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Illuminating the biophysical, political, and cultural dimensions of tree clearing to inform environmental policy

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Abstract

Deforestation is a well-recognised global threat to biodiversity and ecosystem function, and the conversion of forests to productive lands is responsible for the majority of world-wide deforestation. These patterns are mirrored in Queensland, Australia, which has exhibited some of the highest deforestation rates around the world in the last three decades. In response, the Queensland government enacted the contentious *Vegetation Management Act (VMA) 1999* to regulate the clearing of remnant (i.e. old-growth) trees on private lands across the state. Since its inception, however, the policy has spurred heated debate from the agricultural sector, with landholders arguing its lack of transparency, inconsistency, and ignorance of economic impacts on the agricultural sector. To date, no robust, objective investigations have been made into the direct and indirect roles of the VMA in changing tree clearing behaviours. Yet if we want to develop relevant and effective policy instruments to create sustainable change in tree clearing, it is imperative that these instruments are tailored to reflect the drivers of clearing across all relevant dimensions. In this thesis, I explore the biophysical, political, and cultural dimensions of tree clearing in Queensland to highlight how landholders have responded to policy intervention, uncover the potential perversities of its implementation, quantify its effectiveness, and understand its influence within the cultural landscape of tree clearing.

I begin with an exploration into the underlying factors driving changes in historic tree clearing patterns, where I use principal component analyses to monitor changes in the biophysical, socioeconomic, and property characteristics of clearing events across Queensland during 1989–2015 (**Chapter 2**). These patterns are compared between key bioregions of interest and between key periods along the vegetation management policy timeline, revealing spatially and temporally dynamic clearing preferences—from the consistent profitability- and availability-driven patterns in the Brigalow Belt South bioregion, to the opportunistic patterns in the Great Barrier Reef catchment that fluctuate with policy changes. These drivers of tree clearing are further explored using spatial longitudinal analyses (**Chapter 3**), where I quantify the influence of a suite of traditional deforestation drivers on both net forest cover change and remnant forest loss in Queensland since 1991, with particular emphasis on quantifying the influence of the broad-scale clearing ban of 2007 and peak periods of policy uncertainty along the political timeline. Importantly, I identify a positive effect of the clearing ban yet a negative effect of policy uncertainty on forest cover. Particularly for remnant forests, the negative effects of policy uncertainty were large enough to negate most forest cover benefits provided by command-and-control regulation.

Given the prevalence of perverse clearing outcomes amidst policy intervention, I perform the first robust causal impact analysis of the VMA to determine if the policy has successfully reduced remnant tree clearing in the Brigalow Belt South beyond two counterfactual scenarios (**Chapter 4**).

Overall, I find the VMA had limited effectiveness; the maximum amount of remnant trees saved is less than 5% of the total amount cleared since 2000. Interestingly, the indirect effects of the policy may be more effective than its direct effects, as it is evident that landholders have since redirected their clearing efforts away from protected vegetation even when given legal opportunities to do so. These potential social effects are further investigated using the responses obtained from a state-wide survey of landholders that recorded their tree clearing behaviours, as well as numerous psychosocial factors related to tree clearing and vegetation management policy (**Chapter 5**). I identify five psychosocial typologies and four clearing typologies of Queensland landholders and determine the underlying demographic, socioeconomic, and psychosocial characteristics describing each typology. I then discuss how these heterogeneous groups of landholders can help us identify targets and strategies for promoting positive clearing behaviour change while minimising potential perversities that top-down regulation can provoke.

Finally, I discuss the significance of these results for informing the following key components along the policy intervention cycle: design and implementation, monitoring and enforcement, impact evaluation, and communication (**Chapter 6**). A more diverse suite of policy instruments should be employed to combat ongoing clearing, and their design should be informed by greater communication with landholders, which will promote knowledge exchange and trust-building. Monitoring the absolute clearing rates and their characteristics at smaller spatiotemporal scales will also allow the government to monitor how landholders are differentially responding to intervention, including identifying early warnings of perverse outcomes. There must be a shift from an overarching reliance on impact indicators to more robust causal inference analyses, and policy instruments will need to be designed to make these inferences accordingly. Lastly, greater regulatory compliance could likely be achieved using more strategic communication approaches that emphasise the stewardship values of landholders and target messages to the most prolific clearing communities. Ultimately, greater consideration for top-down and bottom-up approaches will be needed to ensure sustainable land management behaviour change can be achieved in Queensland.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, financial support and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my higher degree by research candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

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Publications included in this thesis

Simmons BA, Law EA, Marcos-Martinez R, Bryan BA, McAlpine C, Wilson KA. 2018. Spatial and temporal patterns of land clearing during policy change. Land Use Policy **75**:399–410.

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Simmons BA, Wilson KA, Marcos-Martinez R, Bryan BA, Holland O, Law EA. 2018. Effectiveness of regulatory policy in curbing deforestation in a biodiversity hotspot. Environmental Research Letters **13**:124003.

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Simmons BA, Wilson KA, Marcos-Martinez R, Bryan BA, Holland O, Law EA. 2018. Effectiveness of regulatory policy in curbing deforestation in a biodiversity hotspot. Environmental Research Letters **13**:124003.

Prist PR, Levin N, Metzger JP, de Mello K, de Paula Costa MD, Castagnino R, Cortes-Ramirez J, Lin D, Butt N, Lloyd TJ, López-Cubillos S, Mayfield HJ, Negret PJ, Oliveira-Bevan I, Reside AE, Rhodes JR, **Simmons BA**, Suarez-Castro AF, Kark S. 2020. Collaboration across boundaries in the Amazon. Science **366**:699–700.

Simmons BA, Wilson KA, Dean AJ. 2020. Landholder typologies illuminate pathways for social change in a deforestation hotspot. Journal of Environmental Management **254**:109777.

Reports

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Contributions by others to the thesis

In addition to my supervisors, Kerrie Wilson, Elizabeth Law, Raymundo Marcos-Martinez, and Clive McAlpine, my readers, Rod Fensham, Jonathan Rhodes, and Chris McGrath, provided critical review of the overall concept, design, and structure of the thesis.

While most data included in the thesis was obtained from the public repository of the Queensland Government (Queensland Spatial Catalogue), Don Butler provided the most accurate initial remnant vegetation spatial data from the Queensland Herbarium, Raymundo Marcos-Martinez provided spatial panel data from the CSIRO data repository for Chapter 3, and Pureprofile Pty Ltd recruited participants needed for Chapter 5.

For Chapter 5, the following people provided comments on the content, structure, and style of the survey: Angela Dean, Kerrie Wilson, Elizabeth Law, Tracy Schultz, Valerie Hagger, Gwen Iacona, and Julia Van Velden. Additional input on the design of the survey was obtained from four anonymous social scientists in one-on-one interviews, as well as four anonymous local stakeholders during a focus group.

All other significant and substantial inputs made by others are detailed in the page immediately preceding each chapter in the thesis.

Statement of parts of the thesis submitted to qualify for the award of another degree

No works submitted towards another degree have been included in this thesis.

Research Involving Human or Animal Subjects

All research involving human subjects (**Chapter 5**) was approved by The University of Queensland Science, Low & Negligible Risk Ethics Sub-Committee prior to commencement of the study (Approval #2017001054). This project complies with the provisions contained in the *National Statement on Ethical Conduct in Human Research* and complies with the regulations governing experimentation on humans. A copy of the ethics approval letter can be found in Appendix J.

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Australia, biodiversity conservation, conservation policy, deforestation, environmental behaviour, environmental decision making, forest transition, land clearing, natural resource management, policy impact

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FoR code: 0502, Environmental Science and Management, 80%
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List of Abbreviations

AIC	Akaike information criterion
ARIA	Accessibility/Remoteness Index of Australia (dataset)
ATT	Average treatment effect on the treated
BBS	Brigalow Belt South
BLUP	Best linear unbiased predictor
CYP	Cape York Peninsula
eCDF	Empirical cumulative distribution function
EPBC	Environment Protection and Biodiversity Conservation
eQQ	Empirical quantile-quantile distribution
FCI	Forest cover index
FE-MLE	Fixed effects spatial maximum likelihood estimation
FL	Freehold and leasehold tenures
FO	Freehold only tenures
GBRC	Great Barrier Reef catchment
IPA	Integrated Planning Act
KMO	Kaiser-Meyer-Olkin
NCAS	National Carbon Accounting System (dataset)
NKN	Nearest *k* neighbours matching
NN	Nearest neighbour matching
NRM	Natural resource management
PC	Pre-emptive clearing (scenario)
PCA	Principal component analysis
QLD	Queensland
RC	Rotated component
RCI	Remnant forest cover index
RE	Regional ecosystem
SD	Standard deviation
SEQ	South Eastern Queensland
SLATS	Statewide Landcover and Trees Study (dataset)
SP	Social preference (scenario)
VIF	Variable inflation factor
VMA	Vegetation Management Act

Chapter 1: Introduction

1.1 Tackling conservation issues

The majority of terrestrial biomes across the planet are experiencing a crisis in biodiversity conservation and ecosystem service provision (Newbold et al. 2016). As the planet experiences unprecedented extinction rates (Pimm et al. 2014; Ceballos et al. 2015), land use change and habitat loss are the dominant drivers of species decline in many areas (Murphy & Romanuk 2014). These changes are primarily the result of human modification of the environment (Song et al. 2018). Agricultural expansion represents one of the greatest threats to biodiversity; it is responsible for a significant increase in the global human footprint (Johnson et al. 2017), and the coverage of agricultural landscapes is expected to increase 18% by 2050 (Tilman et al. 2001). This expansion is the most commonly cited proximate driver of deforestation (Barbier & Burgess 2001a; Hosonuma et al. 2012), and it is estimated to account for 80% of global deforestation activities (Kissinger et al. 2012). Despite recent global forest cover gains, net forest loss continues in tropical regions (Song et al. 2018), resulting in severe habitat fragmentation (Haddad et al. 2015) and subsequent species decline (Betts et al. 2017). As these negative effects of deforestation are likely to be exacerbated by future climate change (Segan et al. 2016), it is imperative that nations take effective action to mitigate rapid land use change and conserve remaining habitats, including already highly-fragmented landscapes (Di Marco et al. 2015; Wintle et al. 2019).

Global recognition of this precarious state of the environment has launched a number of international agreements, such as the United Nations' 2030 Sustainable Development Goals (UN 2015) and the Convention on Biological Diversity's 2020 Aichi Biodiversity Targets (CBD 2010). From voluntary, aspirational goals to national strategic action plans, more than 100 countries are increasingly committed to protecting the health and function of ecosystems in order to achieve environmental sustainability and, consequently, improved human well-being (Bertzky et al. 2012; Pogge & Sengupta 2015). Despite growing efforts, however, previous targets of the Millennium Development Goals and Aichi 2010 Targets were largely unaccomplished (Le Blanc 2015; Waldron et al. 2017), and there are mixed expectations for reaching the current targets (Bertzky et al. 2012; Tittensor et al. 2014; Johnson et al. 2017). For example, despite increasing protected area coverage around the world (Aichi Target 11), the most important sites for biodiversity remain unprotected (Bertzky et al. 2012), and conservation efforts on farmlands (Aichi Target 7) are frequently unsuccessful due to high costs or the displacement of agricultural activities elsewhere (Johnson et al. 2017). As governments strive to implement conservation policy interventions to meet their approaching sustainability targets, it is essential that the appropriate policy instruments are used, knowing that some alternative approaches may be more successful in certain contexts (Butchart et al. 2015).

1.1.1 Effectiveness of policy intervention

Governments have a number of options for promoting conservation and minimising environmental degradation. The most common approaches include direct or 'command-and-control' regulation, market-based incentives, and voluntary (binding and non-binding) programs (Cocklin et al. 2007; Kamal et al. 2015). Direct regulation is the most popular tool at countries' disposal, and this approach has been used around the world for national and international initiatives ranging from individual species protection (Lueck & Michael 2003) to land use change (Bos et al. 2017) and trade bans (Rivalan et al. 2007). Similarly, the establishment of protected areas is another common instrument—partly due to Aichi Target 11—that typically places strict land use restrictions inside the protected area (Barnes et al. 2018). Such command-and-control approaches, however, can be polarising, inflexible, and may reduce the public's motivation to protect the environment (Smith & Vos 1997; Dresner et al. 2006; Jordan & Matt 2014). Incentive-based schemes and voluntary agreements have thus become popular alternative instruments, including forest certification, payments for ecosystem services, conservation covenants or easements, and local extension-based programs (Jack et al. 2008; Kamal et al. 2015). The use of these policy instruments, however, does not guarantee success. For example, voluntary approaches may be more flexible, collaborative, and promote understanding and collective action (Lockie 2009; Ives et al. 2010; Ens et al. 2013), yet compared to strict regulations, they may be less impactful, require the public to be knowledgeable of environmental complexities, and are less 'comfortable' than applying strict laws (Santos et al. 2006; Kollmann & Schneider 2010; Jordan & Matt 2014).

Impact evaluation is crucial to the political process, as it guides political development forward and can illuminate successes and failures of previous policy instruments (Bovens et al. 2006; Pawson 2006). Despite its pivotal role in shaping future regimes, thorough evaluations of environmental policy interventions are scarce due to a number of difficulties, including the degree of subjectivity, time and resource availability, and its translation into policy recommendations (Bovens et al. 2006; Howlett et al. 2009; Marsh & McConnell 2010; McGrath 2010; Perche 2011). Yet a number of studies in the last decade have undertaken this demanding effort, determining the effectiveness of direct regulations (e.g. Assunção et al. 2012), protected areas (e.g. Joppa & Pfaff 2011), and payments for ecosystem services (e.g. Calvet-Mir et al. 2015). Despite some success stories, many instruments fail to create significant change or result in unintentional 'perverse' outcomes (Miteva et al. 2012). For example, regulations may only result in short-term impact if activities are poorly monitored or enforced (Azevedo et al. 2017), financial incentive schemes may fail if they are poorly designed to inspire compliance or participation on at-risk properties (Lockie 2013; Moon 2013), and protected area targets can create a perverse incentive to focus on protection quantity over quality (Barnes et al. 2018), resulting in spatial selection biases towards areas that are under minimal threat (Joppa & Pfaff 2011; Miteva et al. 2012).

Direct regulations, perhaps counterintuitively, are highly susceptible to ineffectiveness or perverse outcomes because they are reliant upon behavioural compliance and the support of the public and political regime. Environmental regulations are particularly volatile due to the dynamic nature of policy: they affect and are affected by social norms and their trends, they may be promoted or denigrated based upon politicians' desires for support from their party, constituents, or donors, and they are susceptible to frequent adaptation and, in some cases, complete repeal (Zohlnhöfer 2009; Kollmann & Schneider 2010; Bauer & Knill 2014). While this is an inherent part of politics, problems arise as the number and intensity of policy instruments increase over time, especially for environmental policies with significant impacts on property rights and land management (Knill et al. 2012). Controversial policies complemented by high political instability, legislative ambiguity, and frequent regime changes have been known to provoke perverse reactions from landholders, leading to increased deforestation rates over time (Deacon 1994; Barbier & Burgess 2001b; Brown et al. 2016). Thus, command-and-control approaches to conservation have the potential to create substantial positive or negative environmental outcomes; which outcome, however, is dependent upon the behavioural responses of those targeted for intervention and the multi-dimensional factors influencing those behaviours.

1.1.2 Dimensionality of conservation behaviour

Creating desired behaviour change is a significant challenge for researchers and practitioners, both in theory and practice (van der Linden 2015). More than 100 theories of behaviour change have been proposed by researchers around the world (Kwasnicka et al. 2016), illustrating the complexity of generalising decision-making in different contexts. Historically, the majority of theories and models of decision-making have been based on economic 'rationality,' where linear processes are driven by the expected profit- and utility-maximisation strategies of individual actors (Hargreaves 2011; Groeneveld et al. 2017). Mounting evidence, however, suggests that this approach will not adequately represent the myriad of social, psychological, and contextual factors shaping individual preferences (Lynne et al. 1988; Howley et al. 2015). Behaviour is influenced by internal and external factors, which may fluctuate in dominance or act synergistically through complementary goals or motivations (de Snoo et al. 2013; Steg et al. 2015; Kwasnicka et al. 2016). If policy instruments are to create effective behaviour change, Kok et al. (2016) assert that the relevant determinants of the behaviour must be identified and changed, and the intervention needs to produce practical applications that can be embedded into the targeted culture.

A number of external drivers of environmental behaviours have been identified in various contexts—from market signals (DeFries et al. 2010), to income (Barbier & Burgess 2001a), to biophysical constraints (Laurance et al. 2002). Internal drivers are becoming more prominent in these investigations, in large part due to the growing contribution of social science theory to environmental management, such as the theory of planned behaviour (Ajzen 1985) and the value-belief-norm theory (Stern & Dietz 1994; Stern et al. 1999). Using these frameworks, as well as other individually-tailored behavioural models (e.g. Austin et al. 1998), studies have identified significant psychosocial modifiers of environmental behaviour, like social norms (Fielding et al. 2005), personality traits (Willock et al. 1999), values (Maybery et al. 2005), and sense of control (Price & Leviston 2014). Despite a number of success stories using these more inclusive models to predict behavioural *intentions*, predicting actual *behaviour* remains difficult (Bamberg & Möser 2007). This sobering realisation is of paramount importance to implementing conservation interventions, as numerous contextual, hidden, or unexpected factors may ultimately impede upon successful behaviour change.

Environmental decision-making, in particular, is further complicated by the highly polarised nature of environmental policy (Lucas & Warman 2018). Environmental issues are becoming increasingly partisan (Karol 2018), are grounded in ethics and morality (Dickman et al. 2015), and provoke strong emotional responses (Wilson 2008; Recher 2017), which may profoundly diminish or even negate other factors driving behaviour. In some instances, the influence of one's political or social identity can be so strong that they directly align their behavioural intentions or support with those of their own in-group, even if this contrasts with their own knowledge or attitudes about the issue (Unsworth & Fielding 2014; Mason 2018). This places environmental policy instruments in a precarious position; external factors may alter the underlying value orientations of those targeted for behaviour change, and this dynamic re-structuring of underlying values can affect other related behaviours (Crompton 2010). Complex temporal dynamics of environmental decision-making have also been observed. For example, farmers may be driven by intrinsic motivations early in life, which evolve into extrinsic motivations later in life (Farmar-Bowers & Lane 2009). Consequently, different policy instruments may be more appropriate for different sectors of the target population. This highlights the general consensus that successful environmental management demands more investigations into the different landholders that are ultimately responsible for pro-environmental behaviour, accounting for their demographic, economic, social, and personality characteristics (Emtage et al. 2007; Moon & Cocklin 2011; Moon et al. 2012). Overall, the cultural dimensions of environmental decision-making encompass this complex suite of individual and collective factors reflecting beliefs about morality, tradition, and normative or acceptable behaviours, which have an influential effect on deforestation (Geist & Lambin 2002; Hoelle 2018). More interdisciplinary approaches, or at the very least, more diverse disciplinary approaches are likely needed to capture a more thorough understanding of the myriad of internal and external drivers of land management behaviour to develop effective conservation policy interventions (McGregor et al. 2001).

1.2 An Australian case study

Mirroring global biodiversity losses, the clearing of remnant (i.e. old-growth) vegetation due to agricultural expansion has significantly threatened biodiversity in Australia (Kirkpatrick 1999; Smith et al. 2013). In its relatively brief colonial history, Australia has seen agricultural development drive a reduction in forest coverage by nearly 15% since colonization, with 7.2 million ha (7%) of primary forests having been cleared in the last 40 years alone (Bradshaw 2012; Evans 2016). This rate of deforestation was so intense that it marked Australia with the sixth-highest annual deforestation rate in the world during 1990-2000 (Lindenmayer 2005). The impacts of tree clearing present significant challenges to the health, function, and sustainability of many Australian landscapes, including changes in soil fertility and nutrient loss (Graham et al. 1981; Dowling et al. 1986), salinity (Lindenmayer 2005; Ponce-Reyes et al. 2014), and water balance/runoff (Cowie et al. 2007; Thornton 2012).

Despite the federal government's commitments to biodiversity conservation—with targets including national increases in protected/managed areas, restoration of fragmented landscapes, and improved ecological connectivity (NRMMC 2010)—as well as some recent reports listing Australia as the second-best country in reported annual net gain in forest area (FAO 2016a), remnant vegetation continues be lost, particularly in the State of Queensland. In some deforestation hotspots, like the Brigalow Belt South (BBS) bioregion, such intense clearing rates have reduced ecosystems' vegetation cover to less than 10% of their historical extent, leaving the landscape severely fragmented with small, isolated patches of remnant vegetation (Dwyer et al. 2009; McAlpine et al. 2011), further increasing the potential for microclimate shifts, habitat degradation, and increased mortality risk for species within these patches (McAlpine et al. 2002; Lindenmayer 2005). Unfortunately, the ecological value of these remnant forests often cannot be easily substituted by recent reforestation efforts (Bowen et al. 2009).

