilderness areas that have been lost between 1993 and 2009, and areas that were still considered wilderness in 2009.

Protected Areas

Protected areas (PAs) are defined as all public areas under land-use restrictions that contribute to protecting native ecosystems (IUCN, 1998). Currently, the Brazilian Amazon harbours 338 PAs, that are classified under two main groups: strictly protected and sustainable-use reserves, in addition to indigenous lands and wetland Ramsar Sites. We obtained PAs maps from the World Database on Protected Areas (IUCN/UNEP-WCMC, 2016).

Anthropogenic data

Human footprint

The Human Footprint aims to represent the combined ecological footprints of the human population. Major patterns of human influence on nature are expressed through combining direct measures of human infrastructure and population that have the most immediate impact on wildlife and wild lands. Effects of pollution, global warming, increased exposure to ultraviolet radiation, and other global phenomena are not included in these data. The Human Footprint, as a global map of human influence on the land surface, was devised using four types of data as proxies for human influence: population density, land transformation, accessibility, and electrical power infrastructure (Sanderson et al., 2002). We obtained a Human Footprint map of cumulative pressures on the environment for 2009 at a spatial resolution of 1 km, that includes built-up environments, population density, electric power infrastructure, crop lands, pasture lands, roads, railways, navigable waterways, and factors such as the size and remoteness of an area (Venter et al., 2018).

Fire data

Burnt Area

Burnt areas are characterized by deposits of charcoal and ash, total or partial removal of vegetation, all of which cause spectral, temporal, and structural changes that the MODIS mapping algorithm uses to derive the burnt area product (Giglio, Boschetti, Roy, Humber, and Justice, 2018). These data are derived from daily surface reflectance inputs detected by the MODIS (Moderate Resolution Imaging Spectroradiometer) sensor aboard the Aqua and Terra satellites, and contain burning data on a per-pixel basis at a spatial resolution of ~500 m. We obtained monthly maps of burnt area from 2001 to 2018, made available through the re-projected GeoTIFF version from the University of Maryland (MCD64 – Burned Area Products).

Active Fires

The active fires product from MODIS consists of fire spot daily detections in ~1 km pixels under relatively cloud-free conditions using a contextual algorithm detecting thermal anomalies. We obtained these data (Collection 6) spanning 2001 to 2018 for the Brazilian Amazon from MODIS repository (Giglio, Schroeder, and Justice, 2016) (Active Fires Products).

Data manipulation

Data manipulation was conducted in R (R Core Team, 2017).

Burnt Area

Monthly rasters of burnt area contained information classified as burned and unburned land, water, and unmapped due to insufficient data per ~500 m pixel. At the original spatial resolution, this dataset for the entire Brazilian Amazon spanning 2001 to 2018 sums to over 370 million observations, which poses a computational challenge. Thus, after cropping the dataset using a spatial polygon of the Brazilian Amazon (ESRI), we decreased the spatial resolution by 100×, and calculated the proportion of burnt pixels (sum of burnt pixels divided by the total number of pixels) within the new grid cell at spatial resolution of ~5 km using the 'raster' R package (Hijmans and van Etten, 2012). Proportion of burn pixels was used to derive one of the response variables representing fire occurrence in our analyses.

Active Fires

The active fires product consists of point locations of each fire spot detection along with temporal information of their acquisition. We organised these data according to month and year of acquisition, and overlaid each layer with a grid cell at a spatial resolution of ~11 km. Within each grid cell, we calculated the sum of active fires spots for each month of each year. Count of fire spots was used to derive the other response variable representing fire occurrence in our analyses.

Climatic *vs* anthropogenic pressure

We used Vapour Pressure Deficit (VPD) data to represent the main climatic driver of fire, and Human Footprint (HFP) the main anthropogenic driver of fire in this analysis.

The data frame derived from burnt area containing proportion of fire across the Brazilian Amazon from 2001 to 2018 summed approximately 3.7 million observations, from which we randomly sampled 10% of the data to obtain a computationally manageable size dataset for the analyses. We then combined this subset with the Vapour Pressure Deficit (VPD) and Human Footprint (HFP) datasets, and extracted mean values of VPD and HFP per ~5 km grid cell for each month of each year. Additionally, we added municipality data to include this geographic spatial component in the analyses as a way of accounting for spatial correlation of observations. Lastly, we summarised this data for each year by calculating monthly maximum 'proportion of burn', 'VPD' and 'HFP' per year for each grid cell, aiming to represent the most fire prone conditions registered, both climatic and human influenced. The final dataset summed approximately 314 000 observations.

We overlaid the spatial information in the data frame derived from active fires with monthly rasters of Vapour Pressure Deficit (VPD) and Human Footprint (HFP), and extracted mean values of VPD and HFP within each grid cell for each month of every year. Additionally, we overlaid a larger grid with a spatial resolution of ~55 km so that the big grid cells would be included in the analyses to account for spatial correlation of observations. We then summarised this data for each year by calculating monthly 'maximum VPD' and 'HFP', and 'sum of active fire spots' within each grid cell (within the smaller spatial resolution of ~11 km), which represents both a temporal duration of fire as well as a spatial spread of fire within each grid cell. Lastly, we normalised the data by dividing fire count within each cell by the maximum fire count value registered across the study time frame (18 years).

Wilderness

We used fire occurrence both from burnt area and from active fires, only for the year of 2009 to match the wilderness classification, and added PDSI in this analysis to account for climatic variability. We randomly sampled 25% of the data frame derived from burnt area and intersected this spatial information with the dataset containing three distinct levels of wilderness: areas that have been cleared before 1993, wilderness areas that have been lost between 1993 and 2009, and areas that were still considered wilderness in 2009. We then extracted mean monthly values of PDSI for each cell. We also added 'municipality' data to account for spatial correlation.

The data frame derived from active fires was intersected with the dataset containing three distinct wilderness levels, and with a larger cell grid at a spatial resolution of ~55 km to account for spatial correlation of observations in the analysis. Additionally, we extracted mean monthly values of PDSI within each ~11 km grid cell. Lastly, we normalised fire occurrence by dividing fire count within each cell by the maximum fire count value registered across 2009.

For each dataset (burnt area and active fires), we summarised information for the entire year by calculating 'maximum proportion of burn' and 'minimum values of PDSI' for each grid cell, thus representing the driest registered values across the year, which is likely to be the worst climatic scenario for fire occurrence. A visual inspection of each final datasets is shown in Fig. 4.2.

Protected Areas

We randomly sampled 10% of the data frame containing burnt area across the Brazilian Amazon from 2001 to 2018, and overlaid this spatial information with Protected Areas (PAs) polygons, keeping the name and size of each reserve. Municipality was added to

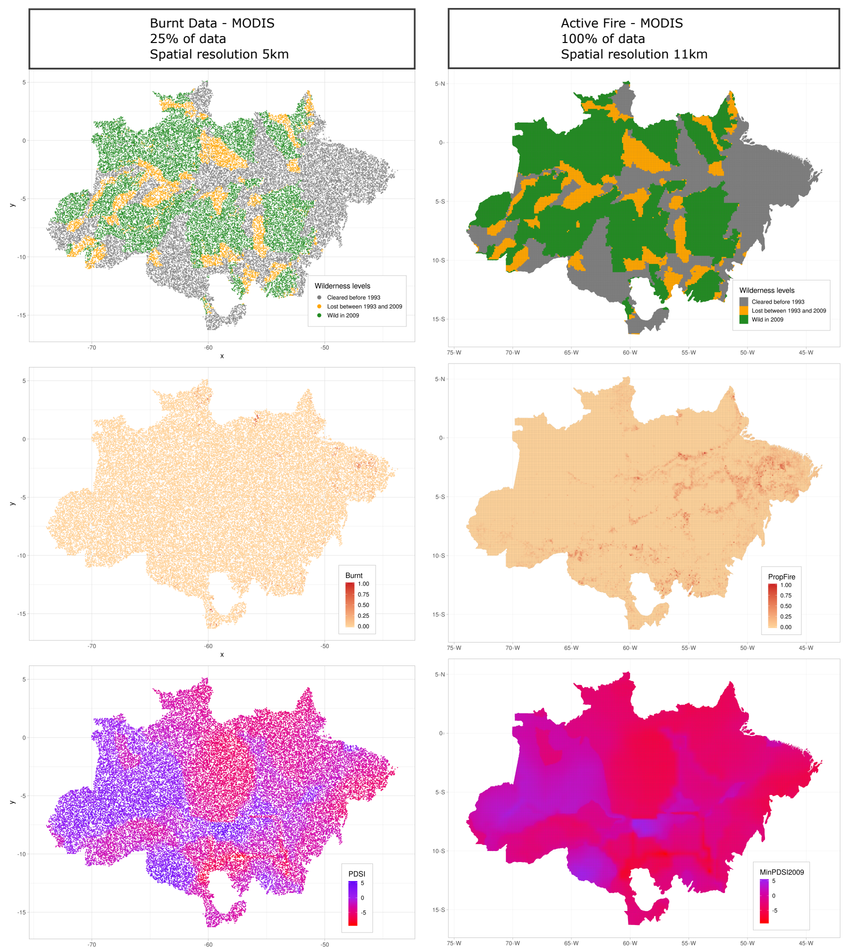

Figure 4.2: Visual disposition of the data used for the wilderness analyses. Maps of the Brazilian Amazon showing the three levels of wilderness on the first row, fire occurrence based on burnt area on the left side of middle row and based on active fires on the right side of middle row, and PDSI on the bottom.

account for spatial correlation of observations, and mean PDSI values for every cell for each month from 2011 to 2018 were extracted.

From the data frame containing proportion of burn based on active fires across the Brazilian Amazon from 2001 to 2018, we randomly sampled 50% of observations. We then intersected this spatial information with PAs polygons, and with a larger cell grid at a spatial resolution of ~55 km to account for spatial correlation in the analysis. We then extracted mean PDSI values for every ~11 km grid cell for each month from 2011 to 2018. Size of reserves was calculated as the amount of grid cells under each distinct reserve name multiplied by the area of each grid cell (11 $\times$ 11 km).

For each dataset (burnt area and active fires), we summarised data for each year by calculating 'maximum proportion of burn' and 'minimum values of PDSI' for each cell across each year. Additionally, we created a variable 'PA' to represent the two most generic situations, inside or outside a protected area. Furthermore, we created a variable named 'Class of Fire Risk' based on the classes assigned to each reserve by the Brazilian Ministry of Environment according to which human activities are permitted inside each management category of Protected Area, and added PDSI in our analyses to account for climatic variability. (MMA; Table 4.1).

Table 4.1: Protected Areas in the Brazilian Amazon, management categories within the main groups, human activities permitted and assigned fire risk – SR: Scientific Research, EE: Environmental Education, Vs: Visitation, LIAgr: Low Impact Agriculture, FP: Forest Production, Ex: Extrativism, Agr: Agriculture, Ind: Industrial Activities, URPop: Urban and Rural Population Settlement.

	Management Category	**Activities Permitted**	**Fire Risk Class**
Integral Protection	Ecological Station	SR, EE	Class 1
	World Heritage Site (natural or mixed)	LIAgr, SR, Vs, FP, Ex	Class 5
	Park	SR, EE, Vs	Class 2
	Biological Reserve	SR, EE	Class 1
	Wildlife Refuge	LIAgr, SR, Vs, FP, Ex	Class 5
Sustainable Use	Environmental Protection Area	Agr, Ind, URPop	Class 6
	Area of Relevant Ecological Interest	Agr, Ind, URPop	Class 6
	Forest (FLONA)	FP, SE, Vs	Class 3
	Sustainable Development Reserve	LIAgr, SR, Vs, FP, Ex	Class 5
	Extractive Reserve	Ex, SR, Vs	Class 4
	Natural Heritage Private Reserve	–	Class 2
Indigenous lands		–	Indigenous lands
Ramsar Site, Wetland of International Importance		–	Wetland
Not protected or undesignated land		–	Not protected

Statistical analyses

All statistical analyses were conducted in R (R Core Team, 2017). Models were selected according to a combination of model comparisons of Akaike's Information Criterion (AIC), which is a tool for model selection where the model with the lowest AIC indicates the best model, i.e. that which offers the best fit whilst penalising for number of parameters (Akaike, 1974), and a visual interpretation of heterogeneity and normality of residuals (Zuur et al., 2013).

Climatic *vs* anthropogenic pressure

Fire occurrence (from burnt area and active fires) was modelled using binomial Generalised Additive Mixed-Modelling (GAMM family binomial with a logit link function; Wood, 2011). To assist the interpretation of results, VPD and HFP were both scaled from 0 to 1 by dividing each value by the maximum registered value of each variable across the study time frame. Scaled VPD and HFP were included in the model as smoothed terms in the fixed structure, as was the variable 'year'. In the analysis with burnt area it was not possible to add 'municipality' as a random structure and thus account for spatial correlation due to computational limitations. In the analysis with active fires, however, it was possible to add 'larger grid cell ID' as a random effect and account for spatial correlation of observations.

Wilderness

Fire occurrence (from burnt area and active fires) was modelled using binomial Generalised Additive Mixed-Modelling (GAMM family binomial with a logit link function; Wood, 2011) against the three-level categorical variable 'wilderness' and 'PDSI', to account for climatic variability. 'Municipality' was added in the random structure of the burnt area analysis, and 'big grid cell ID' in the random structure of the active fires analysis to account for spatial correlation.

Protected Areas

Fire occurrence (from burnt area and active fires) was modelled using binomial Generalised Additive Mixed-Modelling (GAMM family binomial with a logit link function; Wood, 2011). To investigate and compare the proportion of fire inside and outside protected areas, fire occurrence was modelled against 'PA', 'PDSI', to account for climatic variability, and smoothed 'Year', to account for temporal variability. To investigate the role of each class of protected area in inhibiting fire, its occurrence was modelled against 'Class of Fire Risk' and 'PDSI', excluding observations outside of protected areas. We also added 'reserve size' and 'year' as smoothed terms in the fixed structure.

For the analyses with burnt area it was not possible to add 'municipality' as a random structure and thus account for spatial correlation due to computational limitations. In the analyses with active fires, however, it was possible to add 'big grid cell ID' as a random effect and account for spatial correlation of observations.

4.4 Results

4.4.1 Climatic *vs* anthropogenic pressure

Considering both predictors on the same scale (0 – 1), Vapour Pressure Deficit (VPD) had a near three-fold stronger effect on fire occurrence based on burnt area than Human Footprint (HFP) (Fig. 4.3). VPD increased fire occurrence by 0.61 (± 0.01), and HFP increased it by 0.23 (± 0.01). For fire occurrence based on active fires, VPD had a near two-fold stronger effect than HFP (Fig. 4.4). VPD increased active fires occurrence by 0.29 (± 0.02), and HFP increased it by 0.16 (± 0.02).

4.4.2 Wilderness

Fire occurrence in 2009 based on burnt area (Fig. 4.5a) was consistent with that based on active fires (Fig. 4.5b), in that areas cleared before 1993 showed higher proportion of fire, followed by wilderness areas lost between 1993 and 2009, and lastly by areas still considered wilderness.

At the lowest values of PDSI, which represents the driest condition, areas cleared before 1993 had 3.6 times higher proportion of burnt area than areas cleared between 1993 and 2009, and 8.3 times higher than areas still considered wilderness. At the wettest conditions, however, these differences are smaller across the three levels, with areas cleared before 1993 having 3.0 times higher proportion of burnt area than areas cleared between 1993 and 2009, and 6.0 times higher than areas still considered wilderness. Furthermore, areas cleared before 1993 were more influenced by PDSI than the other two levels, with proportion of fire occurrence dropping by 8.3 times from the driest to

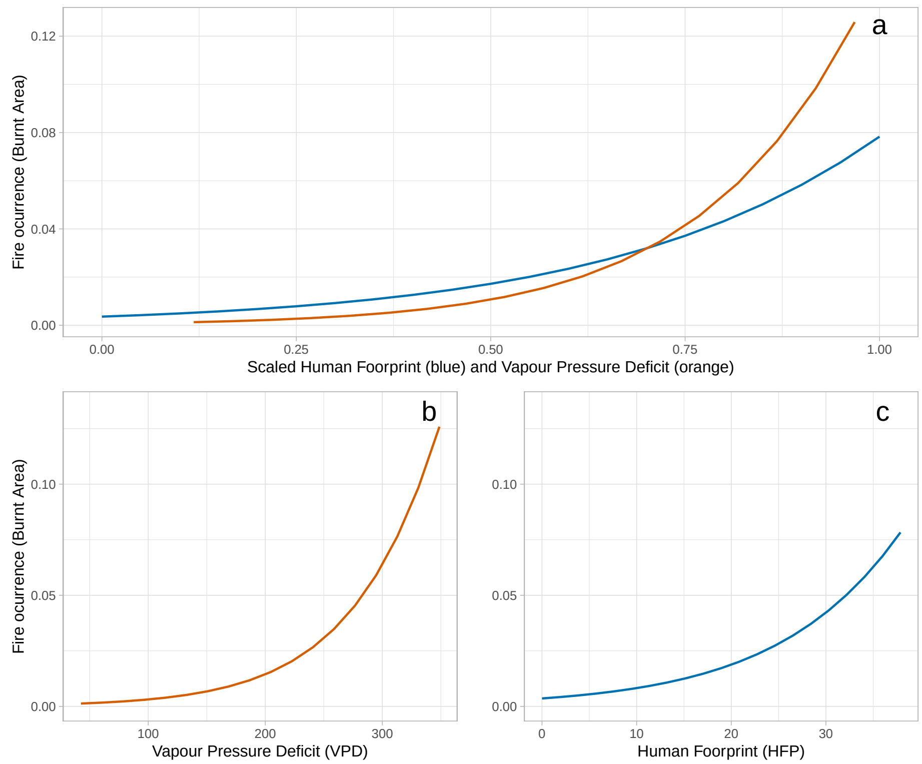

Figure 4.3: Fire occurrence based on burnt area against scaled VPD and HFP (0 – 1) (a), and against the same variables on their original scales: VPD (b) and HFP (c).

wettest condition, compared to 7.0 times in areas cleared between 1993 and 2009, and 6.0 times in wilderness areas.