1.2.1 Queensland: the clearing state

In the last four decades, Queensland has lost 9.7 million ha of forest from land clearing, accounting for more than 60% of clearing in the entire country over this period (Evans 2016), and estimates suggest Queensland's native vegetation cover has reduced by at least 50% over the last 200 years (ABRS 2010). A number of extensive reviews have illustrated the importance colonization and government incentives had on driving historic land clearing in Queensland (e.g. Seabrook et al. 2006; Bradshaw 2012). In an effort to raise economic prosperity in the developing country, the Queensland Government actively encouraged—or rather demanded—landholders to clear as much vegetation as possible in order to meet the needs of an international agricultural market (Braithwaite 1996; Bradshaw 2012). Particularly in Queensland, most forms of cropping were not considered to be profitable (unless they were used for fodder production) in many regions, so the majority of landholders were pastoralists, clearing land in which to graze sheep and cattle (Seabrook et al. 2006). The rate of land clearing began to increase significantly as the population grew, commodity prices became favourable and export opportunities increased (AGO 2000), and the government acquired mounting revenue (Seabrook et al. 2006). By the mid-20th century, clearing (and maintaining a cleared property) became much more feasible due to improved clearing technology (Fensham & Fairfax 2003). New bulldozing techniques expedited the removal of stubborn brigalow (*Acacia harpophylla*) stands more effectively than previous laborious techniques; this was shortly followed by blade ploughing, which proved to be a more effective method of preventing brigalow regrowth, providing for an increase in cropland development (McAlpine et al. 2011). It wasn't until the 1990s that public opinion began to change regarding the value of this 'nuisance' vegetation, and the Queensland Government began shifting from a focus on incentivizing clearing to regulating clearing.

1.2.1.1 Controversial vegetation management policy

The public's newfound appreciation for the value of native, remnant vegetation led to a new wave of policy reform in Queensland that followed in the footsteps of other states that had previously began regulating land clearing (Evans 2016) (Fig. 1.1). The first official recognition of biodiversity protection as a legislative objective came about with the *Land Act 1994*, which placed stricter land clearing controls on leasehold and State lands (McGrath 2007; Evans 2016). As environmental concerns grew, clearing regulations were then extended to freehold lands with the enactment of the *Integrated Planning Act (IPA) 1997* and the *Vegetation Management Act (VMA) 1999*. According to the VMA 1999 s 3.1:

> The purposes of this Act are to regulate the clearing of vegetation on freehold land to (a) preserve the following: (i) remnant endangered regional ecosystems; (ii) remnant of concern regional ecosystems;

(iii) vegetation in areas of high nature conservation value and areas vulnerable to land degradation; (b) ensure that the clearing does not cause land degradation, (c) maintain or increase biodiversity, (d) maintain ecological processes, and (e) allow for ecologically sustainable land use.

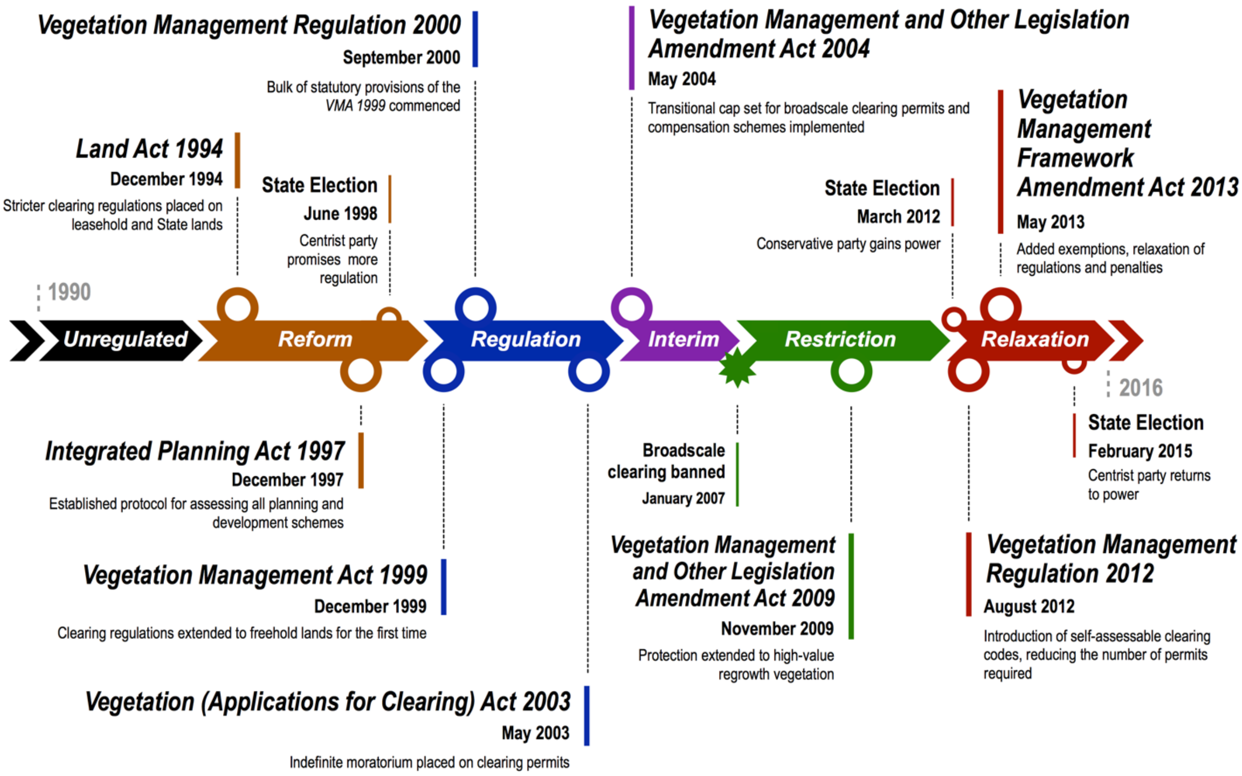

Fig. 1.1. The evolution of vegetation management policy in Queensland. Political timeline of pivotal legislation and regime shifts, categorised according to six policy periods between 1990 and 2016: *unregulated*, *reform*, *regulation*, *interim*, *restriction*, and *relaxation* (cf. **Chapter 2**). State elections of 2001, 2004, 2006, and 2009 where the centrist government maintained power are not shown.

Together with the *Vegetation Management Regulation 2000* that followed shortly thereafter, the VMA 1999 serves to (1) identify and define the different types of vegetation and their conservation value/protection status, and (2) outline the policy framework underlying clearing permits, which then guides the IPA 1997's requirements for assessing and enforcing these permits (Productivity Commission 2004; McGrath 2010). After the VMA 1999 passed, its official proclamation was delayed until September 2000 amidst difficulties reaching agreements surrounding landholder compensation (Productivity Commission 2004; Senate Inquiry 2010), leaving a window of uncertainty amongst landholders as to what the future had in store for them and their ability to clear vegetation on their property.

What followed in the infamous years after the passing of the VMA 1999 would eventually be described as a period of 'panic clearing.' This period, extending primarily through 1999 to 2003, was characterised by peak clearing rates throughout Queensland stemming from landholders' uncertainty of what exactly they would be permitted to do on their freehold land in the future, resulting in what many suggest were unplanned, pre-emptive clearings of vegetation (Productivity Commission 2004; Lindenmayer 2005; Taylor 2015). In light of these unforeseen clearing events, the *Vegetation (Applications for Clearing) Act 2003* was enacted, placing a temporary moratorium on clearing applications until new reforms were set in place a year later with the *Vegetation Management and Other Legislation Amendment Act 2004* (McGrath 2007). Within several new objectives added to the VMA, the Act declared that 'broad-scale' clearing of remnant vegetation would be banned by the end of 2006.

The new clearing restrictions, however, fell under a number of caveats. The Act only provided broad-scale clearing protection to remnant vegetation, defined as "the vegetation, part of which forms the predominant canopy of the vegetation, (a) covering more than 50% of the undisturbed predominant canopy, and (b) averaging more than 70% of the vegetation's undisturbed height" (VMA 1999, sch). Thus no protection or regulation was extended to non-remnant vegetation or (at that time) forms of regrowth vegetation. Further, broad-scale clearing—the only clearing to be prohibited—was particularly vague, defined as clearing that is "not for a relevant purpose under section 22A" (VMOLAA 2004, s 28.2). Some of the 'relevant purposes' included clearing for control of exotics, pests, or encroachers, public safety reasons, fodder harvesting, thinning (restorative), and 'necessary' fences, firebreaks, and infrastructure if there is no other suitable location. To ease potential transitioning burdens, the Act allowed for a total of 500,000 ha worth of broad-scale clearing permits to be issued and executed prior to 2007, and these were allocated through ballots across seven regions within Queensland. In addition, AU$130 million was allocated to provide financial assistance to landholders over the subsequent five years, and $20 million to provide incentives for landholders to retain high-valued vegetation on their property (Productivity Commission 2004; McGrath 2007).

The years immediately following the ban of broad-scale clearing in 2007 saw few changes to the VMA 1999, save for the *Vegetation Management and Other Legislation Amendment Act 2009*, which extended the protection from broad-scale clearing to 'high-value regrowth' vegetation—vegetation that had not been cleared since 31 December 1989—and regrowth in watercourse areas (VMOLAA 2009, s 20AB). Growing frustrations over the vegetation management regulations, however, began to reach a pinnacle, resulting in a shift in political regimes from the 2012 state election that placed the conservative (despite the name) Liberal National Party in power under the new Premier of Queensland, Campbell Newman. Shortly thereafter, the new government enacted the *Vegetation Management Regulation 2012*, which introduced new self-assessable vegetation clearing codes to reduce the number of permits needed for clearing, as well as the *Vegetation Management Framework Amendment Act 2013*, which removed protection of high-value regrowth and regrowth watercourses and introduced ‘high-value agriculture’ as a relevant purpose for clearing; clearing for high-value agriculture constitutes “clearing carried out to establish, cultivate and harvest crops, other than clearing for grazing activities or plantation forestry” (VMFAA 2013, s 65.2). Accordingly, this legislation was seen as a victory for many landholders, yet presented a real setback for those emphasizing the destruction of land clearing. The return of the centrist Australian Labor Party in 2015 was met with great promise by the party and new Premier, Annastacia Palaszczuk, to reverse the relaxations set in place by the Newman Government (Hough & McKillop 2015). After several years of heated debate, and a rejection of the proposed *Vegetation Management (Reinstatement) and Other Legislation Amendment Bill 2016*, the Palaszczuk Government successfully passed the *Vegetation Management and Other Legislation Amendment Bill 2018*, which amended the VMA 1999 by reinstating former protections of high-value regrowth, extending protections into additional Great Barrier Reef catchments, and eliminating high-value agriculture as a relevant purpose for clearing.

1.2.1.2 A demand for answers

Land clearing in Queensland has recently been at the forefront of eco-political debate, and the future of land clearing has never been more uncertain than it is today. Native vegetation management encompasses biophysical, socioeconomic, political, and cultural dimensions that are astoundingly complex. Even more daunting, native vegetation management has become deeply embedded into the fabric of morality, transforming these seemingly simple tree clearing codes into profound issues surrounding landholder rights, public trust, political stability, and economic and environmental sustainability. In seeking pro-environmental change, there must be a shift from a constricted focus on emphasizing nature to an interdisciplinary focus on emphasising human behaviour. Considering the extensive policy “ping pong” (Maron et al. 2015) observed with the VMA in the last seven years, it bears questioning why such a policy may be so vulnerable to dramatic changes. Some of the major criticisms surrounding the VMA include a lack of clear and defined indicators with which to measure the policy’s impact, a lack of transparency and frequent uncertainty regarding the policy’s objectives and methodologies, and poor internal organisation and implementation of regulations (Productivity Commission 2004).

Taken further, the overall effectiveness of the VMA warrants some investigation. The evaluation of policy effectiveness is by no means a new concept, yet it is infrequently tested despite its important implications (McGrath 2010). It is important to understand the different tools vegetation management policies may use, what a ‘good’ policy might look like, and what factors may drive the success or failure of these policies to produce their intended outcomes. At the bare minimum, it is obvious that vegetation management policies will need to deviate from the business-as-usual attitude in Australia (Bradshaw 2012). If bottom-up approaches can be developed that emphasize the roles, knowledge, and rights of landholders, are open and adaptable to new information, and can adequately capture the complex dimensions of land clearing, then it is likely that landholders will become more responsive to policies, leading to less reactive clearing and minimal policy ping pong (Ryan & Deci 2006; Cocklin et al. 2007; Lockie 2013). While it is no easy task, an understanding of relevant drivers of land clearing in Queensland can aid in the selection of appropriate policy instruments that may more effectively drive the success of future vegetation management policies.

1.3 Thesis overview and structure

This thesis answers the recent call to challenge the field of conservation science to become more integrative, comprehensive, and adaptable in our attempt to target, understand, rationalise, and inspire change in conservation behaviours (Reddy et al. 2016; Bennett et al. 2016, 2017). In the chapters that follow, I tackle the biophysical, socioeconomic, political, and cultural dimensions of tree clearing in Queensland through an interdisciplinary, behaviour-focused lens (Fig. 1.2). **Chapter 2** explores the spatial and temporal patterns of historical tree clearing throughout Queensland—with emphasis on the unique clearing characteristics of four bioregions of ecological and political importance—amidst the background of a dynamic policy timeline. In **Chapter 3**, I provide the first statistical evidence for the existence of 'panic clearing' at the state- and bioregional-scale, and I develop a spatial econometric model of two different metrics of tree clearing, identifying a range of biophysical, socioeconomic, and political factors driving forest cover dynamics. **Chapter 4** presents the first statistical analysis of the effectiveness of the *Vegetation Management Act 1999* using robust causal inference techniques in order to estimate how well legislative protections have been able to successfully curb targeted clearing of remnant vegetation in the Brigalow Belt South. In **Chapter 5**, I apply psychosocial theories of behaviour to the context of landholders' clearing decision-making, distinguishing two sets of landholder typologies, mapping their distribution in the landscape, identifying their unique demographic and psychosocial characteristics, and proposing multiple strategies to target relevant landholders for creating land management behaviour change. Each chapter investigates multiple dimensions of tree clearing, and the results provide important insights into the following factors that drive successes and failures of many policy interventions: design and implementation, monitoring and enforcement, impact evaluation, and communication. These lessons are expanded upon in **Chapter 6**, which provides a final discussion of the overall thesis for vegetation management policy in Queensland and similar environmental policies around the world. In this concluding chapter, I also highlight the contribution of the thesis to the interdisciplinary space surrounding conservation science and policy, and I outline directions needed for future research to answer the remaining questions about tree clearing behaviour.

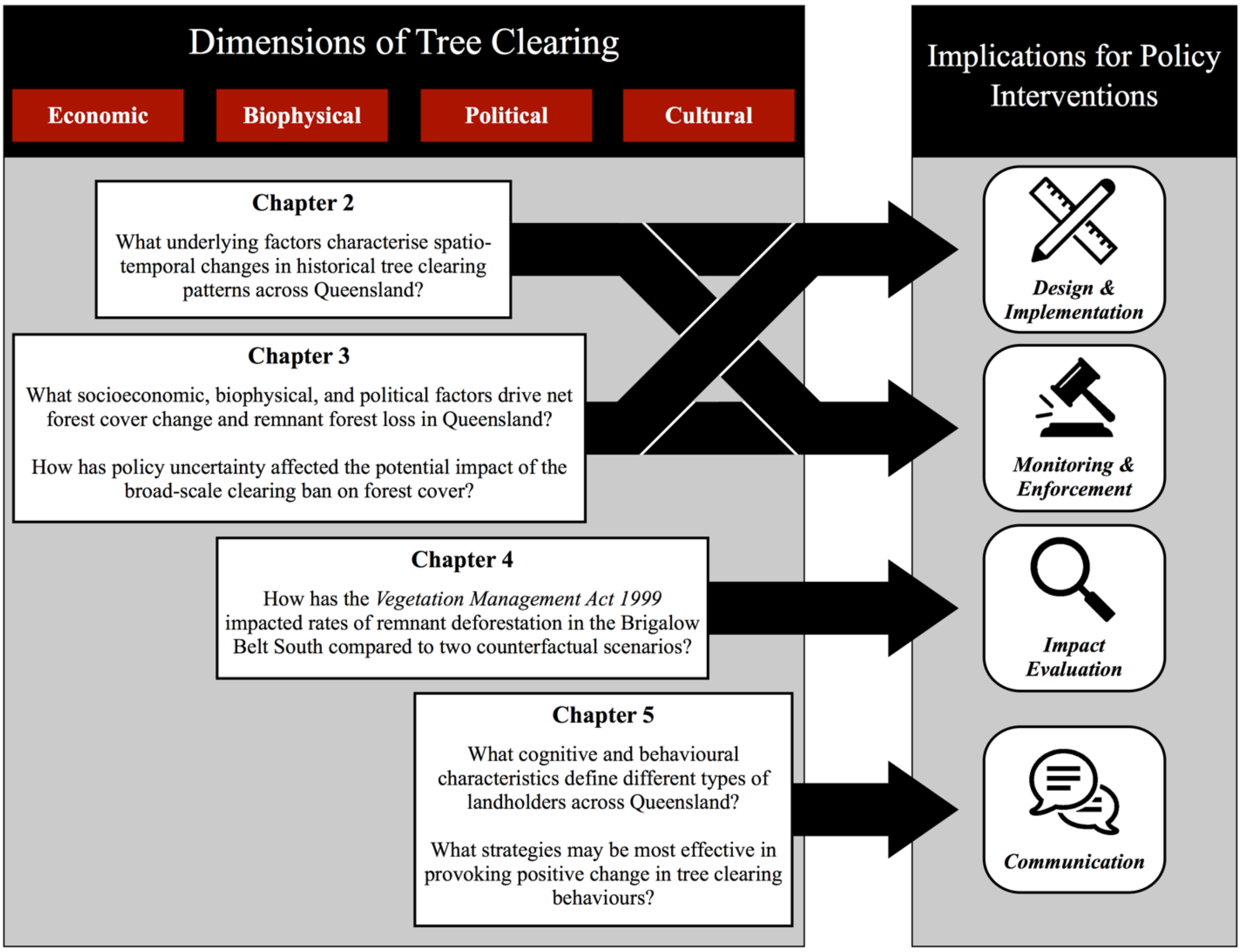

Fig. 1.2. Outline of the content and structure of the thesis. Each chapter investigates a suite of economic, biophysical, political, and/or cultural factors influencing tree clearing behaviours, and highlights important lessons for four key issues determining the success of environmental policy interventions: design and implementation, monitoring and enforcement, impact evaluation, and communication.

<u>Chapter 2</u>

Simmons BA, Law EA, Marcos-Martinez R, Bryan BA, McAlpine C, Wilson KA. 2018. Spatial and temporal patterns of land clearing during policy change. Land Use Policy **75**:399–410.

Contributor	Statement of contribution
Author BA Simmons (Candidate)	Paper concept (90%), analysis (100%), wrote and edited the paper (65%)
Author EA Law	Wrote and edited the paper (10%)
Author R Marcos-Martinez	Wrote and edited the paper (5%)
Author BA Bryan	Wrote and edited the paper (5%)
Author C McAlpine	Wrote and edited the paper (5%)
Author KA Wilson	Paper concept (10%), wrote and edited the paper (10%)

Chapter 2: Spatial and temporal patterns of land clearing during policy change

2.1 Abstract

Environmental policies and regulations have been instrumental in influencing deforestation rates around the world. Understanding how these policies change stakeholder behaviours is critical for determining policy impact. In Queensland, Australia, changes in native vegetation management policy seem to have influenced land clearing behaviour of landholders. Periods of peak clearing rates have been associated with periods preceding the introduction of stricter legislation. However, the characteristics of clearing patterns during the last two decades are poorly understood. This study investigates the underlying spatiotemporal patterns in land clearing using a range of biophysical, climatic, and property characteristics of clearing events. Principal component and hierarchical cluster analyses were applied to identify dissimilarities between years along the political timeline. Overall, aggregate landholders' clearing characteristics remain generally consistent over time, though noticeable deviations are observed at smaller regional and temporal scales. While clearing patterns in some regions have shifted to reflect the policy's goals, others have experienced minimal or contradictory changes following regulation. Potential 'panic' or 'pre-emptive' effects are evident in the analysis, such as spikes in clearing for pasture expansions, but differ across regions. Because different regions are driven by different pressures, such as land availability and regulatory opportunity, it is imperative that the varying spatial and temporal behavioural responses of landholders are monitored to understand the influence of policy and its evolution. Future policy amendments would benefit from monitoring these regional responses from landholders to better assess the effectiveness of policy and the potential perversities of policy uncertainty.

2.2 Highlights

- Aggregate clearing analyses may ignore factors driving landholders' policy response.
- Land-policy uncertainty could elicit unintended intervention outcomes.
- Identifying regional clearing patterns and drivers can orient more effective policy.

2.3 Introduction

Deforestation, with its consequential effects of habitat loss, fragmentation, and degradation, is a well-recognized threat to biodiversity and ecosystem function (McAlpine et al. 2002; Lindenmayer 2005; Bradshaw 2012). Environmental regulations and other policy instruments greatly influence deforestation rates around the world, whether directly or indirectly (Meyfroidt & Lambin 2011). A number of countries have directly reduced deforestation rates using conservation policies incorporating logging bans (Southworth & Tucker 2001; Mather 2007), mandated reforestation or afforestation (Klock 1995; Wang et al. 2007), and land use restrictions (Fox et al. 2009; Assunção et al. 2012). Other countries such as Costa Rica and India have experienced a decline in deforestation indirectly, due to economic and ideological pressures (Kull et al. 2007; Daniels 2009) and forest management decentralisation (Agrawal 2007; DeFries & Pandey 2010), respectively. Angelsen and Kaimowitz (1999) argue that policy instruments and macroeconomic variables represent the underlying causes of deforestation, and these factors will directly influence more immediate causes of deforestation, such as institutions, infrastructure, markets, and technology.

Policy instruments can thus modify the dynamics of the human-environment system, but by doing so, may not always work as intended. Policies can even lead to the potential for perverse, or unintentional, outcomes to emerge (Miteva et al. 2012). Some conservation policy instruments have resulted in leakage effects, whereby deforestation is displaced from the regulated region into unregulated areas (Wear & Murray 2004; Oliveira et al. 2007; Gaveau et al. 2009). Other policies meant to indirectly curb deforestation, like those reducing agricultural rents or removing clear-to-own property laws, may also result in accelerated clearing rates when they are poorly implemented, lack public support, or introduce high levels of legislative uncertainty (Kaimowitz et al. 1998; Angelsen 2009).

Vegetation management policies directly affect the livelihoods of agricultural landholders, placing constraints on economic growth, property rights, and potentially tenure security (Alston et al. 2000; Sant'Anna & Young 2010; Aldrich 2012). The link between deforestation and issues of property rights and tenure security has been most obvious in developing nations, where landholders clear forest to lay their claim on the land, prevent squatters from infiltrating, and receive financial incentives (as well as property legitimacy) from the government (Alston et al. 2000; Aldrich et al. 2012; Brown et al. 2016). When this sense of security and autonomy is threatened by incoming policies dictating how landholders are permitted to manage their land, some may react by pre-emptively clearing vegetation. If controversial policies are complemented by high political instability, regime changes, or legislative ambiguity, the reactions from landholders to this uncertainty can significantly increase deforestation rates over time (Deacon 1994; Barbier & Burgess 2001b).

Deforestation patterns in Australia are broadly reflective of the rapid rate of modern deforestation globally (Lindenmayer 2005). In its relatively brief colonial history, Australia has seen agricultural expansion reduce forest cover by nearly 15%, with 7.2 million ha (7%) of primary forests cleared in the last 40 years alone (Bradshaw 2012; Evans 2016). Since the 1970s, the State of Queensland has lost 9.7 million ha of total forest from land clearing, accounting for more than 60% of clearing in the entire country over this period (Evans 2016), with native vegetation cover reduced by at least 50% over the last 200 years (ABRS 2010). Like many developing countries, the first century of development in Queensland was marked by heavy governmental encouragement for landholders to clear as much vegetation as possible in an effort to raise economic prosperity (Braithwaite 1996; Bradshaw 2012). It was not until the end of the 20th century that public opinion began to change regarding the value of native vegetation, and the Queensland Government entered into a period of land clearing policy reform, which brought about the first strict regulations on vegetation management practices with the *Vegetation Management Act (VMA) 1999*. Landholders in Queensland have since experienced considerable evolutions in state vegetation management policy.

The most infamous period of land clearing in Queensland in recent history involved the rapid increase in clearing rates during 1999–2000 and 2002–2003, likely in response to the initial enactment of the VMA 1999 and subsequent stricter implementation in 2003—periods commonly referred to as *panic clearing* (Productivity Commission 2004; Lindenmayer 2005; Taylor 2015). The definition of panic clearing, however, is unclear; it has been used to describe rushed clearing activities (i.e. future plans that were expedited) or unplanned clearing activities (i.e. activities that the landholder had no future intentions of executing), though evidence of both types of panic clearing have been reported anecdotally in this case (Senate Inquiry 2010). Further, it is unclear whether panic clearing constitutes increased business-as-usual clearing (i.e. clearing locations similar to locations cleared in the past), increased atypical clearing (i.e. clearing locations dissimilar to those cleared in the past), or a combination of both. Identifying how these different characterisations of panic clearing contributed to the increased volume of clearing across regions is imperative to our understanding of how landholders make reactive, short-term land clearing decisions. One attribute of panic clearing remains consistent, however, which is that panic clearing is pre-emptive, due to expected clearing limitations imposed by future regulations (McIntyre et al. 2002; Productivity Commission 2004; McGrath 2007). Such perverse pre-emptive responses from landholders and stakeholders can also be found elsewhere in the conservation realm, following listings on the U.S. Endangered Species Act (Lueck & Michael 2003) and trade bans under the Convention on International Trade of Endangered Species (CITES; Rivalan et al. 2007).

The convoluted introduction of strict vegetation management regulations in Queensland led to landholder uncertainty regarding future property rights and tenure security (Productivity

Commission 2004; Senate Inquiry 2010), which has also been observed in developing countries undergoing substantial policy evolution (Alston et al. 2000; Aldrich et al. 2012). Queensland thus serves as an important and relevant global case study to highlight how these clearing behaviours may change over time amidst continual (and sometimes contradictory) changes to a single vegetation management policy. Further, the availability of quality data on the characteristics of clearing in Queensland allows for more thorough investigations that may not be present in other cases.

To date, the *extent* of state-wide vegetation clearing in Queensland has been widely publicised in the literature (e.g. DSITI 2016; Evans 2016), yet minimal attention has been placed on the *characteristics* of clearing over time in this case. This provides associative evidence of how vegetation management policy has affected aggregate landholder *actions* (i.e. the 'what'), rather than using the characteristics of clearing to investigate the dynamic and differential *behaviours* of landholders (i.e. the 'how'). Such temporal analyses have recently been used to assess global patterns of deforestation to identify drivers of clearing behaviour and forest transition (Hosonuma et al. 2012; Sandker et al. 2017), but these same concepts can be applied at finer scales. Previous investigations into the trends of land clearing in Queensland have also relied upon state- or national-level drivers of deforestation (e.g. Evans 2016; Marcos-Martinez et al. 2018), despite the global recognition of regionally dependent deforestation drivers and landholder responses (Geist & Lambin 2002). Thus these studies may produce generalised patterns and policy recommendations that may not adequately capture or identify regional landholders' behaviours and potential motivations.

This study investigates the underlying spatial and temporal characteristics and patterns of land clearing within the context of evolving vegetation management policies, using Queensland as a case study. Using a range of biophysical, climatic, and property characteristics to identify underlying patterns in clearing events across the political timeline, we analyse (1) how the observable biophysical, socioeconomic, and property characteristics of clearing events change over time, (2) what principle components can be derived from the spatial characteristics of clearing events, and (3) how these components differ between key policy periods. Further, we focus on periods described as panic clearing and assess how their clearing characteristics differ from previous years. To compare the potentially different spatial patterns, our analysis is undertaken at multiple scales: (1) an aggregate state-level analysis, (2) contrasting bioregion analyses, within a historical clearing hotspot (Brigalow Belt South), a relatively intact frontier for clearing (Cape York Peninsula), and an area of dense urban sprawl (South Eastern Queensland), and (3) a composite region of particular current environmental concern (Great Barrier Reef catchment).

2.4 Methods

2.4.1 Study areas

Queensland (QLD, 2.04 M km^2) is the most climatically diverse state in Australia, with 50–3000 mm mean annual precipitation depending on the region, including equatorial, tropical, subtropical, temperate, grassland, and desert bioregions. We examined clearing patterns across the entire State of Queensland, Australia, with a focus on four subregions of interest (Fig. 2.1): the Brigalow Belt South bioregion (BBS), Cape York Peninsula bioregion (CYP), South Eastern Queensland bioregion (SEQ), and the Great Barrier Reef catchment (GBRC) as defined by the former Department of Environment and Resource Management (Rollason & Howell 2012). The BBS bioregion (267,000 km^2), in south-central QLD, is a subtropical (500–750 mm) biodiversity hotspot that has been extensively historically cleared for agricultural development, especially pasture expansion (Cogger et al. 2003; Fensham & Fairfax 2003). The CYP bioregion (131,000 km^2), in contrast, is one of the most intact of the QLD bioregions, though interest in grazing is increasing in this tropical savannah and rainforest (1000–2000 mm) region (Crowley & Garnett 1998). SEQ bioregion (77,500 km^2) is the most densely populated bioregion in QLD. This subtropical region is highly diverse in climate and production, and, despite being already one of the most extensively cleared in QLD, is currently experiencing substantial expansion of urban areas (Wilson et al. 2002; Peterson et al. 2007). The GBRC (388,000 km^2) spans multiple tropical and subtropical bioregions (Rollason & Howell 2012), where the expansion and intensification of agricultural industries continues to cause concern for the health of the Great Barrier Reef (GBRMPA 2014).

2.4.1.1 Timeline of vegetation management policy in Queensland

Queensland's entrance into strict command-and-control land clearing regulation began following the enactment of the *Integrated Planning Act (IPA) 1997* and the *Vegetation Management Act (VMA) 1999* (Fig. 2.2). The VMA 1999 serves to (1) identify and define the different types of vegetation and their conservation value/protection status, and (2) outline the policy framework underlying clearing permits, which then guides the IPA 1997's requirements for assessing and enforcing these permits (Productivity Commission 2004; McGrath 2010). This controversial legislation was hastily developed, according to members of Parliament during debate (Kehoe 2009), and approved by the end of 1999, but the official proclamation of the Act was delayed by the Premier until financial assistance could be provided from the Commonwealth. By September 2000, the VMA was

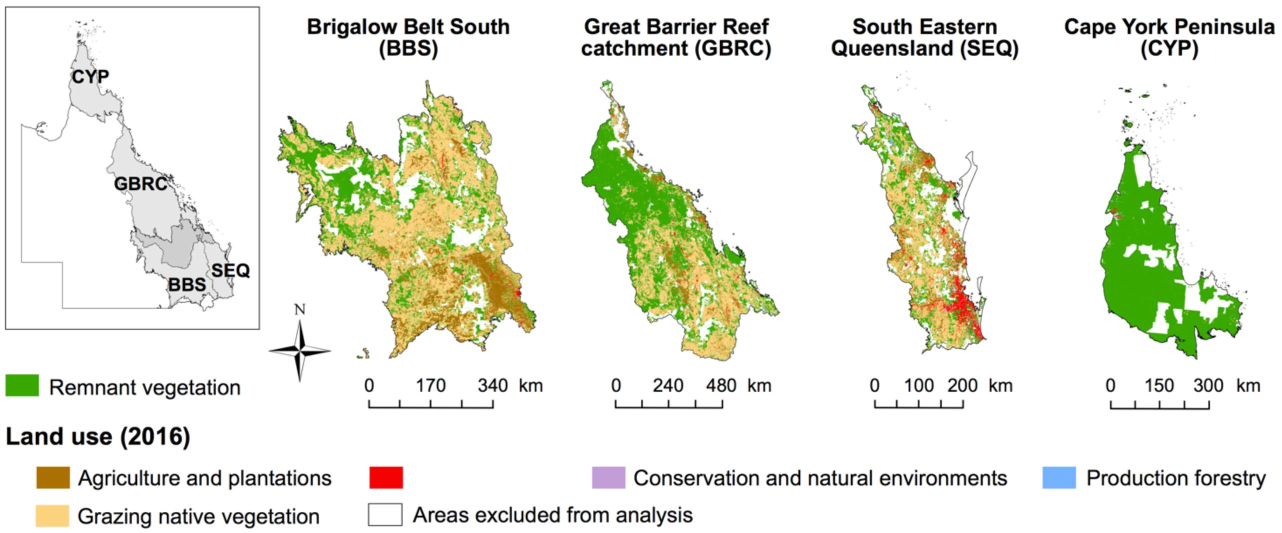

Fig. 2.1. Current land use and remnant vegetation extent within the four study regions of Queensland. Excluded areas include national and regional parks, state forests, reserves, forest reserves, timber reserves, and water resources. Land uses are derived from the Australian Land Use and Management Classification system.

proclaimed and the bulk of statutory provisions commenced (Kehoe 2009). This period between assent and proclamation provided a window of uncertainty amongst landholders as to what the future held for their ability to clear vegetation on their property, and is associated with peak clearing rates across the state. In an attempt to halt the rate of pre-emptive clearings, the centrist government passed an unexpected moratorium on clearing applications in 2003, followed by a pivotal amendment to the VMA in 2004, which declared that broad-scale clearing would be banned by the beginning of 2007. The following interim period (2004–2007) aimed to ease the transition for landholders prior to the broad-scale clearing ban, as the government offered some monetary compensation packages and allowed a transitional cap of 5000 km^2 of broad-scale clearings to be carried out across the state before 2007 (McGrath 2007; Kehoe 2009). The period following the ban saw additional amendments to the VMA, further restricting the clearing activities permissible on freehold and leasehold lands. In 2012, political power switched to the more conservative party, beginning a period of clearing policy relaxations in an attempt to reduce the burdens felt by landholders. Despite the return of a centrist premier in 2015, efforts to reinstate previous clearing restrictions in 2016 have been unsuccessful due to the party's lack of majority representation in Parliament.

2.4.2 Clearing data and characterisation variables

Land clearing data were obtained from the annual Statewide Landcover and Trees Study (SLATS)

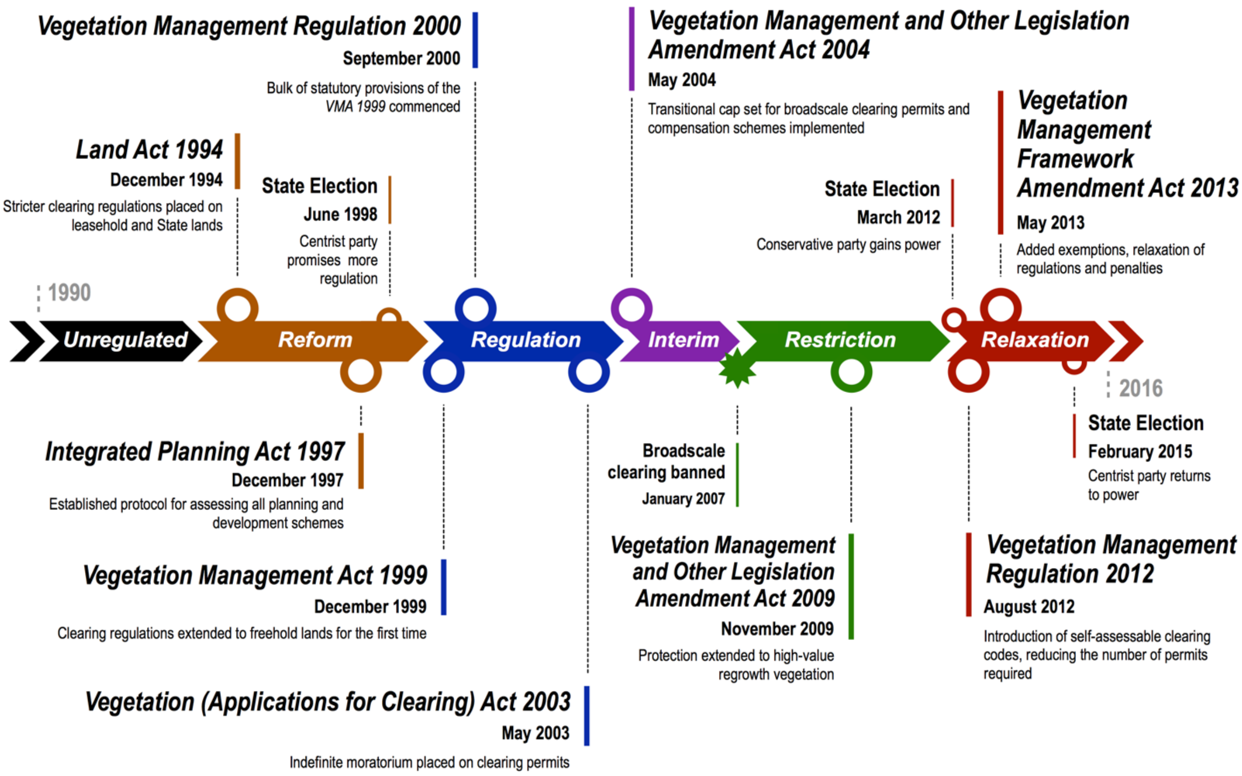

Fig. 2.2. The evolution of vegetation management policy in Queensland. Political timeline of pivotal legislation and regime shifts, categorised according to six policy periods between 1990 and 2016: *unregulated*, *reform*, *regulation*, *interim*, *restriction*, and *relaxation*. State elections of 2001, 2004, 2006, and 2009 where the centrist government maintained power are not shown.

dataset (QSC 2016h), for fiscal-year periods 1988–1991, 1991–1995, 1995–1997, 1997–1999, and annually from 1999–2000 to 2014–2015. We denote the fiscal year periods by their end year, and use a per year average for those spanning multiple years. The SLATS data are based on the supervised classification of multiple Landsat satellite images and digital terrain models at a resolution of approx. 30 m (Macintosh 2007). We defined policy periods as (Fig. 2.2): *unregulated* (1988–1995), *reform* (1995–1999), *regulation* (1999–2004), *interim* (2004–2007), *restriction* (2007–2012), and *relaxation* (2012–2015). Each incident of clearing is coded according to the clearing type (see Scarth et al. 2008). To focus on private landholder-driven clearing, which represents 97% of total deforestation in the state during this time period, we excluded natural tree loss, as well as tree loss within natural resource management areas (national parks, reserves, state forests, forest reserves) and on aquatic tenures (ports, harbours, water resources). To estimate annual remnant vegetation clearing, the earliest and most accurate map of remnant vegetation was obtained from the Queensland Herbarium for 1997 (QSC 2016g). Annual remnant forest maps were developed by first excluding the grassland ecosystems from the 1997 remnant extent, and then removing cells cleared in each period. High-value regrowth was not distinguished in this study. Because maps of remnant vegetation do not exist for the *unregulated* and early *reform* periods, we do not distinguish vegetation according to remnant status for the subsequent pattern analysis in order to facilitate comparability between all policy periods. When discussing the extent of clearing (Section 2.5.1), however, we identify remnant vegetation clearing events for the period in which data are available (1997–2015).

To characterise clearing events, nine temporally constant variables were selected: clearing type, slope, elevation, remoteness, rainfall variability, historical drought declarations, parcel size, tenure, and regional ecosystem threat status (Table 2.1). Henceforth, these variables are collectively referred to as the *characteristics* of land clearing. These variables represent biophysical, climatic, property, and legal characteristics that, together, describe suitability for agricultural conversion, the most common driver of deforestation across the globe (Joppa & Pfaff 2011; Busch & Ferretti-Gallon 2017; Marcos-Martinez et al. 2018), including Queensland (Evans 2016). *Parcel size* was used as a proxy for property size, often identified as a correlate of deforestation (e.g. Pichón 1997; Geoghegan et al. 2001; Seabrook et al. 2007, 2008). *Tenure* was included as a property and legal characteristic, which designates the legislation and benefits of clearing and other property management practices (Turner et al. 1996; Fensham et al. 1998; Lindenmayer 2005). *Regional ecosystem threat status* provides a measure of the percent of clearing within each cell that falls on the pre-clearing extent of 'least concern' regional ecosystems. Regional ecosystems (REs) are vegetation communities characterized by unique geology, soil, and landform combinations (Sattler & Williams 1999), and are designated a threat status of either 'endangered,' 'of concern,' or 'least concern.' This measure is thus a representation of both ecosystem rarity and vulnerability status under the VMA, as 'least concern' REs are most prevalent throughout the state and are under less pressure from traditional clearing trends.

2.4.3 Data analyses

2.4.3.1 Summarising clearing events over time

The historical extent of land clearing was calculated in ArcGIS using SLATS clearing polygons for total clearing (1989–1997) and for remnant and non-remnant clearings (1998–2015) after removing natural tree loss (i.e. 'natural tree death' and 'natural disaster damage') and clearings within protected areas and other resource management areas (see Fig. 2.1). Annual clearing summaries were generated to report the proportion of clearing area consisting of the following clearing purposes identified by SLATS: pasture, crop, settlement, mine, infrastructure, timber plantation, and thinning. The frequency of clearing events per parcel of land was calculated by adding the number of SLATS reporting periods in which a given parcel experienced at least one clearing event, for a maximum of 20 time periods.

Table 2.1. Variables used to characterise clearing events in the principal component analysis (PCA).

Variable	Description	Source
Clearing type	Percent of clearing attributed to 'pasture'	SLATS clearing descriptions (QSC 2016h)
Elevation	Elevation (m.a.s.l.)	QSC 2016d
Historical drought declarations	Percentage of time between 1963 and 2011 in which the relevant Local Government Area was declared in drought by the State of Queensland	QSC 2016a
Parcel size	Area (km^2) of individual parcels of land, used as a proxy for property size	QSC 2016c
Rainfall variability	Standard deviation of average rainfall from 1890 to 2013	QSC 2016b
Regional ecosystem (RE) threat status	Percent of clearing on 'least concern' regional ecosystems	QSC 2016e
Remoteness	Measure of a location's proximity to the nearest urban centre (0 = highly accessible, 15 = very remote)	Accessibility/Remoteness Index of Australia (ARIA), (ALA 2016)
Slope	Slope (deg.)	QSC 2016d
Tenure	Percent of clearing on 'freehold' land	QSC 2016c

2.4.3.2 Comparing components of clearing spatial characteristics across policy periods

The SLATS clearing polygons were converted to raster pixels with a 100 m resolution and attributed with the overlapping clearing characteristics for Queensland, resulting in over 9 million clearing observations (pixels) for the entire timeframe. The dataset was sampled without replacement in R version 2.15.3 (R Core Team 2017) using the package 'kimisc' (Müller 2014) giving 100,000 observations for each of the QLD, BBS, SEQ, and GBRC case studies. The entire CYP region consisted of only 28,263 observations, so no sampling was performed. The validity and representativeness of the QLD sample was confirmed by comparing the variable distributions of the samples and populations, and testing that two independent samples produced equivalent results.