Differences of fire occurrence proportion based on active fires across the three levels were smaller than those based on burnt area. At the lowest values of PDSI, areas cleared before 1993 showed 1.9 times higher proportion of active fires than areas cleared between 1993 and 2009, and 3.7 times higher than wilderness areas. Moreover, at the highest values of PDSI, representing the wettest condition, proportion of fire occurrence in areas cleared before 1993 was higher than that under the driest conditions registered in wilderness areas.

4.4.3 Protected Areas

Protected *vs* not protected

At the lowest values of PDSI, proportion of fire outside protected areas was higher by

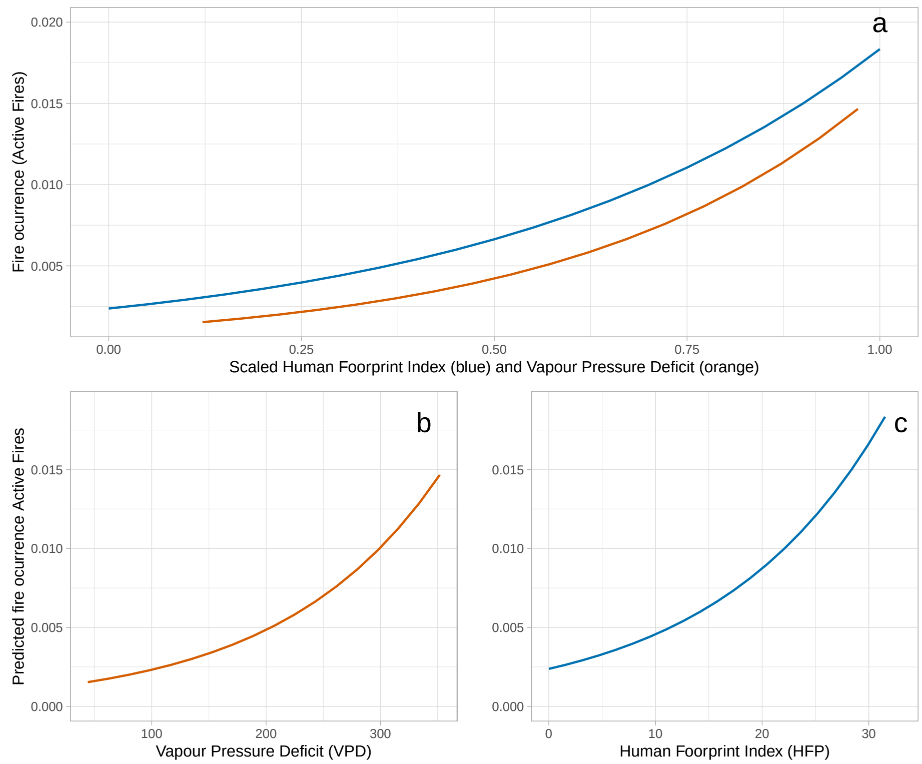

Figure 4.4: Fire occurrence based on active fires against scaled VPD and HFP (0 – 1) (a), and against the same variables on their original scales: VPD (b) and HFP (c).

3.7 times than inside them based on burnt area (Fig. 4.6a), and by 4.5 times based on active fires (Fig. 4.6b).

Classes of protected areas

At the lowest values of PDSI, the highest proportion of fire based on burnt area was observed in protected areas of Class 6, which allows for agricultural and industrial activities, and urban and rural population settlements. Proportion of fire in these areas was 1.4 times higher than in protected areas of Class 2, which allows for scientific research, environmental education and visitation, and 1.6 times higher than in indigenous lands. Furthermore, the proportion of fire in Class 6 areas were nearly two orders of magnitude (94 times) higher than in Class 5, which allows for low impact agriculture, scientific research, visitations, forest production and extractive activities, and where the smallest proportion of burnt area was observed (Fig. 4.7a).

Differently from burnt area, the highest proportion of active fires under the driest conditions of PDSI, was observed in indigenous lands, by 1.7 times higher than in

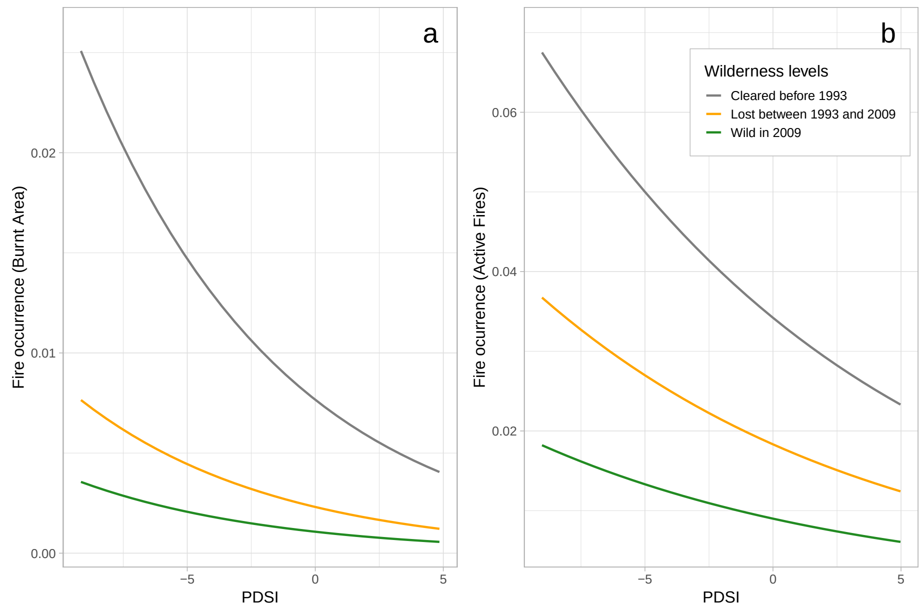

Figure 4.5: Fire occurrence across levels of wilderness areas in 2009 based on burnt area (a) and active fires (b) against PDSI (BA = 25% of data, spatial resolution of ~5 km; AF = 100% of data, spatial resolution ~11 km).

protected areas of Class 6, and 1.9 times higher than in areas of Class 4. The smallest proportion of fire occurrence based on active fires, was observed in protected areas of Class 5, which is consistent with the results based on burnt area (Fig. 4.8a).

Size of reserve had a negative impact of -0.14 ($\pm$ 0.03, $p \leq 0.01$) on fire occurrence based on burnt area (Fig. 4.7b), and of -0.58 ($\pm$ 0.32, $p = 0.07$) on fire occurrence based on active fires and Fig 4.8b).

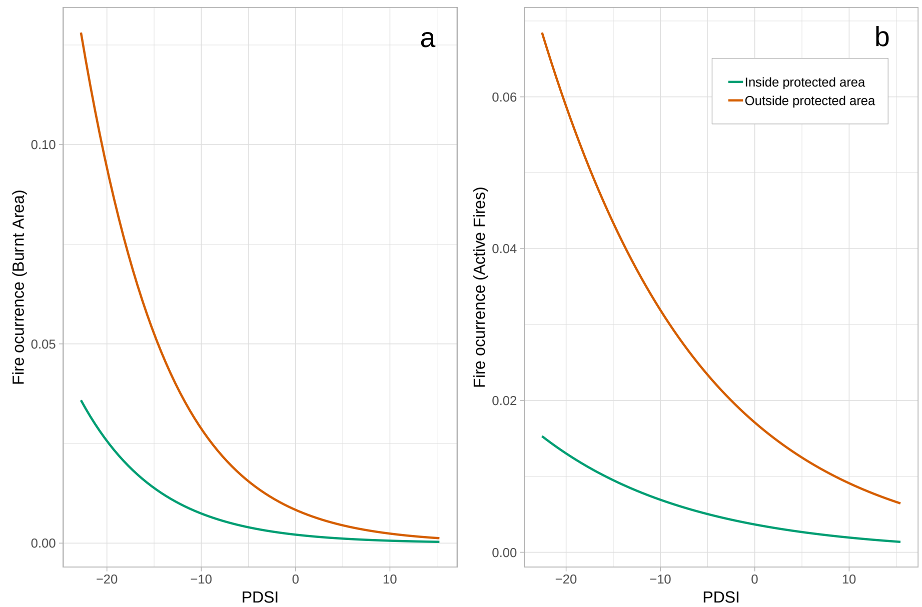

Figure 4.6: Fire occurrence based on burnt area (a) and active fires (b) inside and outside protected areas against PDSI.