2.4.3.2.1 Principal component analysis

Principal component analyses (PCAs) were performed for the entire State of Queensland, as well as for each case study region, in order to identify principle components of the nine spatial characteristics of clearing events. These principle components represent key dimensions of clearing patterns. We apply this PCA only to the attribute space of the spatial data and do not adapt the analysis for effects of heterogeneity or autocorrelation, as we are not producing spatial predictions (Demšar et al. 2013). Prior to analysis, Bartlett's test of sphericity (Bartlett 1950) and the Kaiser-Meyer-Olkin (KMO) test of sampling adequacy (Kaiser 1970) were applied to each case study to assess the usefulness of PCA for the datasets. Keeping with standard practice, we determined a PCA was acceptable for the dataset when KMO > 0.5 (Tabachnick & Fidell 2001). Initial PCAs were performed using the R package 'FactoMineR' (Husson et al. 2017). The number of principal components selected was based upon the commonly used Kaiser Criterion (Kaiser 1958) and verified by a scree test (Cattell 1966). In this analysis, we found that the scree test generally verified use of the Kaiser Criterion (Fig. C1), though we modestly extended the cut-off point ($E > 0.98$, Table C1).

When variables produced significant contributions to more than one principal component, we applied varimax rotation (Kaiser 1958) to the selected principal components using the R package 'psych' (Revelle 2017) to produce rotated components (RCs) with simple structure. Here, we use the term 'rotated components' in lieu of the more traditional term 'factors' in order to eliminate confusion between principal components and factors. In cases when variables exhibited cross-loading on two or more RCs, the variables were removed from the dataset, and the analysis was performed again until rotation produced the desired simple structure (Table C2). The final selection of RCs was made based upon interpretability and variable representation. While an RC with at least three high-loading variables is generally satisfactory (Costello & Osborne 2005), we selected RCs with two high-loading variables when the variables represented a similar conceptual construct, thus enhancing the interpretability of the components.

The variables chosen for interpretation of each selected RC were based upon the strength of their loading according to the scale provided by Liu et al. (2003): strong (>0.75), moderate (0.50–0.75), weak (0.30–0.49). We thus interpreted each RC according to all variables with moderate or strong loadings. Each RC was interpreted based upon the direction and strength of the characteristic variables' loadings and defined according to the relationship of the variables within the component. We classify the final RCs as the components driving land clearing characteristics within the respective region, and compare annual scores across the RCs to identify temporal changes and patterns in the strength of each component on land clearing. For more detail on the PCA methodology, see Appendix A.

2.4.3.2.2 Component score clustering

To visually estimate how the influence of these components differ between key policy periods, we produced a hierarchical cluster scheme based on the values of each observation from their respective RC for each study region. Ward's clustering method was used to maximise intra-group similarity and analyse observations according to variance rather than distance (Ward 1963). Clustering was performed for all study areas by mean component score per policy period. To identify the final number of distinct clusters for each study area, we defined a dendrogram cut off height of 0.40, which was determined post hoc in an effort to select a moderate yet conservative height that was relevant to all study regions.

2.5 Results

2.5.1 Comparative clearing characteristics across Queensland

Land clearing has declined across the study period by approximately 61% throughout Queensland (QLD), from an average of 7425 km^2 per year during 1988–1991 to 2922 km^2 in 2015, though with considerable fluctuation (Fig. 2.3a). Similarly, the proportion of land clearing constituting remnant vegetation has decreased substantially since 1997 throughout the state, from 69% to 40%. Clearing trends at the state level are most similar to those of the Brigalow Belt South (BBS), which has also seen a 62% reduction in clearing and a larger reduction in remnant clearing (Fig. 2.3b). Trends in the Great Barrier Reef catchment (GBRC) are also similar to QLD and BBS, though this region has experienced a greater decline in clearing (76%) (Fig. 2.3c). South Eastern Queensland (SEQ) and Cape York Peninsula (CYP) are most dissimilar from other regions, with SEQ maintaining similar cyclical clearing rates over time and the CYP experiencing a 304% increase in remnant vegetation clearings (Fig. 2.3d,e). The uncharacteristic peak of clearing observed at the state level in 2000 is only reflected in the GBRC. For most regions, the *interim* and *restriction* periods saw a gradual decrease in clearing extent, though all regions experienced increasing clearing rates during the subsequent *relaxation* period.

Clearing purposes within the BBS, GBRC, and SEQ have primarily been for pastures (Fig. B1). For all regions, the proportions of clearing for cropping was substantial during the *unregulated* and *reform* periods, but has since become marginal. Trends in the BBS have remained relatively consistent, though infrastructure and thinning purposes have increased slightly since *restriction*. The GBRC has also shown consistency over time, but clearing purposes are more diverse than the BBS, including a noticeable increase in mining clearance during 2005–2013. Given the population density of SEQ, this region has the highest clearance rates for settlements and consistent clearing rates for infrastructure. Initially moderate, pasture clearings in SEQ increased in dominance to peak rates during the *interim* period, beyond which the proportion of clearing for settlements and timber plantations began to increase, and the frequency of pasture clearing diminished. Clearing purposes in

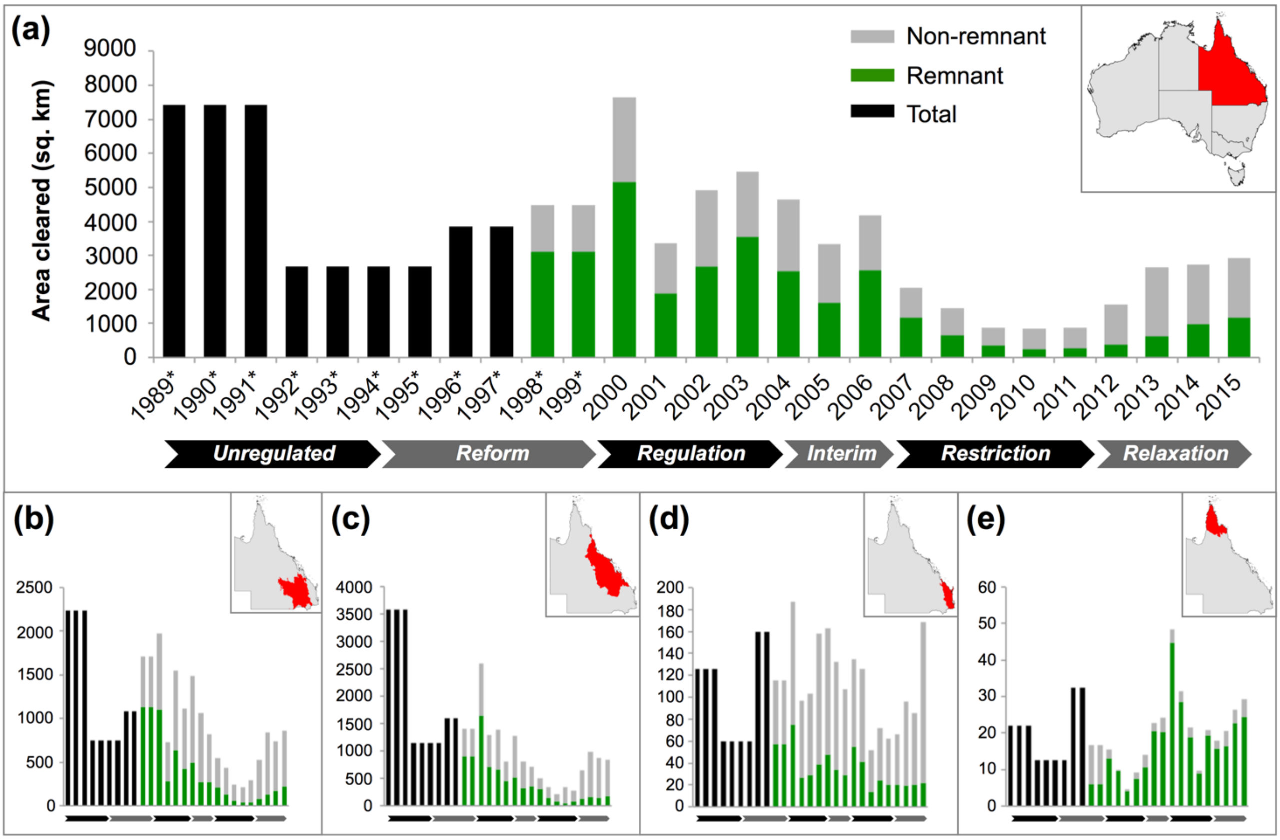

Fig. 2.3. Annual clearing extent across policy periods, broken down by remnant and non-remnant vegetation clearing (where data are available) for (a) the State of Queensland (QLD), (b) Brigalow Belt South (BBS) bioregion, (c) Great Barrier Reef catchment (GBRC), (d) South Eastern Queensland (SEQ) bioregion, and (e) Cape York Peninsula (CYP) bioregion. Data exclude natural tree loss and clearing within protected areas and other resource management areas. (*) *Clearing extent represents an average annual estimate*.

CYP have seen mining replace infrastructure development over time, particularly following the *interim* period. Like SEQ, pasture clearings gained an atypical dominance during *regulation*.

Historical clearing in the BBS consists of patchy hot- and cold-spots in the landscape, where some properties are responsible for a largely disproportionate share of the region's clearing extent during this time (Fig. B2). This is in contrast to the GBRC, which exhibits a more homogeneous extent of moderate- to high-frequency clearings across the landscape, where more landholders have contributed more equally to the overall clearing extent. Few properties in SEQ have frequently cleared in the last 26 years, suggesting that many clearings are one-off events, as would be expected given the frequency of clearing for settlements and infrastructure in this region. Despite the small amount of clearing occurring in the CYP, a number of properties are clearing frequently. Though the greatest frequency of clearing is found on mining sites, most properties undergoing continual small-scale clearing regimes are in relatively natural landscapes, indicative of new pasture clearings or necessary infrastructure. It should be noted that landholders will often need to re-clear previous areas due to the resilience of many tree species. While some regrowth is old enough to produce a height and biomass signature detectable by satellite imagery and classifiable by SLATS, we suspect the majority of regrowth is cleared before reaching such a state. Thus, it is expected that re-clearing of previous areas is continual, and largely unidentifiable, but some landholders clear new areas on their property more frequently than others.

2.5.2 Principal component analyses and clustering

2.5.2.1 State of Queensland

The first rotated component (RC) produced a strong loading for remoteness (0.78) and moderately strong loadings for parcel size (0.73) and tenure (−0.71), indicating that high values on this RC reflect clearing events on more remote areas, larger parcels of land, and greater frequency on leasehold properties (Tables C1, C2). Thus we interpreted this first RC, which captures 24% of the variance, as a measure of property characteristics, deemed the *Property Component*. The second RC captures 20% of the variance and produced strong loadings for rainfall variability (−0.89) and drought declarations (0.76), reflecting clearing events in regions with more consistent rainfall patterns that are historically more prone to droughts, which we interpreted further as a *Climate Component*. The third RC (16% of variance) exhibited a strong loading for elevation (0.82) and a moderately strong loading for slope (0.73), reflecting geographic characteristics of clearing events (higher elevations and steeper slopes), interpreted as a *Terrain Component*. The fourth RC only exhibited strong loadings on RE threat status (0.91) and was thus removed from further analysis (Table 2.2). Cumulatively, the *Property*, *Climate*, and *Terrain Components* captured 60% of the variance in the data.

When plotting the component scores by policy period, large overlaps between policy periods occurred across all RCs, with the most distinguishable deviations occurring during *regulation*/*interim* and *restriction* periods (Fig. 2.4). The *restriction* period was most distinguishable, scoring lowest on the *Property* and *Climate Components* and highest on the *Terrain Component*, indicating a greater proclivity toward clearing on atypical properties (those less frequently cleared in the past) that are under biophysical conditions more classically suitable for agriculture. This is most closely related to patterns during *reform*, but opposes the trends during *regulation*/*interim* periods, which saw a return to clearings on previously common properties but in slightly less optimal locations for agriculture. *Unregulated* and *relaxation* periods remained similar and scored more modestly along all RCs. At the state level, clearing patterns were thus largely consistent over time, though some dissimilarities

Table 2.2. Composition of each rotated component, ordered according to the variance captured (v), and subsequent interpretation of the components' measurement. Composition is represented as *variable* (*correlation with component, r*). Variables are included when $r > |0.34|$.

Region	Component	v	Composition	Interpretation
QLD	1	24%	Remoteness (0.78) Parcel size (0.73) Tenure (−0.71)	*Property Component*
	2	20%	Rainfall variability (−0.89) Drought declarations (0.76)	*Climate Component*
	3	16%	Elevation (0.82) Slope (0.73)	*Terrain Component*
BBS	1	37%	Remoteness (0.88) Elevation (0.79) Drought declarations (−0.71) Parcel size (0.71) Tenure (−0.69)	*Property Conditions Component*
	2	17%	Slope (0.71) RE threat status (0.70) Clearing type (0.51)	*Pasture Expansion Component*
GBRC	1	29%	Remoteness (0.85) Tenure (−0.78) Parcel size (0.78)	*Property Component*
	2	18%	Rainfall variability (0.81) Clearing type (−0.77)	*Climate Guidance Component*
SEQ	1	34%	Drought declarations (0.90) Rainfall variability (−0.83) Elevation (0.79) RE threat status (−0.40)	*Ecosystem Component*
	2	16%	Tenure (0.83) Clearing type (0.60)	*Pasture Growth Component*
CYP	1	28%	Remoteness (0.78) Elevation (0.68) Parcel size (0.68) Clearing type (0.61)	*Pastoral Suitability Component*
	2	26%	RE threat status (−0.74) Slope (0.67) Tenure (0.67)	*Minority Features Component*

can be identified. The cluster analysis confirmed this pattern, distinguishing only two clusters based on the mean component scores of the policy periods: (1) *reform*, *restriction*, and *relaxation*, (2) *unregulated*, *regulation*, and *interim* (Fig. C2). Periods composing the second cluster represent some of the highest clearing rates in the state, indicating that landholders have responded similarly according to how much they clear and where they clear.

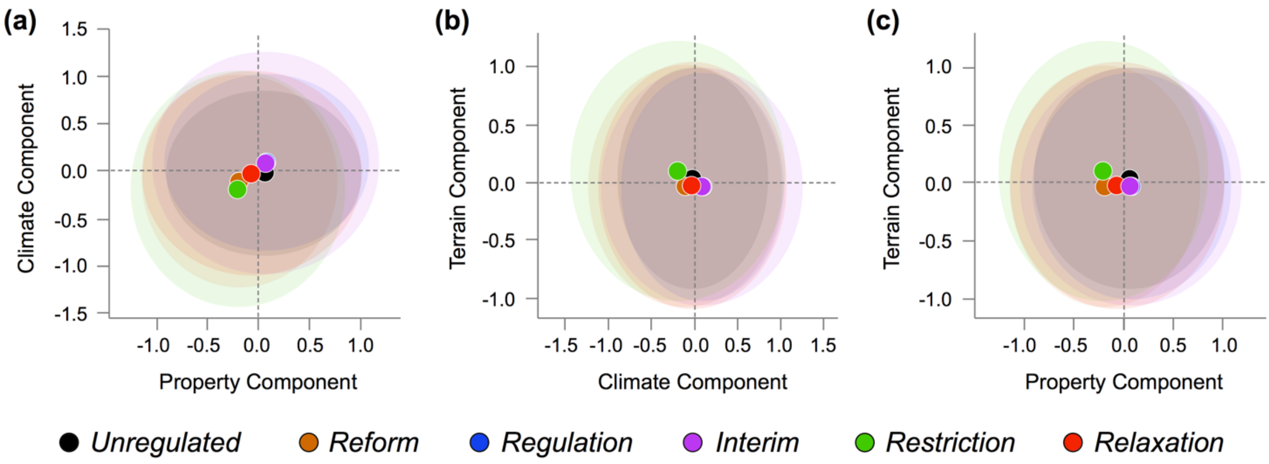

Fig. 2.4. Mean component scores and standard deviation ellipses by policy period across the final three rotated components for the State of Queensland.

2.5.2.2 Brigalow Belt South

The first RC in the BBS represented the same relationships as the *Property Component* for QLD, with the additional influence of drought-prone locations and elevation. Thus we interpreted this component as a *Property Conditions Component*. High values along the second RC represented clearing events on steeper slopes, targeting of 'least concern' (unthreatened) vegetation, and conducted primarily for pastures. We interpreted this component as a measurement of landholders' motivation and ability to clear, whereby landholders would be expanding their pastures to less-attractive locations (steeper slopes) without removing vegetation under VMA protection. We defined this RC as a *Pasture Expansion Component* (Table 2.2).

The *unregulated* period was the most distinct in the BBS across the two RCs, scoring lowest on *Pasture Expansion* and highest on *Property Conditions* (Fig. 2.5a). As expected, clearing during this period was marked by unrestrained preferences, likely guided by choosing the most suitable locations regardless of the type of vegetation present. The period of *reform* signalled a noticeable decline along the *Property Conditions Component*, indicating an increase in the proportion of clearing in historically infrequent locations. Although *regulation* saw the first increase in *Pasture Expansion*, it continued to share common characteristics with the *reform* period. The remaining policy periods generally consisted of negative *Property Conditions* scores and high *Pasture Expansion* scores, and exhibited considerable year-to-year overlap (Fig. C3a). The cluster analysis confirmed this relative ambiguity between years, resulting in two clusters where only the initial *unregulated* period was distinguished: (1) *unregulated*, (2) *interim*, *reform*, *regulation*, *restriction*, and *relaxation* (Fig. C4a). Despite the high variation in clearing extent in the BBS (Fig. 2.3b), it appears that clearing characteristics since policy reform have remained relatively similar.

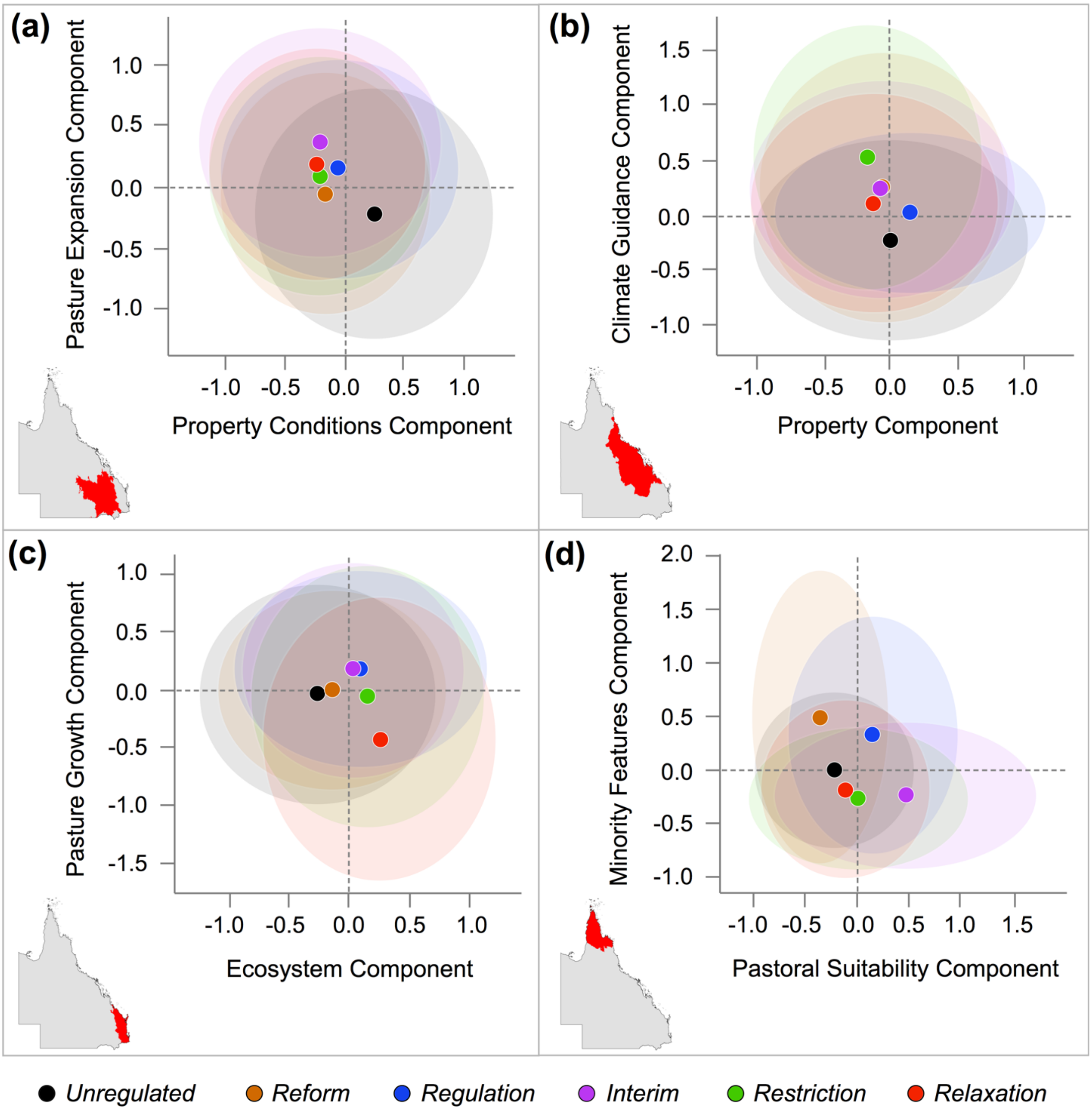

Fig. 2.5. Mean component scores and standard deviation ellipses by policy period across the final rotated components for (a) Brigalow Belt South (BBS), (b) Great Barrier Reef catchment (GBRC), (c) South Eastern Queensland (SEQ), and (d) Cape York Peninsula (CYP).