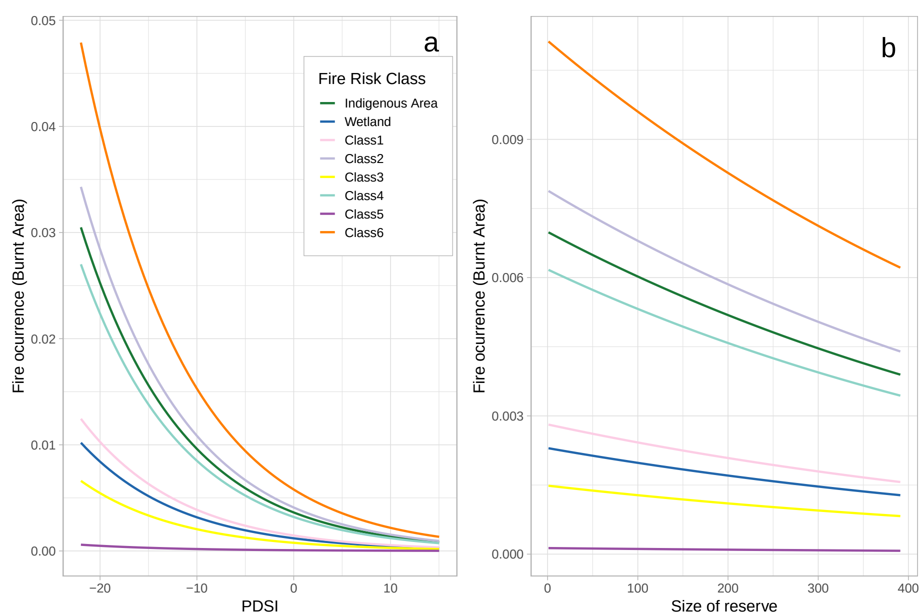

Figure 4.7: Fire occurrence across levels of protected areas based on Burnt Area against PDSI (a) and side of reserve (b) (10% of data, spatial resolution of ~5km).

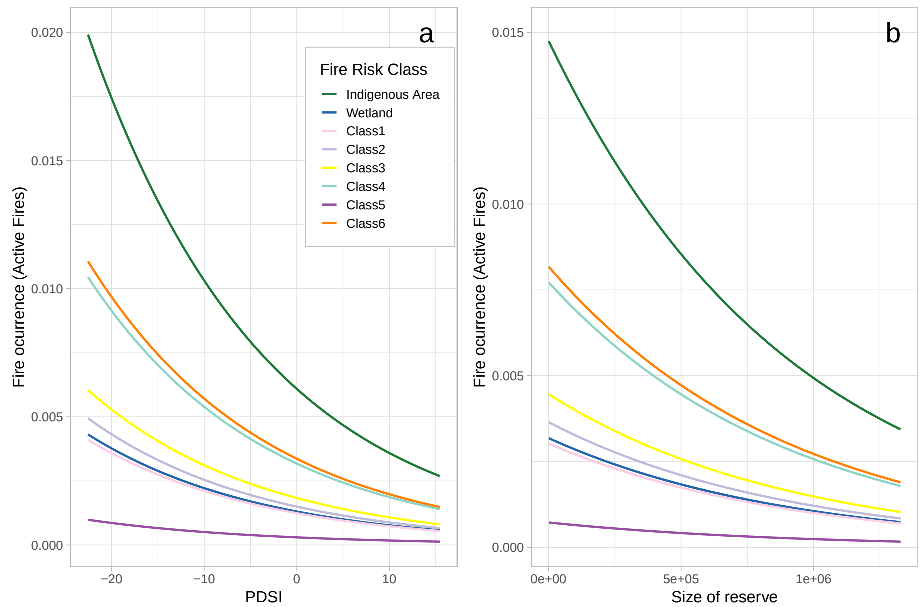

Figure 4.8: Fire occurrence across levels of protected areas based on Active Fire against PDSI (left) and side of reserve (right) (50% of data, spatial resolution ~11km).

4.5 Discussion

Fire in tropical forests is a product of the interaction between droughts and anthropogenic pressures (Malhi et al., 2008; Van Der Werf et al., 2004). Human-induced fires influence regional rainfall regimes (Andreae et al., 2004), degrade forests structure, and facilitate the invasion of flammable grasses (Brando et al., 2019), all of which further increases the fire proneness of forests. We disentangled local climatic variation and anthropogenic pressures to explain fire occurrence in the Brazilian Amazon, and quantified fire occurrence across different categories of Protected Areas (PAs) and wilderness areas to assess their effectiveness in inhibiting fire. Our results show that Vapour Pressure Deficit (VPD) better explained fire occurrence compared to Human Footprint (HFP), suggesting that climate is a stronger predictor of fire than anthropogenic pressures. We also found that the highest proportion of active fires was in indigenous lands, and the highest proportion of burnt area was in Class 6 PAs. Moreover, our study revealed that drought severity magnifies fire occurrence where human pressures are increased, reinforcing the interaction between climate and anthropogenic pressures. Thus, regulating human activities and fire-use in the Amazon forest, especially inside PAs, is crucial to prevent more fires which would then feedback into this cycle.

4.5.1 Climatic *vs* anthropogenic pressure

Previous studies have tried to tease apart climate and human pressures to explain and predict fire using many approaches, including employing VPD to represent climatic fire risk (Silvestrini et al., 2011). For both burnt area and active fires, VPD had a stronger effect on fire occurrence compared to HFP, which suggest that climate is a stronger predictor of fire than human pressures. Regional climatic conditions are likely to be more directly related to fire because droughts represent the necessary weather determinants for fire occurrence (Malhi et al., 2008). Droughts can affect forests biomass productivity (Phillips et al., 2009), increase tree mortality and litter production (Brando et al., 2014), and enable the desiccation of fuel layers, thus exacerbating forest flammability (Laurance, 2004).

Anthropogenic fire risk can be represented through variables that strongly influence fire occurrence in the Amazon, such as distance to transportation networks and recently deforested areas (Barber et al., 2014; Fonseca et al., 2019). The Human Footprint, which was used in this study to represent anthropogenic drivers, aims to depict the strongest pressures from humans on the natural environment by encompassing four major proxies: population density, land transformation, accessibility, and electrical power infra-structure (Sanderson et al., 2002). Thus, despite being comprehensive, the human pressures represented in the HFP are not subject to the seasonal variability that correlates with drought seasons (Alencar et al., 2006), which is likely the reason why it was not as strong a predictor of fire occurrence as VPD.

The HFP map includes cumulative human pressures in urbanized areas. Outside those, however, is where the most problematic fires occur, especially deforestation fires, which cause much higher carbon emissions due to the greater amount of biomass being burnt compared to cropland and pasture maintenance fires (L. O. Anderson et al., 2015). Moreover, different types of agricultural practices require distinct uses and intensities of fire (Alencar et al., 2006), with highly mechanised agriculture not utilising it as much as slash-and-burn (Aragão and Shimabukuro, 2010). Cities and urbanised settlements, therefore, are not where deforestation and cropland fires occur, which suggests that HFP may not be the best indicator of anthropogenic pressures acting directly on fire. Instead, land-cover classes, such as agricultural-land types and secondary vegetation, contribute to explaining fire types in the Amazon (Fonseca et al., 2019), and should be considered in fire-risk modelling and analyses.

4.5.2 Wilderness and Protected Areas

Neither wilderness nor PAs are completely free from human influence, but since only controlled activities are allowed, supposedly causing minimal disturbances, these areas are often not a priority for conservation efforts as they are assumed to be relatively free from threatening processes (Myers et al., 2000; Watson et al., 2016). Forest areas cleared before 1993 hold more established human occupation and activities, which is likely why we found a much higher proportion of fires compared to areas with more recent occupation and without human settlements.

Between protected and not protected, a much lower proportion of fire was observed inside PAs, which is consistent with their demonstrated inhibitory effect on fire and deforestation (Adeney et al., 2009; Barber et al., 2014; Laurance et al., 2012; Nolte and Agrawal, 2013; Silvestrini et al., 2011; Soares-Filho et al., 2010). Further detailing this investigation inside PAs across different levels of human activities, our study revealed a higher proportion of active fires in indigenous areas compared to all other PA classes, but not the highest proportion of burnt area, which likely indicates strategic fire management. Our results demonstrate that regarding the inhibition of active fires, inhabited indigenous areas are less effective than uninhabited parks (Class 2 PAs, $p < 0.05$), contrary to Nepstad et al. (2006). Nonetheless, the higher proportion of active fires is not directly translated into high proportions of burnt area, thus, not indicating signs of deforestation. Therefore, our findings do not contradict that indigenous lands represent an important barrier to Amazon deforestation (Nepstad et al., 2006).

The highest proportion of burnt area was observed in Class 6 PAs, in which more intensive human activities are allowed, including agricultural and industrial uses. These results should raise concern since they likely indicate signs of deforestation in these areas (Aragão et al., 2008), particularly with the current fire season being closely linked to deforestation (Escobar, 2019). The synergy between deforestation and climate change may further aggravate the impact of fire in Amazonian forests (Silvestrini et al., 2011). Thus, further investigation of exact location and types of fire inside PAs is needed to inform deforestation monitoring programs.

Our study also demonstrates that drought severity consistently magnifies fire occurrence where human pressures are increased, which further reinforces the synergy between climate and anthropogenic pressures (Cochrane & Laurance, 2008). Beyond the direct influence of drought severity across all levels of PAs, reserve size also had a strong influence in inhibiting fire, which is consistent with Nepstad et al. (2006). Further efforts to investigate the inhibitory effect of PAs on fire and deforestation should also consider an interaction between reserves size and distance to humans, especially to roads and lands employing traditional farming methods.

4.5.3 Conservation implications

The conservation of Amazon forests critically depends on avoiding the first fire. Our study reinforces that fire in the Amazon is driven by a synergy between climatic conditions and anthropogenic pressures, as drought severity magnifies fire incidence where human activities are more intensive. Beyond the direct effect of human presence increasing ignition sources (Alencar, Brando, Asner, & Putz, 2015), human-induced fires also affect regional climate through interrupting cloud formation and reducing rainfall (Andreae et al., 2004), which further increases forest fire proneness.

The predicted intensification of severe droughts with shorter-return intervals under climate change, coupled with increasingly widespread human occupation providing ignition sources across the Amazon forest, will likely intensify the synergism between climate and human pressures in driving fire, and increase even more the pressure on protected areas. Thus, regulating human activities inside Protected Areas, and careful monitoring of deforestation and fire use across the Amazon forest, are critical to prevent wildfires that will reinforce this cycle of human-induced fires causing droughts and degrading forest, further increasing the chances of more fires.

Acknowledgements

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Chapter 5

Thesis discussion

Figure 5.1: Leakage fire from pastures invading Jamari National Forest, Rondônia, Brazil.

5.1 Summary

The conservation of tropical forests is pivotal to preserve an overwhelming proportion of global biodiversity and crucial ecosystem services (Barlow et al., 2018). The leading cause of deforestation and biodiversity loss in terrestrial ecosystems is land-use change (Sala et al., 2000), which is largely driven by large-scale agricultural expansion to meet global demands of food, feed and fuel (Gibbs et al., 2010). Fire as a tool for land management and advancing deforestation for cropland expansion is nearly ubiquitous across the tropics (Malhi et al., 2008). Alongside deforestation, remaining forests can suffer extensive degradation by anthropogenic pressures, such as selective logging and unintended leakage fires from neighbouring croplands and pastures, both of which can be significantly more widespread than complete land conversion (Asner et al., 2009; Barlow et al., 2016).

Concurrently, tropical forests will be subject to increasingly severe heat-waves and droughts as consequences of global climate change (Corlett, 2011). Moreover, climatic changes are likely to interact synergistically with anthropogenic pressures and alter the fate of tropical biodiversity (Brodie et al., 2012a). More frequent and severe droughts under climate change are expected to increase wildfires occurrence and intensity (Brando et al., 2014), which will directly intensify forest mortality and interfere with ecosystem processes at rates that could outpace the capacity of tropical forests to recover or adapt to more intense disturbance regimes (Lewis et al., 2015; Trumbore et al., 2015).

This study set out to explore and understand how anthropogenic pressures and climatic variations might alter fire risk in the Amazon forest. Through a combination of observational, experimental and modelling exercises, I investigated some of the main drivers of forest flammability at fine scales. By connecting canopy structure with understorey ambient and surface of the forest floor, I explored the potential impacts of selective logging on the forest thermal environment from multiple aspects. Spatially, I investigated the impacts from logging gaps on the thermal environment and on forest flammability of the remaining surrounding forest one year after harvest. Temporally, I assessed how much time is required after harvest operations for logging gaps and roads to recover their baseline thermal environmental conditions, and compared the spatial availability of surface microclimates considering time of recovery since logging. Moreover, to incorporate a broader perspective of fire in the Amazon, I disentangled climatic variation and anthropogenic pressures to explain fire occurrence over the past two decades, and assessed the effectiveness of different categories of Protected Areas in inhibiting fire in the Brazilian Amazon.

In this discussion chapter, I synthesise my findings to illustrate how anthropogenic pressures can impact both fine-scale elements of the forest thermal environment and flammability, and broad-scale drivers of wildfires. I discuss how such impacts may affect forests' ability to cope with future climate change in the tropics and conclude this thesis suggesting priority research directions and providing recommendations for conservation practitioners and policy-makers.

5.2 Fine-scale impacts — Spatially

Looking into selective logging, which is one of the most widespread patterns of forest degradation across the tropics (D. P. Edwards, Tobias, et al., 2014), Chapter 3 investigates its relationship with fire proneness in the Amazon forest and demonstrates that the canopy disruption caused by logging operations negatively impacts the forest thermal environment. Logging gaps are hotter and drier than the surrounding remaining forest, and the thermal environment around larger gaps are more affected than that around smaller gaps, both in the understorey ambient air and the surface of forest floor.

Furthermore, through a controlled fire experiment, Chapter 3 demonstrates the direct influence of selective logging on forest vulnerability to fire by accelerating leaf-litter desiccation, thereby raising the probability of fuel igniting when exposed to an ignition source, and increasing fire intensity, especially in larger logging gaps. Moreover, this study shows that the whole logged landscape is equally able to catch and sustain fire when exposed to an ignition source, which emphasises the importance of preventing human activities that promote ignitions sources in selectively logged forests to avoid fire incursions.

Relative to clear-cut deforestation and wildfires in the conversion of forests into agricultural lands, selective logging is a commercial activity with a much lower detrimental impact on the forest structure. Selectively logged forests can still harbour a substantial amount of biodiversity and carbon (D. P. Edwards et al., 2011; Putz et al., 2012) but keeping their conservation value into the future is highly dependent on preventing further degradation after logging operations, with special focus on wildfires (Nepstad et al., 1999).

5.3 Fine-scale impacts — Temporally

The ability of these forests to rapidly recover their baseline thermal conditions will directly determine how well they can sustain their conservation value, especially under future scenarios of climate change. Chapter 2 investigates the thermal environment recovery of logging gaps and roads in the years following selective logging, and demonstrates that, compared to the unlogged understorey, logging gaps after 3 years of recovery were only marginally warmer, and logging gaps after 5 years of recovery were even slightly cooler. Furthermore, older wide roads (5 years; 6 m) experienced very similar understorey thermal conditions to both narrow roads (3 m) after 1-5 years of recovery, and unlogged forest. These findings highlight that despite the negative impacts on forest structure associated with selective logging (Asner et al., 2006), these forests are able to recover their thermal environments if harvest is performed at low intensity and through the use of reduced-impact logging techniques.

Furthermore, Chapter 2 demonstrates that the thermal spectrum of surface microclimates is heavily affected by logging gaps during warm hours, and that more recent logging gaps present a more challenging landscape in which organisms can operate (Sears et al., 2016). Microclimatic shelters are critical for the persistence of thermally constrained organisms, particularly under global warming (Sinervo et al., 2010).

Thus, this study represents positive news for tropical conservation as it demonstrates that thermal recovery in selectively logged tropical forests can be achieved rather rapidly, which is vital for long-term maintenance of global biodiversity under contemporary scenarios of climate change.

5.4 Broad-scale — Fire across the Brazilian Amazon

Chapters 2 and 3 are focused on the impacts of selective logging on the forest thermal environment and flammability at spatial scales of millimetres to hectares. In the context of conservation and management, this is important for understanding within-forest dynamics and processes, such as the implications of selective logging disturbances for those organisms that depend on forest microclimates as means to avoid suboptimal temperatures, as well as fire proneness within logged landscape.

However, wildfires in tropical forests are a broader scale issue, one which is associated with climatic variation as well as with anthropogenic pressures (Malhi et al., 2008). Thus, to better understand this topic, Chapter 4 disentangles local climatic variation and human drivers, and quantifies their relative contribution in driving fire across the Brazilian Amazon over the past 2 decades. Findings of this chapter demonstrate that local climatic variation is a better predictor of fire compared to human pressures, and also that drought severity consistently magnifies fire occurrence where human pressures are increased, reinforcing the synergy between climate and anthropogenic drivers (Cochrane & Laurance, 2008).