2.5.2.3 Great Barrier Reef catchment

Like QLD, the primary RC identified in the GBRC was the *Property Component*. The second RC was associated with clearing events for pastures in areas with more consistent rainfall patterns—a possible risk-management strategy; we interpreted this as a *Climate Guidance Component* (Table 2.2). The *unregulated*, *regulation*, and *restriction* periods are the most distinct across these two components (Fig. 2.5b), representing a gradual shift from pasture clearings on typical rural properties in more climatically stable locations, toward more non-pastoral clearings (such as mining and settlements) in areas with greater rainfall variability. While the majority of the *regulation* years scored highest along the *Property Component* (and neutral along the *Climate Guidance Component*), the years immediately following *reform* and preceding *interim* were less distinct (Fig. C3b). These distinctions resulted in three clusters: (1) *unregulated* and *regulation*, (2) *restriction*, (3) *reform*, *interim*, and *relaxation* (Fig. C4b).

2.5.2.4 South Eastern Queensland

The dominant RC for SEQ was interpreted as an *Ecosystem Component*, a representation of both climatic and topographic qualities influencing ecosystem characteristics (Table 2.2). Less influential was a *Pasture Growth Component*, a measurement of new pasture clearings on freehold properties, related to (though distinct from) the *Pasture Expansion Component* in the BBS. Prior to the broad-scale clearing ban in 2007, clearing patterns gradually increased along the two RCs, signalling an atypical increase in the proportion of pasture developments on freehold tenures in higher and drier environments (Fig. 2.5c). *Restriction* brought about a return to declining *Pasture Growth*, as settlements and infrastructure development began to replace the previous pastoral clearings. This eventually led to the most distinct period, *relaxation*, which saw a stark decline in the frequency of pasture clearings on freehold lands in historically common ecosystems in exchange for increased timber plantations and thinning (Fig. C3c). These patterns produced three clusters: (1) *relaxation*, (2) *unregulated* and *reform*, (3) *regulation*, *interim*, and *restriction* (Fig. C4c).

2.5.2.5 Cape York Peninsula

Clearing patterns within CYP were distinguished by two final RCs (Table 2.2). The *Pastoral Suitability Component* included the properties most beneficial to pasture conversion (high remoteness, larger parcels of land, relatively higher elevations, and more pasture clearings). The second RC, the *Minority Features Component*, represented more clearing of threatened vegetation on steeper slopes, within primarily freehold properties. Because threatened REs, steep slopes, and freehold properties are less common in the CYP landscape, this RC captures landholders' proclivity for clearing locations within the minority of the region's spatial features. The *reform*, *regulation*, and *interim* periods are most distinct. *Minority Features* peaked during *reform*, when clearing for cropping was prevalent, and eventually declined to previous levels following *regulation*, when the dominant clearing purposes shifted from pastures to mining and infrastructure. *Pastoral Suitability*, however, continued to increase until *restriction* (Fig. 2.5d). Characteristics remained similar during the *unregulated* period and the most recent periods, *restriction* and *relaxation*, indicating a largely cyclical trend in clearing characteristics over time, despite shifting clearing purposes (Fig. C3d). Four distinct clusters were identified: (1) *regulation*, (2) *reform*, (3) *interim*, (4) *unregulated*, *restriction*, and *relaxation* (Fig. C4d).

2.5.3 Synthesis of regional findings

Clearing during the *unregulated* years was characterised by 'frontier' clearing—carried out in large, remote areas with low drought risk, where rural landholders had the freedom to clear large areas of relatively abundant remnant vegetation. At most spatial scales, the *reform* period coincided with the beginning of a shift in the proportion of clearing occurring in locations less suitable for agriculture as more landholders cleared available vegetation on freehold properties now that leasehold lands were under new restrictions (Fig. 2.5). After assent of the VMA (*regulation*), all regions experienced atypical shifts in clearing characteristics, with most turning to larger, remote areas for their pasture expansions, largely irrespective of regional climatic constraints (though at the state level these areas were often in drier regions). These trends remained relatively similar in most regions during the *interim* period, though the allowance of some broad-scale clearing permits by the government likely facilitated regions like the BBS and GBRC to expand their pastures to property-level characteristics reflective of those during *reform*.

The *restriction* period exhibited some of the most distinct changes in clearing patterns, with aggregate clearing events shifting toward smaller, more accessible freehold properties where climatic and terrain conditions were less extreme (Fig. 2.4). This state-wide trend is mirrored in the GBRC, though clearing patterns in smaller regions like SEQ and CYP exhibited their own unique deviations from previous norms. For example, *restriction* was characterised by a decline in pasture clearings on freehold lands in SEQ, which was uncharacteristic of the previous decade, and clearing regimes in CYP dramatically receded from marginal lands, beyond what had characterised the region's clearing history since 1991. While the BBS continued to exhibit high inter-year variability, clearing characteristics of landholders in this region have remained generally consistent since *regulation*. With the notable exception of CYP, the reduction of pasture developments during this period is a likely result of the increasing policy restrictions, and more intensive land uses in private, semi-urban areas began to rise. Aside from SEQ, the final *relaxation* period was characterised by a return to more moderate characteristics (near-zero component scores), reflective of previous policy periods, in all regions. The aforementioned trends are most applicable to the large clearing hotspot regions of the BBS and GBRC, which are most representative of state-level patterns.

2.6 Discussion

2.6.1 Highlighting the heterogeneity of clearing patterns

This study investigated the characteristics of spatial and temporal patterns of land clearing at state and regional levels amidst considerable policy development and uncertainty. The results highlight the importance of identifying regional-scale patterns across multiple facets of land clearing, as we observed some similarities, but also many regional differences in landholder clearing patterns relative to *regulation*, in terms of the extent, frequency, timing, and characteristics of clearing events. Overall, aggregate landholders' clearing characteristics remain generally consistent over time—areas that are most suitable for pasture development and expansion are primarily cleared. Clearing in each region, however, is likely driven by different factors based upon their unique characteristics. The results of this analysis illustrate how landholders in different regions were differentially altering their clearing behaviours amidst policy change and what different factors characterised their clearing regimes. This improved understanding of state- and regional-level responses surrounding clearing regulation is likely to benefit future policy development, as goals and targets can be adapted to reflect the relevant clearing dynamics across the state. Conclusions drawn from these results thus present a cautionary tale for researchers and policy-makers around the world: using coarse measures to understand deforestation patterns and landholder responses to conservation policy may not result in the intended outcomes if they overlook more locally-relevant drivers of clearing.

In the BBS and GBRC, clearing behaviours prior to *regulation* largely represented 'frontier' clearing, reflecting historical broad-scale clearing patterns driven primarily by targeting remote lands with greater agricultural suitability and potential profitability (Kirkpatrick 1999; Lindenmayer 2005). This apparent economic rationality diminished as new regulations developed, affecting these two clearing hotspots in different ways. The importance of potential profitability appears strongest for BBS landholders, yet the region's extensive clearing history has reduced the number of profitable clearing options available. BBS landholders likely showed minimal variation in their clearing spatial characteristics in the years following policy reform due to their continued reliance on selecting the most profitable, available areas to compensate for growing policy restrictions and declining terms of trade (Seabrook et al. 2006). These landholders may thus be selectively clearing with a focus on the quality rather than the quantity of cleared land. Non-pastoral land uses in the GBRC, however, are less dispersed throughout the region and more vegetation is available for clearing (Fig. 2.1), allowing for pasture clearings to be less concentrated into hotspots (Fig. B2). Landholders in the GBRC thus are limited more by regulatory opportunity than spatial constraints; this is reflected in their tendency for frontier clearing prior to the broad-scale clearing ban and the subsequent shift during policy *restriction*, where clearing for exempt or permissible purposes became more prominent, such as mining, settlements, and infrastructure. These motivations reflect documented testimonials in Productivity Commission (2004), which highlighted BBS farmers' proclivity for targeting as much productive vegetation as possible, as well as GBRC sugarcane farmers' unwillingness to conserve unproductive lands due to clearing bans on productive, vegetated lands.

Because the CYP and SEQ, in contrast, are less representative of state clearing patterns in terms of extent and characteristics, we do not discuss their patterns at length. SEQ represents a region of dense urban sprawl surrounded by pastoral land, and thus landholders have responded by taking advantage of new pasture additions on their property until the broad-scale clearing ban, when pasture clearings dropped substantially and intensive uses like settlements and infrastructure became the more dominant purposes for clearing. Similarly, the CYP may have tried to capitalise on developing new pastures during the early years of *regulation*, which meant identifying rarer locations in the region that could prove suitable for these new developments. Following the clearing ban, clearing for more intensive purposes increased, such as mining and infrastructure—purposes less constrained by the influences of agricultural suitability. These regions' tendencies to capitalise on pasture developments during early *regulation* may represent a perverse response to the VMA. Thus, even in regions where pastoral clearings are less common, the uncertainty of future property management restrictions may have provoked pre-emptive and atypical clearings typically seen in areas with greater reliance on pastoral and agricultural land uses, like the BBS and GBRC (Mendelsohn 1994; Zhang 2001).

2.6.2 Landholder responses to policy: effectiveness, panic, and uncertainty

The introduction and modification of vegetation management policy has had a significant influence on landholders' clearing behaviours in the last 25 years, though the impact may vary substantially between regions. This impact can be characterised in two ways: the extent of clearing and the spatial characteristics of clearing. The strengthening of the VMA and the introduction of the broad-scale clearing ban coincided with a large reduction in remnant clearing extent across most regions, a reduction in pasture developments, and less frontier clearing. When coupled with the subsequent rise in total clearing extent following policy relaxation, some have argued that this presents (associative) evidence for the effectiveness of the restrictions set forth by the VMA (e.g. Maron et al. 2015; Evans 2016). In relation to the clearing characteristics, however, this effectiveness may be limited. Landholders in regions like the GBRC and SEQ have changed their clearing behaviours in ways more reflective of the goals of the VMA (i.e. less pastoral clearing in historical locations), which is more reflective of successful forest conservation policies (Fox et al. 2009). Yet in the BBS, clearing patterns have generally been consistent following initial policy reform, and in the CYP, the immunity of mining activities from VMA regulations has likely minimised the effectiveness of the policy. The VMA may thus have created general change in the extent of clearing events, yet its ability to change *what* landholders are clearing varies throughout Queensland. Indeed, this has recently been identified by Rhodes et al. (2017), who found the VMA to be ineffective at reducing clearing rates of the most threatened types of vegetation relative to non-threatened vegetation, despite an overall reduction in clearing events.

Our results shed additional light on the perverse nature of panic clearing following the introduction of the VMA. While anecdotal evidence reveals unplanned clearing occurred (Productivity Commission 2004; Senate Inquiry 2010), our analysis suggests this is more reflected in the amount of clearing rather than the characteristics of clearing: clearing characteristics during the peak period of panic clearing (1999–2000) did not differ substantially from the previous years in all regions except SEQ (Fig. C3c). While these clearing events may not have been planned in the short-term (Productivity Commission 2004), the lack of significant departures from previous clearing norms suggests landholders may have reasonably anticipated clearing these areas further in the future. Panic clearing may be best represented as a four-year period, in which landholders responded to anticipated regulations by immediately increasing previous clearing practices on their land, followed by a progression of selective pasture expansion into more available, potentially viable locations. Given the characteristics of panic clearing, we hypothesise that the initial panic clearing response may represent expedited plans by landholders, while the progression may represent unplanned clearings guided by landholders' existing knowledge of potentially profitable locations for expansion. This behaviour is reflective of other pre-emptive behaviours immediately following the introduction of policies restricting property management rights (e.g. Alston et al. 2000; Aldrich et al. 2012). Despite considerable policy uncertainty still present throughout the timeline, similar incidences of panic clearing in Queensland have likely been avoided due to the implementation of more retrospective policies and amendments, though some amendments have continued to be rapidly ascended (Kehoe 2009).

While the ongoing changes to vegetation management policy may have effectively produced a continuous blanket of uncertainty for landholders, we would expect peak uncertainty to occur immediately prior to (and potentially following) the introduction of new policies or political shifts—or most notably at the transitions between policy periods. Particularly considering the haste with which the VMA 1999 and additional amendments were enacted (Kehoe 2009), effects of this uncertainty could result in dramatic short-term shifts in clearing characteristics during these two-year windows. The potential effects of peak policy uncertainty are most observable in the BBS, where (in addition to panic clearing) the frequency of clearing by leasehold landholders immediately dropped following the *Land Act 1994*, and clearings for pasture expansion dramatically increased in the lead-up to the new conservative government in 2012. This region is likely most sensitive to uncertainty given the importance of potential profitability and spatial limitations for expansion. Because policy uncertainty often results in increased deforestation (Zhang 2001), the effects of uncertainty in a hotspot such as the BBS have the potential to significantly diminish the effects of the VMA. SEQ and CYP also have frequent short-term deviations, but these may be due to the influence of outliers in these regions where significantly less clearing activity has occurred. The GBRC, in contrast, has experienced minimal changes surrounding peak periods of policy uncertainty, potentially due to the region's suspected reliance on regulatory opportunity rather than availability.

2.6.3 Implications for policy and future directions

During the recent push by the centrist political party to reinstate previous land clearing restrictions, AgForce—Queensland's primary lobby group representing beef, sheep, wool, and grain producers—argued that the inconsistency of the VMA "severely impacts on the ability of landholders to plan and implement effective long-term property and business management decisions" (AgForce 2016, p. 2). When coupled with arguments of a lack of transparency in the VMA's goals, inflexibility of assessment codes, and inconsistencies in landholders' interpretations of the Acts (Productivity Commission 2004; Senate Inquiry 2010), it stands to reason that the degree of political and legislative uncertainty over the last 20 years may have dramatically affected landholder's clearing regimes. This is most suggestive in the historical clearing hotspot of the BBS, where pastures have continued to expand despite suboptimal biophysical conditions—a trend that emerged after the first clearing regulations were introduced.

To date, scientists and conservation groups have primarily relied upon the mere extent of land clearing to quantify the impact of the VMA. This measure, however, does not account for the large degree of complexity of ecological systems nor the behavioural responses of landholders (Dovers 2005; Knill et al. 2011). In some cases, the change in clearing extent coincides with expected changes in clearing characteristics, such as in the GBRC during the *restriction* period. Other regions, such as the BBS, do not exhibit such similarities between extent and characteristics. Most notably, the large similarities in land clearing characteristics during regulation and pre-regulation are disconcerting, as landholders have continued to clear in areas where vegetation has been extensively cleared already, thus jeopardising biodiversity and increasing the potential for land degradation in these areas—two other purposes for which the Act was meant to address. In regions with such consistent clearing characteristics, initial attempts at regulating clearing were likely negated by both the large volume of panic clearing and the characteristics of the areas targeted. Indeed, numerous accounts from landholders and industry representatives have argued that the early impacts of the VMA were negligible at the regional level due to panic clearing and market or industry conditions, such as the lack of expansion of the sugar industry (Productivity Commission 2004). Possibly more comforting is the degree of similarity between clearing during *restriction* and *relaxation* periods. That is, despite concerns over increasing rates of clearing since policy relaxation (Maron et al. 2015), landholders largely have not returned to targeting previous locations observed during pre-regulation, and the proportion of remnant clearing remains relatively small compared to previous years of similar clearing rates. Successful future policy amendments would thus benefit from explicit considerations and monitoring of these heterogeneous, spatiotemporal variations in landholder clearing behaviours, allowing for more accurate indicators of the successes and potential perversities of vegetation management policy.

This study provides the first step in illuminating the complexities of land clearance, allowing us to identify regional patterns of clearing and develop hypotheses that can be tested at a finer scale and with more robust causal inference methods. While we focus on Queensland, the findings are relevant to other regions implementing legislation to regulate deforestation. This study outlines the patterns in the extent of land clearing across Queensland (the 'what') and provides the most in-depth spatiotemporal analysis of the characteristics of land clearing patterns to date (the 'how'). However, the reasoning behind land clearing behavioural patterns (the 'why') is yet to be fully understood. Recognisably, a number of potential influential factors are not included in this analysis that may explain why landholders are expanding pastoral lands, why they may preferentially target marginal lands to clear, or why they continue to clear amidst unfavourable biophysical conditions. Using the spatially-constant biophysical and property variables as aggregate measures of agricultural suitability accounted for 47–60% of the variance in the data, depending upon the region. Additional factors must then contribute to a considerable amount of the variation observed in clearing locations, and these may include a number of demographic, economic, cultural, and personality characteristics that have noticeably influenced landholders' environmental behaviours in Queensland (e.g. Seabrook et al. 2006, 2008; Moon & Cocklin 2011; Emtage & Herbohn 2012).

Some studies have investigated the various spatiotemporal drivers of deforestation in Queensland (e.g. Seabrook et al. 2007; Evans 2016; Marcos-Martinez et al. 2018), yet as is evident from this study, generalising drivers often misses important regional drivers of deforestation. Using coarse, state-level resolutions for pattern analysis may identify overarching trends, but important localised effects may go unnoticed (Dong et al. 2015). Future studies looking at regional- and even subregional-scale drivers of clearance would greatly benefit vegetation management policy, with the potential to guide local initiatives, programs, or interventions that may be more successful and sustainable. These finer scales have been the backbone of natural resource management programs in Australia (Hajkowicz 2009), where polycentric or multi-level approaches encourage positive environmental outcomes at multiple scales (Ostrom 2010). An important piece to the land clearing puzzle also lies in the effectiveness of the VMA. Recent investigations have been made into the effectiveness of this policy by analysing the impact on threatened remnant vegetation (e.g. Rhodes et al. 2017), yet there is little account for the myriad of confounding factors that may be masking the direct causal link between regulation and observed clearing. Identifying causal linkages, however, requires a thorough understanding of regional patterns, their characteristics, and how much variation is captured by relevant confounding factors, and this study will provide the first step for such causal inference analyses. Future studies seeking more comprehensive evaluations of the causal impacts of historical vegetation management policy in Queensland will be crucial to developing new policies that can achieve greater long-term, bipartisan stability.

2.7 Conclusions

Analysis of deforestation patterns based simply upon the extent of tree loss ignores the characteristics of deforestation and the factors that may be driving landholders' responses to deforestation policies. In particularly large regions or countries, aggregate trends may not capture localised drivers of deforestation. When policies utilise these generalisations to implement regulations and restrictions, this could elicit uncertainties for landholders, who may not be able to reconcile these policies with their own motivations and rationales for clearing. More studies investigating the role of conservation policy, and particularly the consistency of such policies, are needed to enhance our understanding of the effectiveness of conservation policy instruments. Further, the effectiveness of these policy instruments needs to extend beyond the sheer numbers, where policy-makers can determine if the realised characteristics of clearing are aligning with the intended goals and objectives of the policy. If regional patterns and drivers of deforestation can be identified, more relevant and explicit interventions can be developed that may ultimately prove most effective and sustainable over time.

2.8 List of Appendices for Chapter 2

Appendix A: Details of the principal component analyses.
Appendix B: Additional spatial and temporal characteristics of clearing across Queensland.
Appendix C: Full results for the principal component and clustering analyses.

Chapter 3

Simmons BA, Marcos-Martinez R, Law EA, Bryan BA, Wilson KA. 2018. Frequent policy uncertainty can negate the benefits of forest conservation policy. Ecosystem Science and Policy **89**:401–411.