Furthermore, increasing deforestation rates and accessibility in the Amazon forest are intensifying the pressure on Protected Areas (PAs), which represent powerhouses of biodiversity and ecosystem services (Nolte & Agrawal, 2013). Chapter 4 assesses the effectiveness of different categories of PAs in inhibiting fire, and reveals a higher proportion of active fires inside indigenous lands compared to all other classes of PAs, but not the highest proportion of burnt area, which indicates good fire management. The highest proportion of burnt area was observed in Class 6 PAs, which allows for more intensive activities, including agricultural and industrial uses. This finding suggests increased incidence of deforestation and should be closely monitored.

Chapter 4 reinforces that fire in the Amazon forest is driven by a synergy between climatic conditions and anthropogenic drivers, which is likely to be intensified under future scenarios of climate change with more frequent and severe droughts. Moreover, this chapter's findings highlight the importance of regulating human activities inside protected areas and closely monitoring deforestation and fire use across the Amazon to prevent wildfires that will reinforce this synergism between climate and human pressures.

5.5 Relevance and urgency

There is an urgent need to stabilise global climate within safe limits, which means to hold the increase in global average temperature to below 2°C above pre-industrial levels (Parmesan & Yohe, 2003b; UN, 2015). In this context, one of the major concerns is to avoid tipping points in the biosphere, where interactions with climate change and direct human pressures lead to widespread release of carbon dioxide from the biosphere to the atmosphere. The triggering of such feedback would render climate mitigation goals almost impossible to achieve and would further intensify the global biodiversity crisis (Butchart et al., 2010). Amongst the most iconic of these potential tipping points is the potential dieback of the Amazon rainforest caused by an interaction between direct deforestation and degradation, climate change and fire (Brando et al., 2014; Malhi et al., 2008). This thesis emphasises that fire in the Amazon forest is driven by a synergy between climate and anthropogenic pressures.

5.6 Recommendations for conservation

With the broadest geographical scale, results of Chapter 4 demonstrate that drought severity magnifies fire incidence across the Amazon where human activities are more intensive. Under the prospect of PAs having their protection levels downgraded to allow for more intensive human uses, as recently announced by the Brazilian government (OECO, 2019), fire incidence inside PAs is likely to increase, even more so during severe drought events. An increase in burnt area directly relates to an increase in deforestation rates (Escobar, 2019), which should be strictly prohibited inside PAs.

Chapter 3 emphasises that the increased fire proneness of selectively logged forests is likely driven by a synergy between accelerated desiccation of fuel-loads from altered microclimates and greater exposure to ignition sources. Given selective logging is widespread across the Amazon and is one of the activities allowed in Class 6 PAs, with the highest proportion of burnt area (Chapter 4), this thesis has identified two crucial points to reduce fire risk across selective logging concessions: (1) strategic and careful harvest planning to minimise damages to the thermal environment and forest flammability, and (2) strict regulations to control ignition sources post-logging activities.

Downgrading protection levels in PAs will invariably increase human presence providing ignition sources in these areas. If PAs are converted into logging concessions, it is crucial that we reiterate to logging companies the importance of smart and strategic planning of selective logging operations that include intensity limits, reduced-impact logging techniques, efficient design of road networks, and post-logging management that include controlling the use of logging roads by local communities, and ensuring their closure and protection post-logging activities.

Despite the negative impacts on the forest thermal environment and flammability shortly after logging (Chapter 3), results from Chapter 2 demonstrate that the forest can recover its thermal environment conditions rather rapidly (Mollinari et al., 2019; Senior, Hill, Benedick, & Edwards, 2017), which suggests that the increased fire proneness of selectively logged forest can also decrease as forest regenerates. We do highlight, however, that such recovery of the thermal environment is achievable under a low-intensity harvest guided by reduced-impact logging techniques (Burivalova et al., 2014). Thus, we reinforce the importance of strategic planning of selective logging operations followed by strict prevention of illegal activities and fire incursion, with special attention to those 3-5 years post-harvest.

Conservation programs aimed at ensuring the long-term permanence of forest carbon stocks, through global carbon markets, must consider forest degradation from selective logging and fire, as well as deforestation (Berenguer et al., 2014). Carbon-based payments for ecosystem services schemes, such as the 'Reducing Emissions from Deforestation and forest Degradation' (REDD+; UNFCCC, 2008), have the potential to improve logging managements and minimise the damages to the forest (e.g., Reduced-impact logging techniques; Bicknell et al., 2014; Putz et al., 2008). This thesis demonstrates the different ways in which selective logging can increase forests fire proneness and fire incidence in the Amazon. Accounting for the interaction between selective logging and fire will further increase the potential for REDD+ to not only reduce emissions via better logging management, but also to minimise fire occurrence. The amount of carbon released from burnt logged forests is much higher than from timber extraction alone, making REDD+ an even more economically viable option.

5.7 Conclusions

Fire in the Amazon is driven by a synergy between climate and human pressures. With climate change and increasing demands for agricultural goods, deforestation and forest degradation, and ultimately, fire, are likely to be intensified. In this thesis, I have demonstrated that forest fire proneness is strongly related to exposure to ignition sources. Regulating human activities and fire use in the Amazon forest, especially inside Protected Areas, is crucial to preventing fires, and thus preserving primary forests, which are unparalleled for sustaining biodiversity. Nonetheless, selectively logged forests are becoming increasingly ubiquitous and likely represent the next best alternative to sustaining biodiversity and ecosystem services across the tropics. Strategic and careful harvest planning to minimise damaging the forest structure and accelerating desiccation of fuel-loads, as well as strong post-logging management regulations to control ignition sources should be priorities to prevent fire incursion and preserve forest structure after logging. Selectively logged forests can recover their thermal environment to baseline levels of a primary forest, and thus decrease their fire proneness as forest regenerates. Preventing further degradation and fire, with special attention to the first five years after harvest, is crucial for these forests to retain their conservation value.

Appendices

Appendix A

Supporting information for Chapter 2

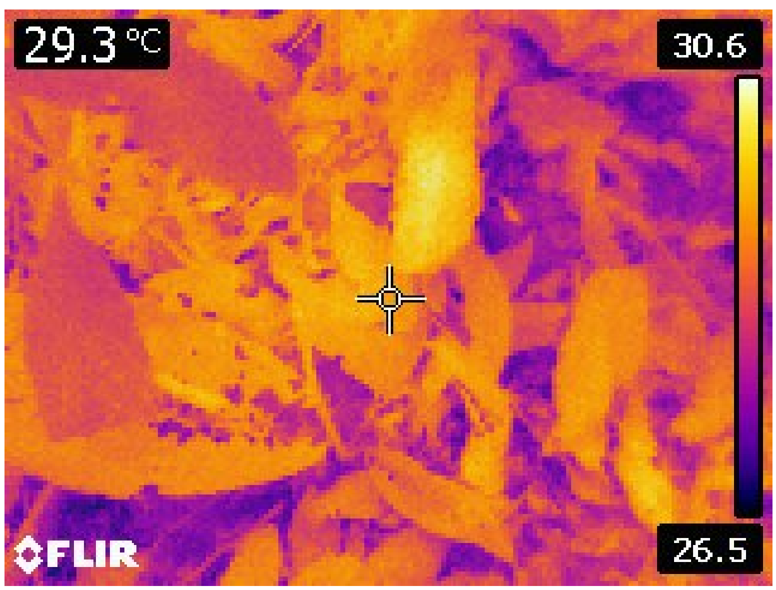

Figure A.1: A thermal image taken of the forest floor somewhere inside Jamari National Forest, Rondônia, Brazil.

A.1 Meteorological assessment FLONA Jamari

We analysed meteorological data of FLONA Jamari, Rondônia state, Brazil, of a time period from 2008 to 2018 to better understand the context in which our study (conducted in 2016 and 2017) fits. Results showed that yearly precipitation levels were not different among all these years (TukeyHSD). Maximum air temperatures in 2016 were a little warmer than in years 2008 (-0.46°C), 2009 (-0.47°C), 2013 (-0.59°C), 2014 (-0.79°C) and 2018 (-0.58°C, all Std. Error were ± 0.17 and $p \leq .01$) and not different from the other four years of this period ($p > .05$). Maximum air temperatures in 2017 were a little cooler than those in years 2010 (0.42°C) and 2015 (0.38°C), and a little warmer than in 2014 (-0.52°C, all Std. Error were ± 0.17 and $p \leq .05$) and not different from the other six years of this period ($p > .05$).

Minimum air temperatures in 2016 were a little cooler than 2009 (0.42°C), 2010 (1.10°C), 2015 (0.75°C) and 2017 (0.47°C, all Std. Error were ± 0.13 and $p \leq .01$) and not different from the other five years of this period ($p > .05$). Minimum air temperatures in 2017 were slightly warmer than all other years by ~0.42°C ($p \leq .01$) except 2010 and 2015 when they were a little cooler (0.63°C and 0.28°C, $p \leq .05$) and 2009 when there was no difference ($p > .05$).

Even though there were statistically significant differences, ecologically our sampling periods fell well within the bounds found across the ten year period observed in that region.

A.2 Analytical procedure for extracting and processing data from thermal images

The use of very fine-scale temperature measurements generated by thermal imagery is relatively unexplored. This is even more accentuated for the post-field protocol of extraction and processing of photos, which is not yet standardised and readily available (Caillon et al., 2014; Faye, Rebaudo, Yánez-Cajo, Cauvy-Fraunié, & Dangles, 2016; Scheffers et al., 2017; Senior, Hill, Benedick, & Edwards, 2017). For this, we here providing an analytical procedure as the first steps for working with thermal images. Our thermal data were collected in the field (in the Amazon forest) with a FLIR Systems model E40 camera, which, at each shot, generates a matrix of 120 × 160 distinct measurements (19,200) containing raw data from the infrared sensor. We then used the function `readflirJPG` to transform images into integer matrices, followed by

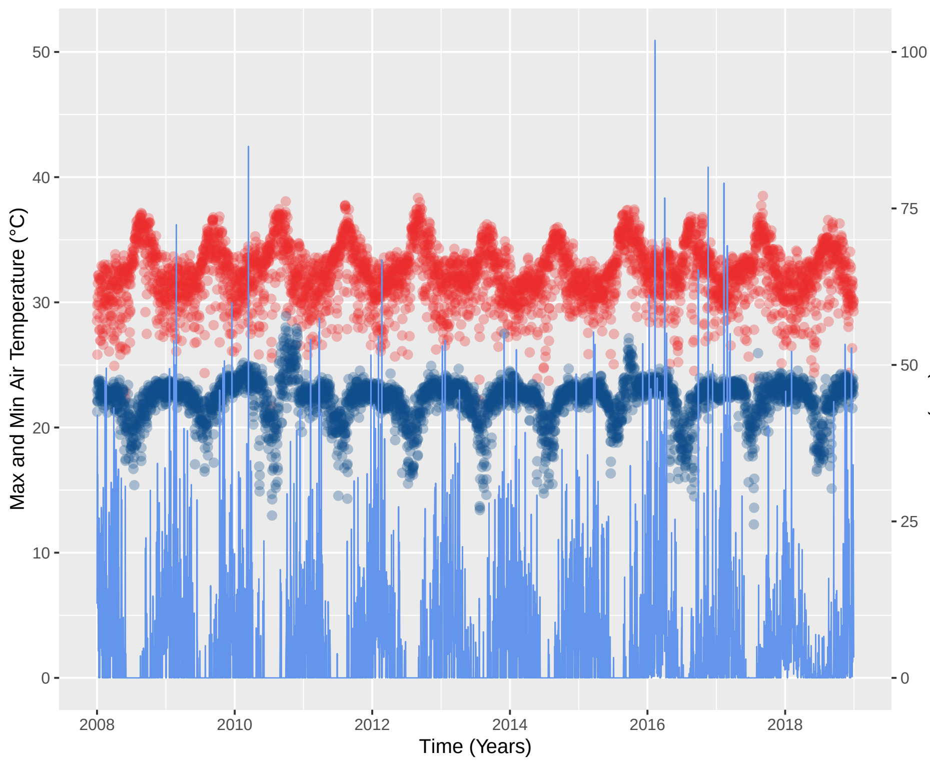

Figure A.2: Maximum (red) and minimum (dark blue) values of air temperature, and precipitation (light blue) recorded from 2008 to 2018 at FLONA Jamari, Rondônia state, Brazil.

the function raw2temp to transform raw values into estimated temperature values, from the R package *Thermimage* (Tattersall, 2017) which handles thermal image data input and conversion to temperature using established physical equations. We also detail the adjustment of the function's parameters in the transformation process to generate more accurate results.

Extracting raw data

The function readflirJPG reads an image from a FLIR JPG file and transforms it into an integer matrix. We then create a vector to be filled as a list of matrices from all selected files in a given directory. The object 'file.names.thermal' is the match between the thermal photo name in the metadata table with the thermal photo path.

```
library(Thermimage)

final.raw  <-  vector("list",  length(file.names.thermal))

names(final.raw) <- thermal_names

for(i  in 1:length(file.names.thermal))
 {
    cat("Reading file number", i, "\n")
    o <- tryCatch(readflirJPG(imagefile = file.names.thermal[i]),
          error  =  function(x)  NA)
    final.raw[[i]] <- o
 }

save.image(file = "thermal_output.RData")
```

Transforming raw into temperature data

The function raw2temp transforms raw values from thermal images into estimated temperature values using standard equations used in infrared thermography. The function allows us to adjust its parameters, which are likely to vary according to each situation that photos were taken. We show the function with its parameters adjusted with the default values, and the resulting matrix of temperature values plotted (top image). We then show the same function but with its parameters adjusted with the values from the metadata table collected alongside the thermal photos in the field, and its resulting matrix (bottom image).

```
load("thermal_output.RData")

temp_photos  <-  mapply(raw2temp, E = 1, OD = 1, RTemp = 20,
                        ATemp = RTemp, IRWTemp = RTemp,
                        IRT = 1,  RH = 50)
```

Adjusted parameters:

• For emissivity (E) a value of 0.986 was used, which represents values for ground vegetation of broadleaf forest and organic bare soil (Snyder, Wan, Zhang, & Feng, 1998).
• For air temperature (ATemp) and relative humidity (RH) we used measurements taken in the field simultaneously with the thermal photos using a psychrometer.
• The object distance from thermal camera in metres (OD) was the hypotenuse of the isosceles triangle formed by the observer's body (until breast height where the camera was held) and the ground (until the point where the camera was aimed at).

```
thermal_table <- read.csv("Thermal_study_Manoela.csv")

o <- match(names(final.raw), thermal_table$PhotoNo)

temp_photos <- mapply(raw2temp,
                                                        E = 0.96,
                        OD = (sqrt(2)*115),
                        RTemp = thermal_table_ground$DryBulb[o],
                        ATemp = thermal_table_ground$DryBulb[o],
                        IRWTemp = thermal_table_ground$DryBulb[o],
                        IRT=1,
                        RH = thermal_table$Humidity[o], final.raw)

names(temp_photos) <- names(final.raw)

temp_photo1 <- raw2temp(final.raw[[1]]) # default settings

# both images
image.plot(cbind(raw2temp(final.raw[[1]]),temp_photos[[1]]))
```

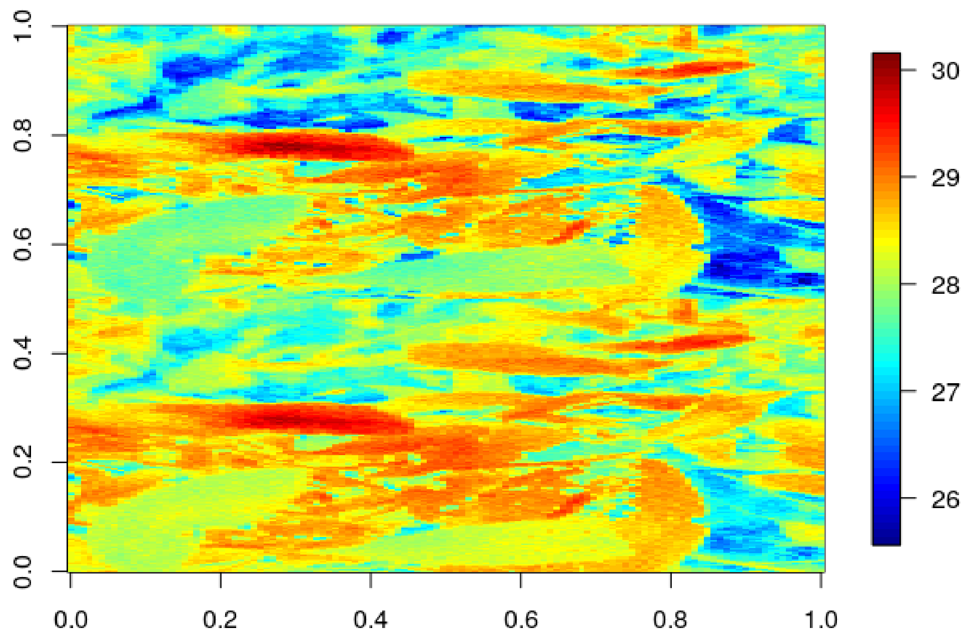

Figure A.3: Processed thermal image with default settings (top) and adjusted parameters (bottom).