Contributor	**Statement of contribution**
Author BA Simmons (Candidate)	Paper concept (80%), model design and analysis (70%), wrote and edited the paper (60%)
Author R Marcos-Martinez	Paper concept (10%), model design and analysis (30%), wrote and edited the paper (15%)
Author EA Law	Paper concept (5%), wrote and edited the paper (10%)
Author BA Bryan	Wrote and edited the paper (5%)
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Chapter 3: Frequent policy uncertainty can negate the benefits of forest conservation policy

3.1 Abstract

Policy-driven shifts from net deforestation to forest expansion are being stimulated by increasing social preferences for forest ecosystem services. However, policy uncertainty can disrupt or reverse the positive effects of forest transitions. For instance, if the loss of remnant (primary) forest continues, the ecological benefits of net forest gains may be small. We investigated how peak periods of uncertainty in forest conservation policy affected forest transition outcomes in Queensland, Australia, as well as a globally-relevant biodiversity hotspot in the state, the Brigalow Belt South (BBS) bioregion. Political, socioeconomic, and biophysical factors associated with net forest cover change and remnant forest loss from 1991 to 2014 were identified through spatial longitudinal analysis. This informed a Bayesian structural causal impact assessment of command-and-control regulation and policy uncertainty on remnant and non-remnant forest cover. The results indicate that forest cover was negatively influenced by increasing temperatures, food prices, and policy uncertainty, and positively influenced by strengthening regulation. Regulation during 2007–2014 avoided 68,620 ± 19,214 km^2 of deforestation (with 18,969 ± 10,340 km^2 of this in remnant forests) throughout Queensland, but was ineffective on remnant forests in the BBS. For state-wide remnant forests, perverse effects from policy uncertainty (e.g. pre-emptive deforestation) were strong enough to negate regulatory impacts. This study reveals a cautionary tale for conservation policy: despite strict environmental regulations, forest transition can be delayed (or reversed) when political inconsistency or instability provoke unintended reactions from landholders.

3.2 Highlights

- Political factors are significant drivers of deforestation.
- Regulation reduced deforestation inconsistently across forests types and regions.
- Policy uncertainty increased deforestation, particularly in remnant forests.
- Perverse outcomes delayed forest transition and may reverse further transition.
- Focusing on forest gains will ignore biodiversity threats of remnant forest loss.

3.3 Introduction

3.3.1 Deforestation and policy feedbacks

Since 1990, over 185,000 km^2 of forests have been converted to other land uses around the world (FAO 2016a), with others estimating a complete loss of 50% of global forest cover prior to the 21st century (FAO 2016b). Agricultural expansion is the most commonly cited proximate driver of deforestation (Barbier & Burgess 2001a; Hosonuma et al. 2012), and it is estimated to account for roughly 80% of global deforestation (Kissinger et al. 2012). However, despite a wealth of case studies, few generalizations can be made regarding the causes of deforestation (Allen & Barnes 1985; Deacon 1994; Busch & Ferretti-Gallon 2017). The drivers of deforestation often occur in complex feedbacks, operate at different scales, and are spatially and temporally dynamic; regulation of deforestation will likely not have homogenous effects on all stakeholders (Rudel et al. 2009; Seabrook et al. 2006). In many instances, the causes of forest loss in tropical deforestation hotspots can be linked to general characteristics of the countries' development, including less secure property rights, political corruption, and desires for rapid economic growth (Angelsen & Kaimowitz 1999; Barbier & Burgess 2001a,b; DeFries et al. 2010). Deforestation rates in developed countries receive much less attention and scholarly treatment.

Evidence suggests that societal preference for forest conservation and expansion represented through policy could result in forest transition (Rudel et al. 2005). While significant environmental and socioeconomic benefits may be expected from sustained forest transitions, forest conservation policies place significant constraints on landholders by introducing restrictions on property rights, profitability, and tenure security in some cases (Alston et al. 2000; Aldrich et al. 2012). Such constraints could disrupt or reverse transition processes and outcomes, particularly when influential policies change frequently, as the threat of future restrictions may provoke unintended behavioural responses, such as pre-emptive deforestation (Brown et al. 2016). Further, if forest conservation policies fail, are poorly implemented, or provoke perverse responses, this can result in delays, inconsistencies, and reversals of forest transition (Barbier et al. 2010). Political timelines are significant drivers of policy change (Kingdon 2003; Pierson 2004), and fluctuations in the number and intensity of policies may provoke higher policy uncertainty for landholders, resulting in increased deforestation (Zhang 2001; Gasparri & Grau 2009; Knill et al. 2012). The frequent use of 'command-and-control' regulations—i.e. direct regulations defining legal and illegal activities (McManus 2009)—may also encourage negative feedbacks, as these tactics are often polarising, inflexible, and may reduce landholders' inherent motivations to protect the environment (Smith & Vos 1997; Dresner et al. 2006; Jordan & Matt 2014).

3.3.2 Contentious forest policy in Australia

Australia, and particularly the State of Queensland, represents an important and globally-relevant case study in the impacts of policy on forest transition and the differential effects on net forest cover and remnant forest loss. Global deforestation patterns are mirrored in Australia, where rapid industrialization and agricultural expansion resulted in the loss of nearly 15% of native forests, with 7% of primary forests lost since 1972 (Bradshaw 2012; Evans 2016). Deforestation drivers in Australia may represent a suite of characteristics reflective of both developed and emerging economies, such as potential profitability of the land (Bartel 2004; Lindenmayer 2005), agricultural prices (Kaimowitz & Angelsen 1998; Seabrook et al. 2006), remoteness (Geist & Lambin 2002; Simmons et al. 2018b, **Chapter 2**), property characteristics (Turner et al. 1996; Seabrook et al. 2007), and command-and-control regulations (Angelsen & Kaimowitz 1999; Assunção et al. 2012). Recent rates of deforestation marked Australia with one of the highest annual deforestation rates in the world during 1990–2000 (Lindenmayer 2005). While some reports have listed Australia amongst the top countries for reported forest area and annual net forest gain (e.g. FAO 2016a), remnant (i.e. primary) vegetation continues to be lost throughout the State of Queensland, Australia (Simmons et al. 2018b, **Chapter 2**), and the ecological value of remnant forests often cannot be easily substituted by recent reforestation efforts (Bowen et al. 2009).

Deforestation in Queensland constitutes over 60% of all deforestation in the country in recent history (Evans 2016) and the state entered the forest transition phase as late as 2008, though recent spikes in deforestation since 2013 may signal a reversal of this transition (Marcos-Martinez et al. 2018). These transitions have occurred in conjunction with the Queensland Government's introduction of regulations on remnant deforestation on private lands via the controversial *Vegetation Management Act 1999*. Since its introduction, the policy has been fraught with debate over its design, implementation, and impacts on landholders (Productivity Commission 2004; Senate Inquiry 2010). The policy has undergone considerable regulatory fluctuations over time. After placing a moratorium on clearing permits in 2003, Parliament entered a policy transition phase, allowing a cap of 5000 km^2 of 'broad-scale' clearing (large-scale clearing for crops and pastures). This was followed by a period of growing policy restrictions, including a complete ban on broad-scale clearing and protection of 'high-value' regrowth (i.e. secondary) vegetation. Following a change in Parliament's majority political party in 2012, amendments to the Act subsequently eliminated high-value regrowth protection, added new clearing exemptions, and allowed landholders to self-assess their clearing practices (Simmons et al. 2018b, **Chapter 2**). Despite some evidence that the broad-scale clearing ban in 2007 resulted in reduced deforestation (Evans 2016) and greater net forest gains (Marcos-

Martinez et al. 2018), this political inconsistency has produced some perverse outcomes, such as pre-emptive or 'panic' clearing during policy introduction (Simmons et al. 2018b, **Chapter 2**).

This study investigates the influence of the broad-scale clearing ban and peak periods of policy uncertainty on deforestation rates alongside more traditional biophysical, socioeconomic, and property-based drivers frequently identified in the literature. We applied a spatial longitudinal analysis to distinguish significant drivers of net forest cover change from drivers of remnant forest loss. This allowed us to determine the role of various factors on two forest metrics with different ecological ramifications and at different scales. We then used Bayesian time series models to estimate the causal impact of the broad-scale clearing ban on deforestation trends under different conditions. To identify potential scale-specific effects, we apply these models to the entire State of Queensland and to the Brigalow Belt South bioregion, a historical biodiversity and deforestation hotspot within the state. We show that command-and-control regulation can spur forest transition, but its effectiveness can be limited or counteracted by frequent policy uncertainty. The results of this study highlight the importance of creating strong and stable deforestation regulations to avoid potential perverse responses from landholders during frequent political regime changes.

3.4 Methods

3.4.1 Study areas

The State of Queensland spans 2.04 M km^2 of diverse habitats, including tropical, temperate, and desert bioregions. Prior to significant deforestation, the state was dominated by eucalypt woodlands along the eastern coast, acacia-dominated open forests in the southern interior, and tussock grasslands in the west (Neldner et al. 2017). Today, however, much of the forests have been cleared, leaving highly fragmented acacia forests and eucalypt woodlands in the south-central bioregions (Fig. 3.1). The Brigalow Belt South (BBS) bioregion encompasses approximately 0.22 M km^2 of south-central Queensland. The bioregion exhibits cyclic and highly variable rainfall typical of subtropical patterns, with an annual mean rainfall of 500–750 mm (Lloyd 1984; Crimp & Day 2003). The dominating vegetation types within the BBS include dry and alluvial eucalypt woodlands and acacia forests (e.g. brigalow, *Acacia harpophylla*) (Seabrook et al. 2006, 2008). These woodlands are frequently structured as 'open' woodlands or forests, containing a diverse composition of plant species and generally maintaining shrub- or low tree-layers (Lucas et al. 2014). This biodiversity hotspot provides habitat for 492 resident bird species, as well as numerous endemic and endangered reptiles, plants, and mammals (McAlpine et al. 2011; Ponce Reyes et al. 2016).

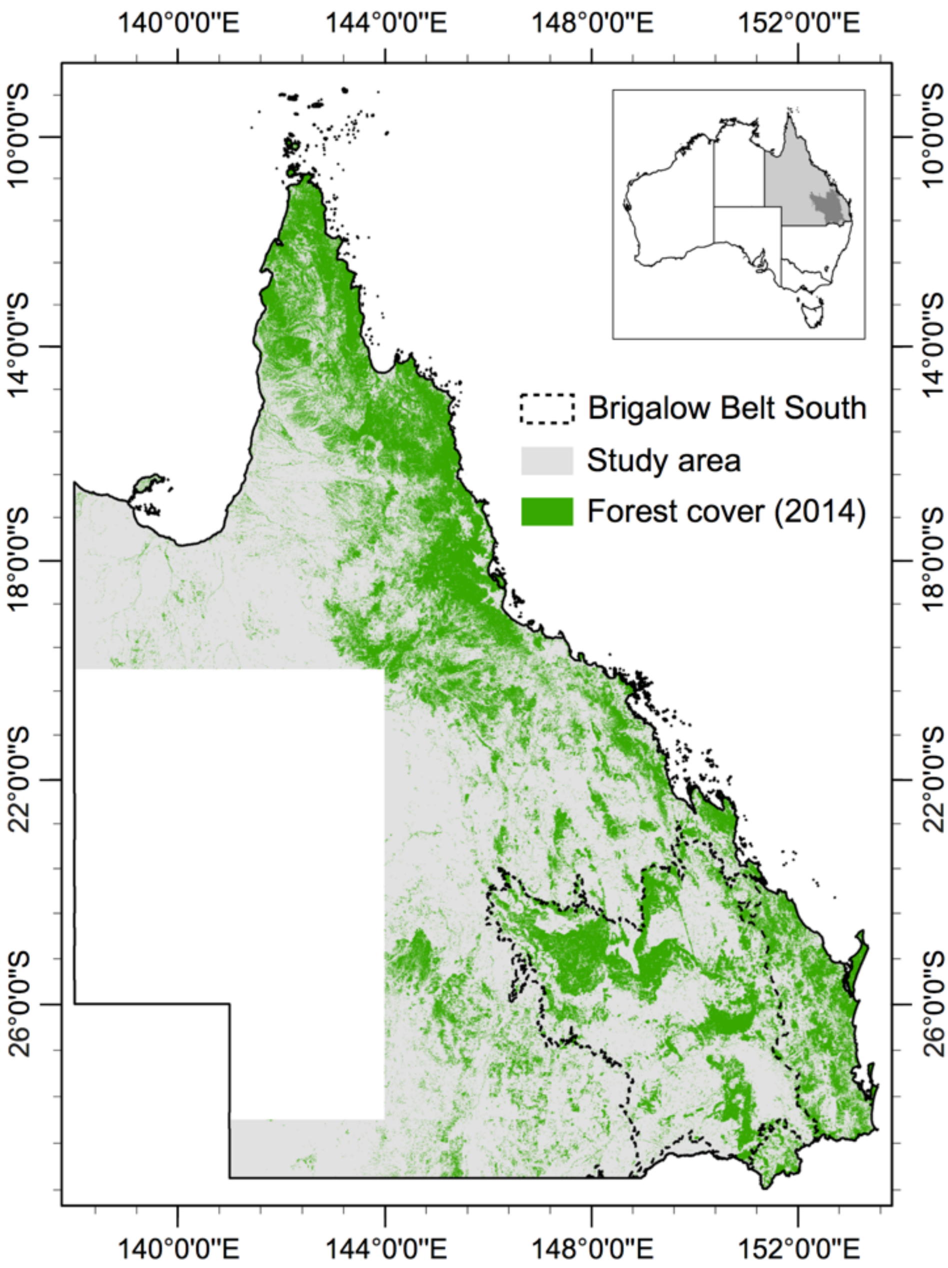

Fig. 3.1. Extent of forest cover in 2014 within the study area of Queensland and the Brigalow Belt South (BBS) bioregion.

3.4.2 Forest cover data

Our analysis relies on binary forest cover data (25 m resolution) generated through supervised classification of Landsat imagery for the Australian Government's National Carbon Accounting System – Land Cover Change Program (NCAS-LCCP) (Caccetta et al. 2012). Forests in such datasets, and throughout this study, are areas of vegetation with potential to reach at least 20% or greater crown cover and 2 m of height (Macintosh 2007). Land cover estimates based on remote sensing data may, however, contain transition errors when temporal dependencies are uncontrolled for (Marcos Martinez & Baerenklau 2015). Thus, we used transition rules to control for illogical forest cover changes in each year (*t*) relative to the conditions observed at $t \pm 1$ and $t \pm 2$. Because we do not have data for 2015, we do not include $t + 2$ for 2013, and we use the original NCAS data for 2014. Additional details on the NCAS methodology can be found in Caccetta et al. (2012).

To reduce the computational requirements to study net forest cover change over large areas, we define a forest cover index (FCI) as the proportion of 1 km^2 cells with designated forest status for the entire State of Queensland. We limit the study area of Queensland to the regions where available forest cover data overlap for all of the following 17 years: 1991, 1992, 1995, 1998, 2000, 2002, and annually from 2004 to 2014 (see study area, Fig. 3.1). The excluded area mostly consists of semi-arid scattered vegetation. Further, deforestation events occurring on natural resource management areas (i.e. national and regional parks, state forests, reserves, forest reserves, and timber reserves) were excluded from the study area. The final dataset consisted of over 22 million FCI observations.

To identify areas of remnant forest, we obtained the earliest map of all remnant vegetation in the state from 1997 (QSC 2016g) and overlapped the extent of remnant vegetation with the FCI of 1998 to produce a remnant forest cover index (RCI) for 1998. Due to a lack of data, the RCI models did not include remnant data in 1991, 1992, or 1995. Because the NCAS data do not distinguish primary and secondary forests, areas of remnant forest loss can experience forest gains in subsequent years (i.e. secondary forest growth). To monitor remnant forest loss over time and exclude any secondary gains, RCI maps for subsequent years were generated by subtracting land clearing data from the Statewide Landcover and Trees Study (SLATS) (QSC 2016h). SLATS quantifies the loss of all woody vegetation identifiable by Landsat imagery with a foliage projective cover above 8% for the following relevant fiscal-year periods: 1997–1999, 1999–2000…2013–2014). This dataset should thus be able to detect the loss of NCAS-defined forests. Because SLATS also identifies the purposes of clearing events, only human-caused clearing events were included (i.e. clearing for pasture, cropping, infrastructure, settlements, mining, thinning, timber plantations, and unknown clearing); natural tree loss purposes were thus excluded from the RCI change (i.e. natural tree death and natural disaster damage). For additional details on the SLATS methodology, see Scarth et al. (2008).

3.4.3 Policy as a driver of forest cover dynamics

We investigated the influence of 17 predictor variables on FCI and RCI for Queensland and the BBS, encompassing biophysical (9 variables), socioeconomic (4 variables), property (2 variables), and political (2 variables) parameters identified in the literature for their effect on deforestation (Table 3.1). These variables were selected due to their historical significance in the literature for driving land cover change dynamics in the Brigalow Belt (Seabrook et al. 2006), Queensland (Evans 2016), agricultural zones of Australia (Marcos-Martinez et al. 2017), and global meta-analyses (Busch &

Ferretti-Gallon 2017). Dummy variables were incorporated to represent the political factors used in the statistical model: when broad-scale clearing was banned by the Vegetation Management Act (2007–2014), and periods of peak policy uncertainty. We represent policy uncertainty as a measure of the volatility of forest conservation policy (Aizenman & Marion 1993; Feng 2001), in which greater probability of policy change provokes greater uncertainty. For this study, we define periods of uncertainty to be one year before and one year after the enactment of pivotal vegetation management policies in Queensland. This window captures periods of campaigning and preliminary Parliamentary debate, which have been shown to represent peak uncertainty in other policy sectors (Baker et al. 2016), as well as the direct aftermath of policy change, where appeals were discussed and stakeholders had to rapidly adjust their land management regimes and gain sufficient knowledge of the new regulations (Productivity Commission 2004).

Table 3.1. Variables included in the econometric model. Expanded descriptions in Table D1.

Category	Variable	Type
Forest cover	Forest Cover Index (FCI)	Spatial time series
	Remnant Forest Cover Index (RCI)	Spatial time series
Biophysical characteristics	Elevation	Spatial
	Slope	Spatial
	Soil pH	Spatial
	Soil clay content	Spatial
	Soil bulk density	Spatial
	Rainfall	Spatial time series
	Rainfall variability	Spatial
	Maximum temperature	Spatial time series
	Drought frequency	Spatial
Socioeconomic characteristics	Food price index	Annual time series
	Potential agricultural profit	Spatial
	Distance to protected areas	Spatial time series
	Accessibility and Remoteness Index of Australia (ARIA)	Spatial
Property characteristics	Parcel size	Spatial
	Tenure	
	Freehold	Spatial
	Leasehold	Spatial
	Other	Spatial
Political characteristics	Broad-scale clearing ban	Annual time series
	Policy uncertainty	Annual time series

In order for a full year to be designated as a year of policy uncertainty, more than six months of that year must have been within the one-year window before or after enactment. The following pivotal policy enactments, and their subsequent uncertainty windows, were distinguished for the policy uncertainty variable based upon the policy timeline of Simmons et al. (2018b, **Chapter 2**): *Land Act 1994* (1994, 1995), *Vegetation Management Act 1999* (1999, 2000), *Vegetation (Applications for Clearing) Act 2003* (2002, 2003), *Vegetation Management and Other Legislation Amendment Act 2004* (2003, 2004), *Vegetation Management and Other Legislation Amendment Act 2009* (2009, 2010), and *Vegetation Management Framework Amendment Act 2013* (2012, 2013). Recognisably, policy uncertainty likely undergoes considerable fluctuations over time and is not completely absent between peak uncertainty periods (Baker et al. 2016). Other events may also heighten political uncertainty, such as state elections or changes to federal environmental policy (e.g. *Environment Protection and Biodiversity Conservation Act 1999*), but changes in political power often have marginal effects on policy uncertainty (Feng 2001), and state regulations have the most direct influence on Queensland landholders.

3.4.4 Modelling forest cover dynamics

To identify deforestation drivers, we applied a spatial panel error analysis akin to models previously used to identify national drivers of land use/land cover change in Australian agricultural zones (Marcos-Martinez et al. 2018). Under this approach, spatiotemporal forest cover changes are modelled as:

$$ln(Y) = \beta' \, ln(X) + u \tag{1}$$

where ln represents the natural logarithm, Y is a vector of N FCI or RCI observations for all the T years during the study period, X is a matrix of spatiotemporal forest cover change drivers, β is a vector of marginal effects estimates, and u is a vector of disturbances. This error vector includes the effects of spatial error correlation,

$$u = (I_T \otimes \rho \, W) \, u + \omega \tag{2}$$

unobserved heterogeneity,

$$\omega = (\iota_T \otimes I_N) \, \mu + \upsilon \tag{3}$$

and random disturbances (υ) (Millo & Piras 2012). Here, I_T and I_N are identity matrices of dimension T and N, ι_T is a vector of ones of size T, $\otimes$ indicates the Kronecker product, W is a spatial weights matrix of size N, ρ is the spatial error correlation parameter, and ω is a vector that captures unobserved heterogeneity (μ) and standard random normal disturbances (υ) (Kapoor et al. 2007; Millo & Piras 2012). Four models were developed: (1) Net forest cover (FCI) in Queensland, (2) FCI in the BBS, (3) Remnant forest cover (RCI) in Queensland, and (4) RCI in the BBS. We performed 1000 iterations of each model for samples with 10,000 observations per year to estimate the mean, standard deviation, and 95% confidence intervals of β per model.

Most explanatory variables used to predict forest cover change exhibited negligible collinearity, though some significant correlations were observed for the temporally constant climatic variables (Fig. D1). For example, rainfall variability was positively correlated with annual rainfall, and drought frequency was negatively correlated with annual rainfall and maximum temperature. These relationships coincide with the longitudinal progression of Queensland's climate, where cooler and wetter regions along the east coast progress to hotter and drier landscapes westward. However, multicollinearity was assessed using the R package 'mctest' (Imdad Ullah & Aslam 2018), and all variables exhibited a variable inflation factor (VIF) well within the accepted range for inclusion in regression analyses (Kutner et al. 2004; Sheather 2009) (Table D2). Thus all variables were included in the initial random effects models, and the most-correlated parameters were only used as control variables in the final fixed effects models, further eliminating any collinearity issues. The final regression results indicated stability of the coefficient estimates to different model specifications.

Results from an iterative Hausman test (Hausman 1978) indicated that for most of the samples a fixed effects approach was recommended (Table D3, Fig. D2). Thus we focus the results and discussion of our analysis to the fixed effects model, while noting that results from random effects regressions were largely consistent, with the statistically significant variables having the same sign and roughly equivalent magnitudes (Tables E1, E2). To compute predictions for each model for all study periods, we followed the fixed effects spatial maximum likelihood estimation (FE-MLE) described by Baltagi et al. (2012). As a goodness-of-fit measure, we generated pseudo R-squared averages for each year, as well as global R-squared averages per model, by using the square of the correlation coefficient between predicted and observed FCI or RCI values described by Elhorst (2014) (see Appendix D for additional details on the methodology). Construction and analysis of the econometric models were performed in R version 3.4.1 (R Core Team 2017) using the packages 'plm' (Croissant & Millo 2008), 'splm' (Millo & Piras 2012), 'RANN' (Arya et al. 2017), and 'matrixStats' (Bengtsson 2018).

3.4.5 Causal impact of regulation

While spatial panel regressions are useful to investigate associations between forest cover change and relevant potential drivers, such methods are limited in inferring the causal impact of policy interventions (Brodersen et al. 2015; Law et al. 2017). We therefore applied Bayesian structural models on time-series data to determine the causal effect of the broad-scale clearing ban on forest cover change based upon an estimated counterfactual. The impact analysis was performed for all four models using the R package 'CausalImpact' (Brodersen et al. 2015), which generates a synthetic control based on the time series data to estimate the amount of avoided deforestation. Using 2007–

2014 as the post-intervention period, the pre-intervention period was defined as 1992–2006 for net forest cover and 1998–2006 for remnant forest cover. Because of data-deficient years for both the NCAS and SLATS datasets, years for which no annual data of forest cover/loss are available were averaged into annual estimates. Variables from the fixed effects model (except the clearing ban) were used as covariates to control for confounding influences on the regulation's impact; for annual spatial time-series variables, the state- or bioregion-wide average was used accordingly.

Because the clearing ban was formally announced in 2004, it may also be reasonable to assume the early impacts of the ban began prior to its official commencement, as financial adjustment packages were implemented and transitional caps were set on broad-scale clearing permits (Kehoe 2009); thus, we also determined the impact when the post-intervention period represented 2004–2014 for comparison. The impact estimates of both post-intervention scenarios were compared to (1) estimates when the policy uncertainty variable was excluded, and (2) estimates excluding 2012–2014, when amendments to the Vegetation Management Act reduced previous restrictions of the broad-scale clearing ban (Simmons et al. 2018b, **Chapter 2**). If policy uncertainty significantly reduces forest cover, then its exclusion from the impact analysis should result in smaller impact estimates of the clearing ban. For additional details on the estimation of causal impacts using this approach, see Brodersen et al. (2015).

3.5 Results

3.5.1 Deforestation trends

During 1991–2014, Queensland experienced a net loss of 37,595 km^2 (11.6%) of forests outside of protected areas, despite gaining 16,806 km^2 (5.16%) of secondary forests since 2008 (Fig. 3.2a). Similarly, in the BBS, gains following the broad-scale clearing ban (3066 km^2) were not enough to avoid a net reduction in 10.9% (5662 km^2) of BBS forests since 1991. Unlike the rest of Queensland, the BBS experienced a net loss of forest in 2014, and the rate of remnant forest loss in the BBS (6.81%; 2914 km^2) has been greater than at the state level (4.58%; 13,124 km^2) (Fig. 3.2b). Remnant deforestation declined to its lowest levels across both scales during 2007–2014, when the broad-scale clearing ban was in force. Placed in the context of other SLATS woody vegetation clearing events, the clearing of remnant forests in Queensland and the BBS accounts for 23.6% and 18.2% of all anthropogenic clearing activities since 1998, respectively. Further, remnant forests account for 42.5% and 43.7% of all remnant vegetation clearing identified by SLATS during this period for Queensland and the BBS, respectively. In most instances, periods of peak policy uncertainty coincided with increased rates of deforestation, though some contradictory trends can be observed between scales and forest types. Most notably, the long period of uncertainty during 2002–2004, when the moratorium was enacted, coincided with both a dramatic increase in remnant deforestation across Queensland and a large decrease in total deforestation in the BBS.

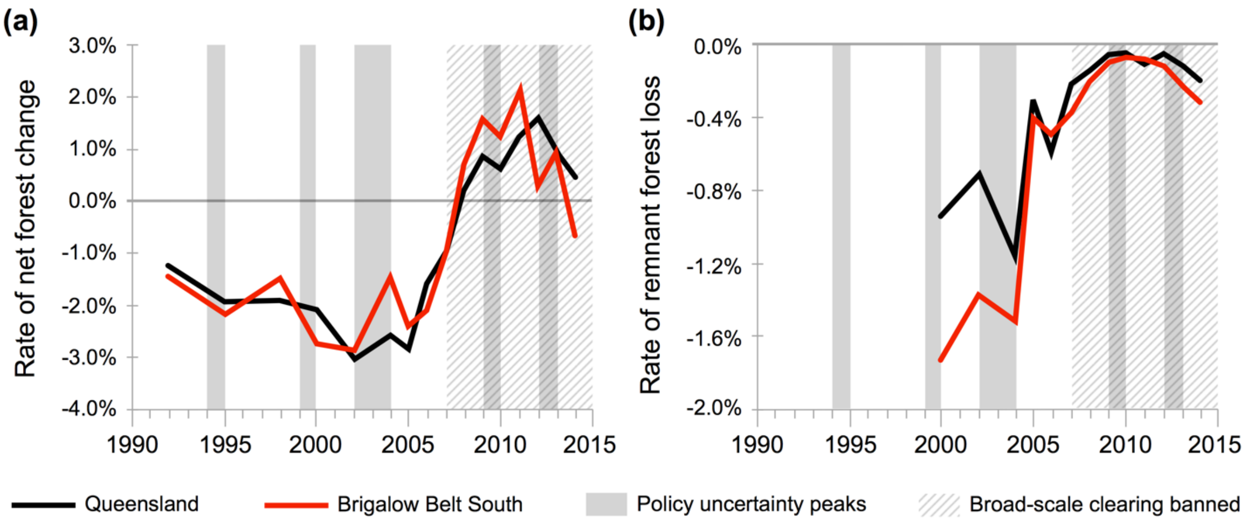

Fig. 3.2. Annual rate of (a) net forest cover change and (b) remnant forest loss over time in Queensland and the Brigalow Belt South bioregion (outside of protected areas). Shaded areas highlight key policy uncertainty periods along the timeline incorporated into the analysis. Reliable data for remnant forest loss prior to 2000 are not available.

3.5.2 Deforestation drivers

The majority of deforestation during 1991–2014 occurred in the intensive agricultural regions throughout central Queensland, with most reforestation occurring in the southeast and in patches of central and northern Queensland (Fig. 3.3a). The spatial fixed effects model of FCI in Queensland explained a high degree of the variance in total forest cover during this time period (global $R^2 = 0.9015$), with the greatest prediction errors occurring in these patches of reforestation in central Queensland (Fig. 3.3b). Similarly, the FCI model in the BBS had a high predictive power (global $R^2 = 0.8993$), with greatest errors in predicting reforestation surrounding local protected areas. Most variables included in the fixed effects FCI models for Queensland and the BBS significantly influenced forest cover dynamics (Table 3.2). At both scales, maximum temperature, food prices, and policy uncertainty had an inverse relationship with forest cover, while distance to protected areas and the broad-scale clearing ban significantly increased forest cover. Rainfall had an insignificant effect on forest cover throughout Queensland, yet had a negative effect within the BBS. The sign and magnitude of the relationship of these variables were largely consistent with those generated in the random effects FCI models (Table E1), which also identified greater forest cover on steeper slopes, in more remote areas, with greater rainfall variability, and on larger properties under leasehold tenure, consistent with results from previous studies (e.g. Marcos-Martinez et al. 2018; Simmons et al. 2018b, **Chapter 2**). The BBS dummy variable in the random effects model was positively associated with forest cover, indicating relatively greater forest gains compared to the rest of Queensland.

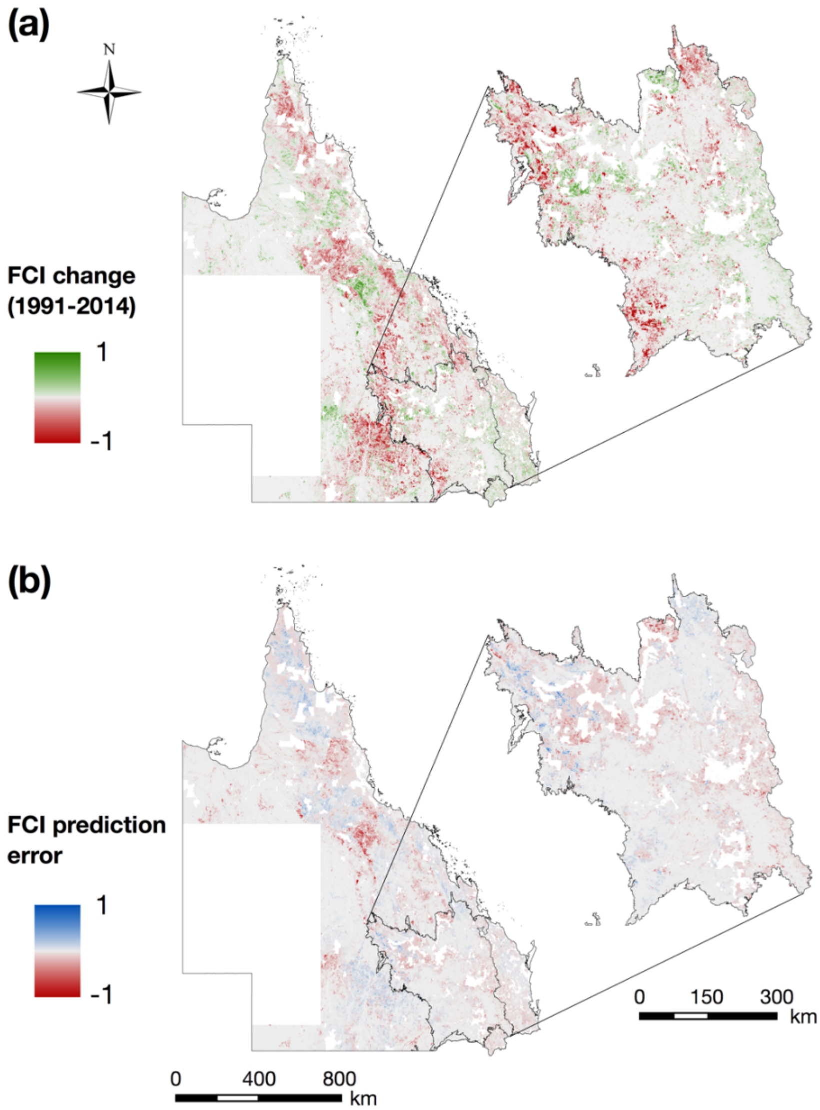

Fig. 3.3. Net forest cover change in Queensland and the Brigalow Belt South bioregion. (a) Change in the forest cover index (FCI) over time. (b) Difference between predicted and observed FCI change, where 1 = complete overestimation of FCI in 2014, and −1 = complete underestimation.

Table 3.2. Coefficients (β) of the variables included in the spatial fixed effects econometric model of net forest cover change. Coefficients represent the percent change in forest cover index (FCI) per 1% change in the explanatory variable.

Variable	Queensland					Brigalow Belt South				
	Coefficient	Std. dev.	95% Conf. Interval			Coefficient	Std. dev.	95% Conf. Interval		
			Lower bound	Upper bound				Lower bound	Upper bound	
Biophysical characteristics										
Rainfall (5-year moving mean)	−0.0019	0.0708	−0.0063	0.0025		−0.8727	0.1095	−0.8795	−0.8659	*
Maximum temperature (5-year moving mean)	−18.777	1.2128	−18.852	−18.702	*	−22.391	1.2367	−22.467	−22.314	*
Socioeconomic characteristics										
Food price index	−0.7299	0.0760	−0.7347	−0.7252	*	−0.7080	0.0789	−0.7129	−0.7031	*
Distance to protected areas	0.0046	0.0037	−0.0044	0.0048	*	0.0153	0.0038	0.0150	0.0155	*
Political characteristics										
Broad-scale clearing ban	0.0953	0.0217	0.0939	0.0966	*	0.1125	0.0243	0.1110	0.1140	*
Policy uncertainty	−0.1391	0.0093	−0.1396	−0.1385	*	−0.1662	0.0112	−0.1669	−0.1655	*
Mean R^2	0.9180					0.9355				
Global R^2	0.9015					0.8993				

* Confidence interval excludes zero

Remnant deforestation was largely concentrated in south-central Queensland within the BBS and the Mulga Lands bioregion, which extends beyond the BBS's western border (Fig. 3.4a). The fixed effects RCI model had an exceptionally high explanatory power for Queensland (global $R^2 = 0.9936$) and the BBS (global $R^2 = 0.9925$) with minimal prediction error (Fig. 3.4b). Like the FCI model, all variables significantly affected RCI, with maximum temperature, food prices, and policy uncertainty reducing remnant forest cover, and the broad-scale clearing ban reducing deforestation at both scales (Table 3.3). For the entire State of Queensland, the relationships of rainfall and distance to protected areas opposed those in the Queensland FCI model, resulting in a decrease in remnant forest cover. Again, the fixed effects results were largely reflected in the random effects RCI models (Table E2). Like the FCI model, the BBS dummy variable showed a positive relationship with remnant forest cover.

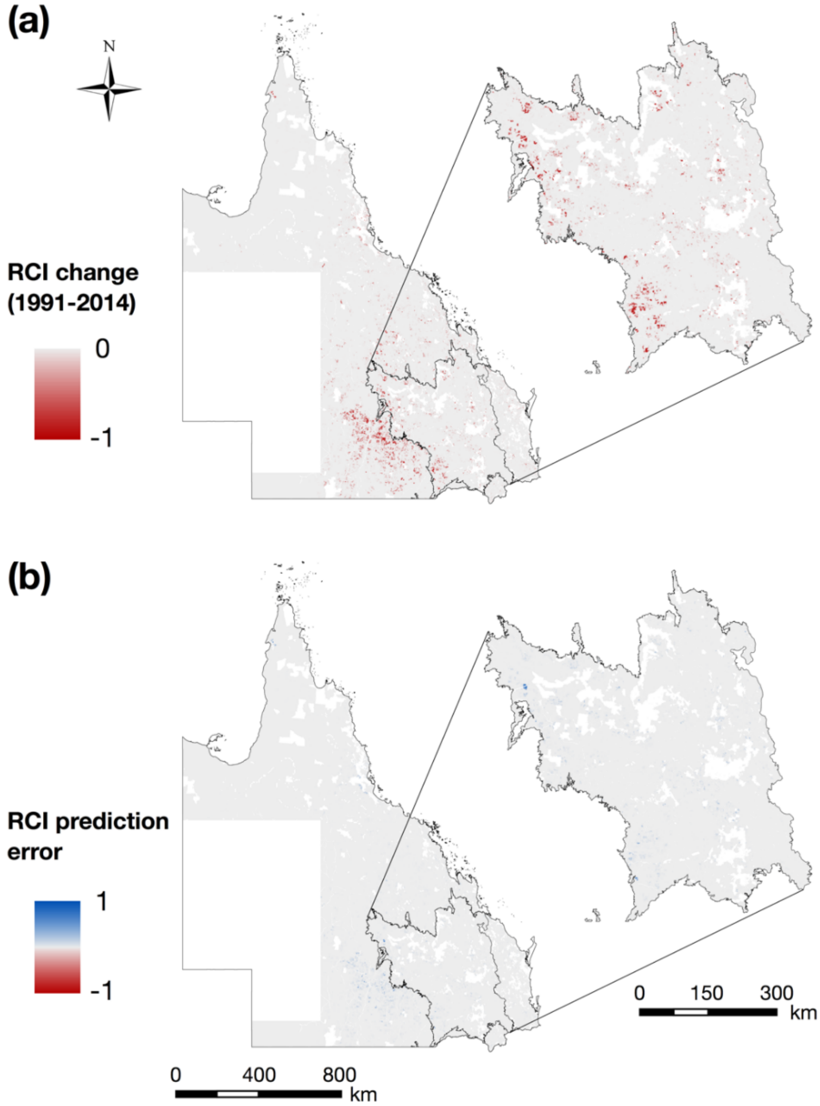

Fig. 3.4. Remnant forest loss in Queensland and the Brigalow Belt South bioregion. (a) Change in the remnant forest cover index (RCI) over time. (b) Difference between predicted and observed RCI change, where 1 = complete overestimation of RCI in 2014, and −1 = complete underestimation.

Table 3.3. Coefficients (β) of the variables included in the spatial fixed effects econometric model of remnant forest loss. Coefficients represent the percent change in remnant forest cover index (RCI) per 1% change in the explanatory variable.

Variable	Queensland					Brigalow Belt South				
	Coefficient	Std. dev.	95% Conf. Interval			Coefficient	Std. dev.	95% Conf. Interval		
			Lower bound	Upper bound				Lower bound	Upper bound	
Biophysical characteristics										
Rainfall (5-year moving mean)	−0.00072	0.00065	−0.00076	−0.00068	*	−0.00049	0.00166	−0.00060	−0.00039	*
Maximum temperature (5-year moving mean)	−0.13509	0.01403	−0.13596	−0.13422	*	−0.09428	0.01685	−0.09532	−0.09323	*
Socioeconomic characteristics										
Food price index	−0.01996	0.00149	−0.02006	−0.01987	*	−0.02128	0.00146	−0.02137	−0.02119	*
Distance to protected areas	−0.00011	0.00005	−0.00011	−0.00011	*	0.00004	0.00010	0.00004	0.00005	*
Political characteristics										
Broad-scale clearing ban	0.00244	0.00033	0.00242	0.00246	*	0.00215	0.00037	0.00213	0.00217	*
Policy uncertainty	−0.00190	0.00016	−0.00191	−0.00189	*	−0.00201	0.00018	−0.00202	−0.00200	*
Mean R^2	0.99377					0.99285				
Global R^2	0.99360					0.99252				

* Confidence interval excludes zero

3.5.3 Regulatory impacts

Despite the broad-scale clearing ban primarily targeting the protection of remnant vegetation, the ban had a significant impact on all forests, increasing forest cover by 8262 ± 2992 km^2 (*area* ± *std. dev.*) in the BBS and 69,918 ± 19,246 km^2 throughout Queensland during 2007–2014 compared to the counterfactual (Fig. 3.5). These impacts did not significantly change when policy uncertainty was unaccounted for, and though excluding the period of policy relaxation (2012–2014) reduced the amount of avoided deforestation, the significant impact was consistent with the trend observed for the full time period (Table F1). The impact on Queensland forests was also significant when setting the intervention period to 2004, the year the broad-scale clearing ban was officially announced, though the amount of avoided deforestation was reduced by approximately 50%. In the BBS, however, this change in the intervention date resulted in insignificant impact estimates (3344 ± 3360 km^2).