A.3 Text S3. Microclimate availability metrics

The investigation of microclimate availability derived from fine-scale thermal imagery data is proving to be an interesting way to understand the physical environment when focusing on organisms using the thermal ambient, especially considering climate change scenarios. We provide an analytical procedure with a script in R to:

Identify spatially explicit thermal patches

Thermal patches can be identified by using the Getis–Ord local statistic for each pixel within the neighbourhood of the nearest eight pixels (function `localG` from the `spdep` package in R (Getis & Ord, 1996; R Core Team, 2017).

Thermal diversity

Patch thermal diversity was calculated as the mean of the warmest warm patch minus the mean of the coolest cool patch.

Proportion of cool area

Proportion of cool area was determined as the ratio between the total number of cool pixels multiplied by the surface area of one pixel (0.52 cm^2) and the total area captured by the four photos (NESW, 4 m^2).

Average size of cool patches

Average of cool patches was calculated as the total number of cool pixels multiplied by the surface area of one pixel (0.52 cm^2) and divided by the total number of cool patches.

Aggregation Index

AI was determined as the number of edges that cool pixels (inside cool patches) share, divided by the maximum number of edges that they could possibly share (i.e. if all pixels were aggregated within a single patch) (He et al., 2000).

```
require(spdep)

require(reshape2)

load("thermal_data.RData")

# Auxiliary function to compute the aggregation index

# bottom of second column, page 592 of He et al. (2000)

max.eii.func<-function(n,  m)
 {
   if(m == 0)
      return(2*n*(n-1))
   else if(m <= n)
```

```
      return(2*n*(n-1) + 2*m - 1)
   else if(m > n)
      return(2*n*(n-1) + 2*m - 2)
 }


## Agregation index according to He et al. (2000),
pages 529 and 530

AI <- function(M)
 {
   M[M==0]<-NA
   eiih <- sum(unlist(apply(apply(M, 1, diff), 2, table)))
   eiiv <- sum(unlist(apply(apply(M, 2, diff), 2, table)))
   eii <- eiiv + eiih
   Ai <- sum(M, na.rm = TRUE)
   n <- floor(sqrt(Ai))
   m <- Ai-n^2
   max.eii <- max.eii.func(n,m)
   AIi <- eii/max.eii return(AIi)
 }


rem.photos<-df<-NULL

for(i in 1:length(temp_photos))
 {

   #Checking if there is NAs in the matrices
   cat("Processing photo ", names(temp_photos)[i], "-->",
   round(100*i/length(temp_photos),1), "%  \n")
   if(any(is.na(temp_photos[[i]])))

  {
   rem.photos<-c(rem.photos, names(temp_photos)[i]) next()
  }

   #Finding patches
   dimnames(temp_photos[[i]]) <- list(c(1:nrow(temp_photos[[i]])),
                                 c(1:ncol(temp_photos[[i]])))
   df.temp <- reshape2::melt(temp_photos[[i]])
```

```
  colnames(df.temp) <- c("x", "y", "temp")
  xycoords <- cbind(df.temp$x, df.temp$y)
  # diagonal (8 pixels around 1)
  nb8px <- dnearneigh(xycoords, 0, sqrt(2))

  G <- localG(df.temp$temp, nb2listw(nb8px, style="B"))
  df.temp$G <- G
  df.temp$cool <- ifelse(G <= -3.886, 1,0)
  df.temp$warm <- ifelse(G >= 3.886, 1,0)

  #Identifying cool pathes
  binary.cool.MAT <- acast(df.temp, x~y, value.var="cool")
  ccl.cool.mat = ConnCompLabel(binary.cool.MAT)
  df.temp$cool.i <- reshape2::melt(ccl.cool.mat)[,3]

  #Identifying warm pathes
  binary.warm.MAT <- acast(df.temp, x~y, value.var="warm")
  ccl.warm.mat = ConnCompLabel(binary.warm.MAT)
  df.temp$warm.i <- reshape2::melt(ccl.warm.mat)[,3]

  #Aggregation Index
  w1<-AI(binary.cool.MAT)
  w2<-AI(binary.warm.MAT)
  df.temp<-data.frame(df.temp, photo = names(temp_photos)[i],
                      AI.cool = w1, AI.warm = w2)

  df <- rbind(df, df.temp)

}
```

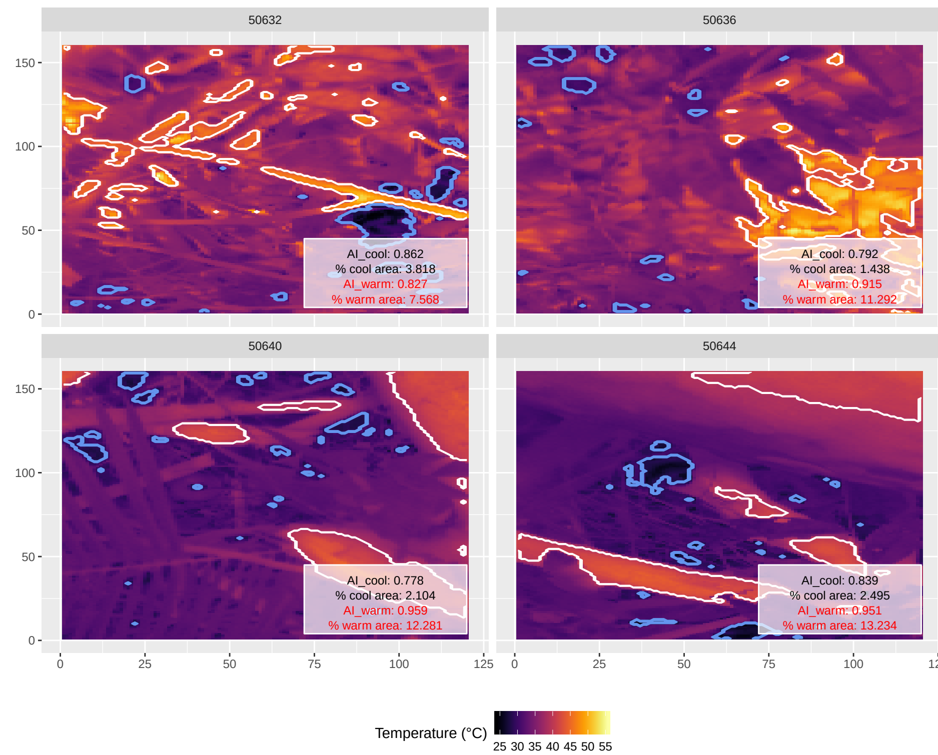

Figure A.4: Example of four thermal images taken at the same time on a given study plot (facing towards North, East, South and West). Pixels are coloured from cold (purple) to hot (yellow). Spatially explicit cool patches (outlined in blue) and warm patches (outlined in white) were identified using the Getis–Ord local statistic for each pixel within the neighbourhood of the nearest eight pixels. Inside the shaded white rectangules are the values of Aggregation Index of cool patches (AI_cool), and warm patches (AI_warm), percentage of cool area (% cool area) and percentage of warm area (% warm area).

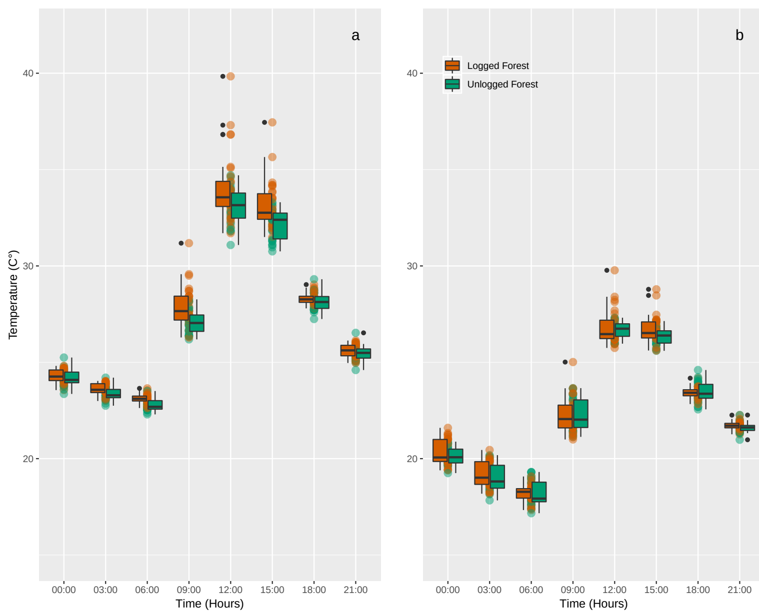

Figure A.5: Fitted values of maximum understorey ambient temperature (a) and fitted values of minimum understorey ambient temperature across the day (b) in logged forest with one year of recovery (orange) and unlogged primary forest (green). Results showed that unlogged forest understorey ambient had lower maximum temperatures per hour across the day (-0.34°C $\pm$ 0.1 $p \leq 0.05$) but no difference in minimum temperatures (p= 0.19) compared to the logged forest.

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