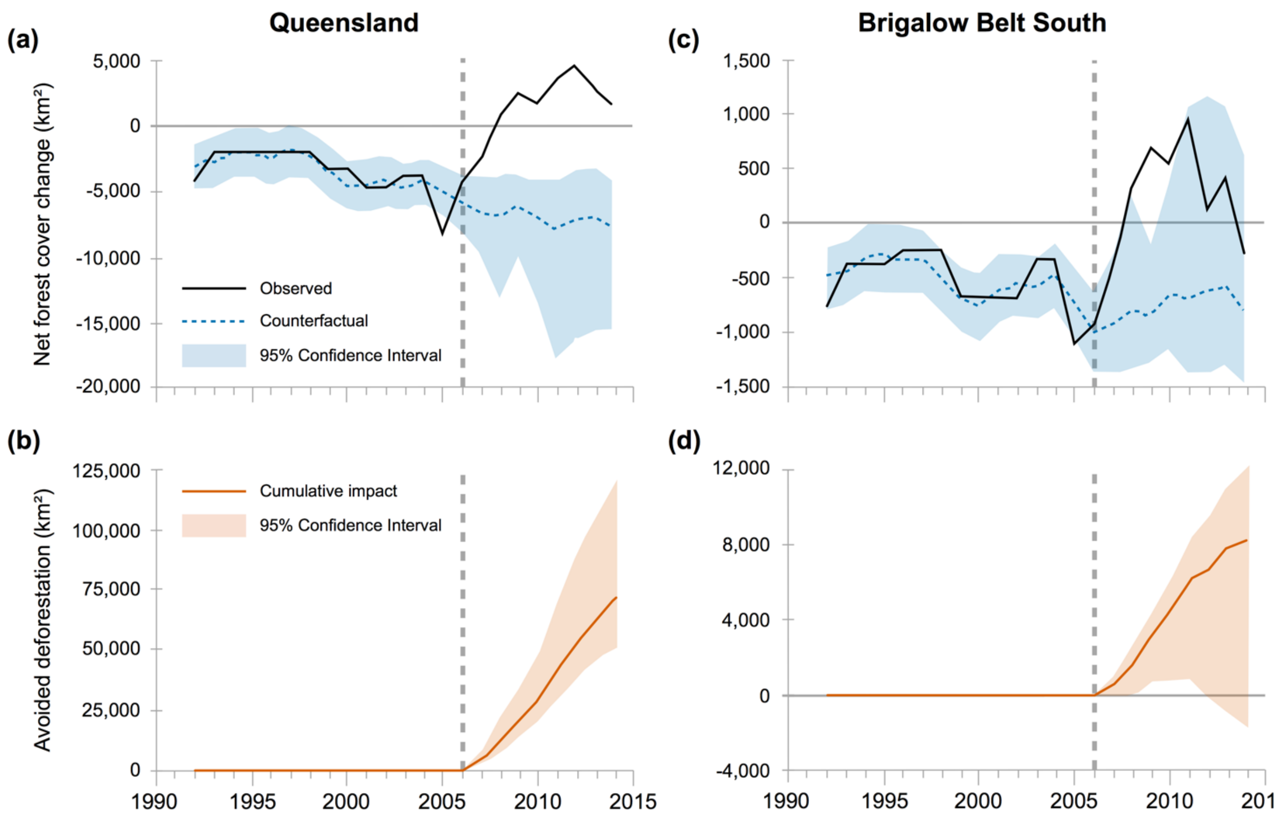

Fig. 3.5. Causal impact of the broad-scale clearing ban on net forest cover change in Queensland (a,b) and the Brigalow Belt South (c,d), after controlling for the influence of temporal variables. Cumulative impact estimates of (b) and (d) are statistically significant ($p < 0.05$). Vertical dotted line separates pre- and post-intervention periods, where the intervention begins in 2007.

The clearing ban also had a significant impact on remnant forests in Queensland during 2007–2014, avoiding 18,969 ± 10,340 km^2 of remnant deforestation compared to the counterfactual (Fig. 3.6). When the influence of policy uncertainty was uncontrolled in the analysis, however, there was no longer a significant impact from the clearing ban (6483 ± 4504 km^2) (Table F1). Under all scenarios, no significant impact was found for the clearing ban on remnant forests in the BBS (94 ± 1502 km^2). Again, excluding the influence of policy uncertainty reduced the estimated impact on remnant forest cover even further (−323 ± 1376 km^2), suggesting a more negative effect from the clearing ban. While excluding 2012–2014 from the analysis increased the ban's impact, the result remained insignificant. The significance of regulatory impacts on remnant forests starting in 2004 were the same as those for all forests.

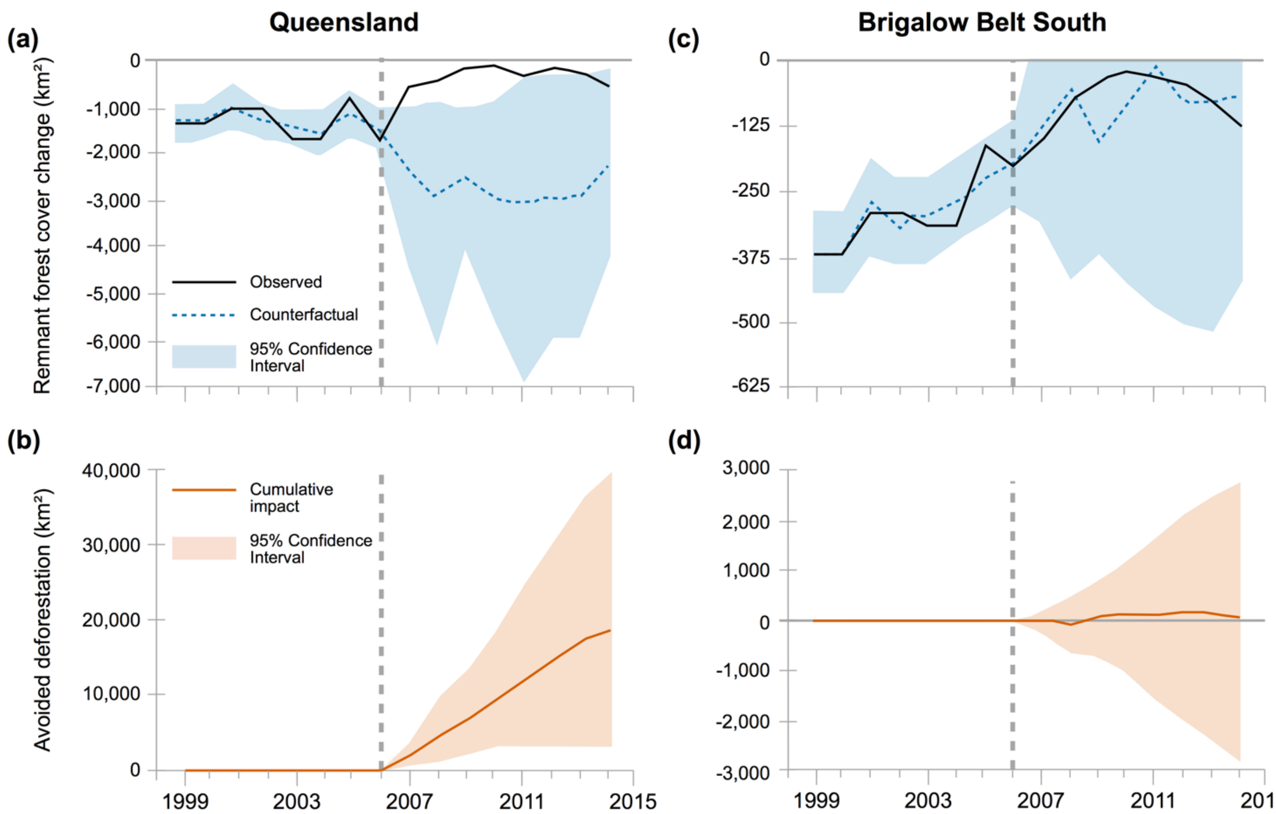

Fig. 3.6. Causal impact of the broad-scale clearing ban on remnant forest cover change in Queensland (a,b) and the Brigalow Belt South (c,d), after controlling for the influence of temporal variables. Cumulative impact estimate of (b) was statistically significant ($p < 0.05$), but (d) was insignificant ($p = 0.41$). Vertical dotted line separates pre- and post-intervention periods, where the intervention begins in 2007.

3.6 Discussion

This study identified a number of deforestation drivers consistent with pressures typically identified in other tropical deforestation hotspots, punctuated with some disconcerting evidence of potential perverse influences of uncertainty associated with forest conservation policy. While the broad-scale clearing ban facilitated forest transition in Queensland, the negative effects of frequent policy changes and associated uncertainty diminished or negated the benefits of regulation on remnant forests—the most threatened and ecologically significant forests—depending upon the spatial scale. Some consistencies were found between trends in net forest cover change (FCI) and remnant forest loss (RCI), but the two metrics will yield different implications for biodiversity, habitat quality, and ecosystem function. The results highlight the importance of strong and consistent deforestation regulation and aligned reporting at different spatial scales.

3.6.1 Drivers of forest cover change

Overall, the majority of drivers considered in this study produced consistent relationships with net forest cover and remnant forest loss. Thus it is likely that these two metrics of forest cover change are capturing similar conditions of deforestation throughout the state. Increases in temperature and food prices were associated with deforestation across all metrics and spatial scales, which is consistent with previous econometric models of deforestation (Byerlee et al. 2014; Marcos-Martinez et al. 2018). While protected areas may directly prevent deforestation within their borders, some studies suggest that protected areas may indirectly increase clearing rates in the surrounding buffer zones due to the displacement of clearing opportunities within the protected area (Ferraro et al. 2011; Miteva et al. 2012). Potential negative spill-over effects of protected areas were only identified for state-wide remnant forests. Particularly in the BBS, a large proportion of forest gains were near these protected areas, which contrasts with national trends (Marcos-Martinez et al. 2018). Greater rainfall significantly decreased FCI in the BBS and RCI across all scales. Favourable rainfall conditions have been known to influence spikes in Queensland deforestation prior to policy reform (Macintosh 2012), and the promotion of grass growth from greater rainfall increases the carrying capacity of livestock, further incentivising and providing the capital for pasture expansion to increase short-term profitability (Rolfe 2000).

3.6.1.1 The influential roles of policy

The broad-scale clearing ban significantly reduced forest loss across all metrics and spatial scales (Tables 3.2, 3.3), but its causal impact differed between forests (Figs. 3.5, 3.6). The broad-scale clearing ban in 2007 primarily regulates deforestation of remnant vegetation, yet total forest cover in Queensland and the BBS was positively impacted by the ban. This may represent indirect, positive spill-over effects from the clearing ban, whereby increased regulation of the most threatened vegetation added perceived public value to all vegetation, reducing the economic and social incentives to clear forests and/or increasing reforestation incentives. Additional indirect effects on deforestation from environmental regulations, such as altering international market demands, have also been observed elsewhere (Larson & Bromley 1991; Angelsen & Kaimowitz 1999). This effect may also be reflective of concurrent changes in the Vegetation Management Act or other policies that more directly affect secondary forests at the state level (e.g. *Vegetation Management and Other Legislation Amendment Act 2009*, *Queensland Biodiversity Offset Policy 2011, 2014*) or national level (e.g. *Australia's Native Vegetation Framework 2012*, *EPBC Act Environmental Offsets Policy 2012*) (Evans 2016).

The impact of the broad-scale clearing ban on its primary conservation target, remnant forests, was limited. State-wide remnant deforestation was successfully reduced by the ban, reflecting more direct impacts of similar deforestation policies around the world (Angelsen & Kaimowitz 1999; Assunção et al. 2012). In contrast, the counterfactual projection for remnant deforestation in the BBS was too similar to the observed rates to identify a significant impact. These mixed effects are likely due to inherent differences between aggregate state-wide deforestation behaviours and those in historical deforestation hotspots like the BBS. For example, Simmons et al. (2018b, **Chapter 2**) identified differential clearing patterns along the political timeline between different regions of Queensland. Clearing patterns in the BBS suggested landholders were driven by the agricultural suitability of the land but limited in the amount of suitable land still available for clearing. The authors also found that other regions of the state, like the Great Barrier Reef catchment, showed greater deviations in clearing patterns after policy intervention, suggesting landholders were more responsive to restrictive regulations. The greatest value of the clearing ban may thus be its ability to avoid increased remnant deforestation in atypical or relatively intact landscapes—which would inherently have a relatively low risk of deforestation—rather than protecting fragments of remnant forests in extensively cleared regions that need protection.

While peak periods of policy uncertainty significantly reduced forest cover across spatial scales, its impact on remnant deforestation was most pronounced. For remnant forests throughout Queensland, the perversities resulting from policy uncertainty were large enough to render the broad-scale clearing ban ineffective at reducing remnant deforestation beyond the counterfactual. In the BBS, policy uncertainty appears to have resulted in deforestation levels far surpassing the positive benefits of the intervention (i.e. the combined effects of policy uncertainty and implementation resulted in increased remnant deforestation). In contrast, the influence of policy uncertainty had an insignificant effect on the clearing ban's impact on net forest cover change. This discrepancy between FCI and RCI may largely be due to the relevancy of the Vegetation Management Act, wherein heightened policy uncertainty regarding future restrictions on remnant forests may not jeopardise future clearing plans for secondary (unregulated) forests. There are also likely to be different responses from different stakeholders; the threat of regulatory relaxations or anti-environmental regime shifts can also provoke unexpected pro-environmental behavioural responses, which may increase the expanse of forest regrowth. For example, the election of Ronald Reagan and his administration's anti-environmental agenda in the United States sparked a pro-environmental movement, leading to the creation of new land trusts from landholders and environmental organisations (Johnson 2014).

3.6.2 Achieving a forest transition in Queensland

This study confirms that Queensland entered a forest transition in 2008 for remnant forest and total forest cover, the latter of which has previously been identified in other analyses (Marcos-Martinez et al. 2018). Regulatory relaxations introduced in the Vegetation Management Act since 2012, however, may be reversing this transition, as recent rates of remnant forest loss are increasing and net forest gains are diminishing. Overall, the broad-scale clearing ban was influential to achieving forest transition in the state, but in the BBS, the commencement of the Act's regulations in 2000 may have been more influential in spurring a trajectory toward remnant forest transition earlier than the rest of the state. Additional state and federal policies on offsets during 2011–2014 also likely played an important role in achieving a forest transition, particularly for promoting secondary forest gains. Moving forward, it is crucial that future deforestation regulations are strengthened to target the most threatened forests in the landscape, as the results of this study support previous evidence that regulation has been comparatively less effective at protecting threatened vegetation in Queensland (Rhodes et al. 2017).

Peak periods of policy uncertainty significantly reduced forest cover, inevitably delaying transition for all Queensland forests. This is especially true for remnant forests, which are more directly affected by changes (and perverse responses) to the Vegetation Management Act. In light of the concerns over the degree of uncertainty and inconsistency in the Act's political timeline (Senate Inquiry 2010; Simmons et al. 2018b, **Chapter 2**), it is important to recognise that policy is inherently dynamic, and some degree of uncertainty will always be prevalent. While this process is important for the adaptive management of natural resources, policies must adapt without provoking perverse responses from stakeholders. Perception is a key instigator for policy change, whereby original goals can evolve and previous 'successes' can be deemed 'failures' (Bovens & 't Hart 1996; Ens et al. 2013). These perceptions come from all stakeholders, and the influence of landholders is especially important. The observed declines in forest cover surrounding policy change are likely a result of psychological reactance, whereby the removal or expected removal of clearing opportunities provoked opposition and resistance from some landholders (Brehm 1966). The results of this study reflect the potential short-term behavioural effects of this reactance, yet long-term cognitive effects may also explain the series of regulatory relaxations since 2012 (Schenk et al. 2007).

Because political factors have both positively and negatively influenced forest transition, it is imperative that future deforestation interventions use the proper tools to reduce forest loss and strategically minimise attitudinal or behavioural retaliations. Command-and-control regulation may be effective at a large scale, but it can produce perverse incentives to over-value the lost opportunities (Kinzig et al. 2013) or increase individuals' self-interest (Cardenas et al. 2000), which may reduce effectiveness at regional scales. Retrospective provisions to the Vegetation Management Act amendments since 2004 have likely curbed many instances of pre-emptive or 'panic' clearing, and this practice has been frequently used in similar policies in other Australian states (Productivity Commission 2004). This may be advantageous, as people are more likely to accept impending regulations when the changes seem more inevitable (Proudfoot & Kay 2014). In contrast, voluntary extension-based approaches may be more flexible and collaborative, and promote understanding and collective action (Lockie 2009; Ives et al. 2010; Ens et al. 2013), but they may incur some pitfalls in terms of large-scale impact, funding, and practical issues with their implementation (Santos et al. 2006; Kollmann & Schneider 2010; Jordan & Matt 2014).

3.6.3 Limitations, opportunities, and future directions

The similarities and dissimilarities between trends in net forest cover and remnant forest cover have important implications for monitoring and reporting in Queensland. It is encouraging that the NCAS and SLATS data used to monitor national- and state-level deforestation, respectively, largely capture the same drivers of forest cover change. Their differences, however, will affect how Australia measures its progress toward achieving international biodiversity targets, as all forests are not equal in ecological impact (Watson et al. 2018). The large amount of reforestation since 2007 is a positive outcome for Queensland, as secondary forests can provide new habitats for threatened species in agroecosystems (Bowen et al. 2009). These new forests, however, often require decades of growth in order to achieve a number of ecosystem services comparable to remnant forests, including greater species richness and abundance, greater carbon sequestration, and maintenance of regional climate (Bowen et al. 2009; Reside et al. 2017; Watson et al. 2018). A reliance on monitoring net forest gains across the state may thus ignore the rates of remnant forest loss, which are likely to have a disproportionately negative impact on biodiversity than the positive impacts of regrowth forests. We recommend broader uptake and reporting of the SLATS methodology for Australia, as it provides critical information unidentifiable by NCAS and monitors a larger range of woody vegetation that is also important for biodiversity (Macintosh 2007).

The Bayesian causal impact estimate used in this analysis does not account for spatial heterogeneities in the landscape. Thus, these estimates are reflective of the overarching goals of the broad-scale clearing ban, but will not distinguish novel deforestation behaviours from traditional behaviours. Nevertheless, this method of causal impact estimation could prove to be an easy tool for initial estimations of policy impact that can be used by policy advisors and practitioners. Future research is needed to assess the full impacts of vegetation management regulations on deforestation across Queensland. Additional research is also needed in order to fully understand the mechanisms through which policy uncertainty and command-and-control regulations alter landholders' clearing behaviours. The indicators used in this study may be capturing specific psychological drivers of change or other unidentified characteristics of these time periods. A greater understanding of the psychological and social implications for deforestation decision-making is needed to determine how to create sustainable behaviour change.

The results of this study may yield significant implications for other deforestation hotspots around the world, and the effects of policy uncertainty may well extend outside of conservation policy. Different contexts, however, will warrant investigations into other drivers of land use change or other perverse outcomes associated with regulatory interventions. For example, the uncertainty provoked by impending policy changes affecting the property rights or tenure security of landholders in some nations may inevitably counteract intended conservation outcomes (Alston et al. 2000; Aldrich et al. 2012). In other tropical, developing country contexts, the influence of different deforestation enterprises (e.g. logging, oil palm plantations, cropping) and socioeconomic conditions (e.g. population size, poverty, access to roads) may be more influential in driving land use changes (Busch & Ferretti-Gallon 2017). Further, the influence of political regime changes may provoke different responses in other countries, such as exporting deforestation activities into neighbouring countries (Meyfroidt et al. 2010). Even within Australia, state-level differences in landholders' response to forest policies and government incentives have contributed to the high rate of forest loss in Queensland relative to other states (Marcos-Martinez et al. 2018). Regardless of the context, it is critical that the intentional and perverse effects from conservation policy are measured alongside more traditional drivers frequently used in the literature, as the psychological and social ramifications of regulatory intervention represent a universal driver of behaviour change.

3.7 Conclusions

Conservation regulations and political uncertainty can be significant drivers of deforestation alongside other biophysical and socioeconomic drivers. Frequent inconsistency or instability along the political timeline can delay or reverse forest transitions and minimise the effectiveness of policy interventions. It is imperative that countries monitor how conservation policy instruments are contributing to forest cover change at national and regional scales, and identify how the flow-on effects of intervention may create perverse outcomes from stakeholders. Further, countries must explicitly consider trends in primary forest loss alongside net forest gains in order to monitor the differential effects that forest cover dynamics will have on biodiversity, ecosystem function, and success rates of deforestation interventions. Governments seeking to use forest conservation policy to effectively reduce deforestation must ensure their interventions account for state- and regional-level deforestation drivers, minimise frequent legislative changes, and be robustly evaluated to ensure regulation is achieving the desired responses from landholders.

3.8 List of Appendices for Chapter 3

Appendix D: Details of the design and selection of the econometric models.
Appendix E: Results for the random effects models.
Appendix F: Full results for the Bayesian impact analyses.

Chapter 4

Simmons BA, Wilson KA, Marcos-Martinez R, Bryan BA, Holland O, Law EA. 2018. Effectiveness of regulatory policy in curbing deforestation in a biodiversity hotspot. Environmental Research Letters **13**:124003.

Contributor	**Statement of contribution**
Author BA Simmons (Candidate)	Paper concept (70%), study design (80%), analysis (100%), wrote and edited the paper (65%)
Author KA Wilson	Paper concept (10%), wrote and edited the paper (10%)
Author R Marcos-Martinez	Wrote and edited the paper (5%)
Author BA Bryan	Wrote and edited the paper (5%)
Author O Holland	Paper concept (10%), study design (5%)
Author EA Law	Paper concept (10%), study design (15%), wrote and edited the paper (15%)

Chapter 4: Effectiveness of regulatory policy in curbing deforestation in a biodiversity hotspot

4.1 Abstract

Recent rates of deforestation on private lands in Australia rival deforestation hotspots around the world, despite conservation policies in place to avert deforestation. This study uses causal impact estimation techniques to determine if a controversial conservation policy—the Vegetation Management Act (VMA)—has successfully reduced deforestation of remnant trees in the Brigalow Belt South, a 21.6 M ha biodiversity hotspot in Queensland. We use covariate matching to determine the regulatory effect of the policy on deforestation rates over time, compared to two counterfactual scenarios representing upper and lower estimates of policy impact. The VMA significantly reduced the rate of remnant deforestation in the highest impact scenario, saving $17{,}729 \pm 1{,}733$ ha during 2000–2016. In the lowest scenario, 'panic clearing' before and after enactment of the VMA minimized the amount of remnant forests saved and may have marginally increased deforestation relative to the counterfactual (-404 ± 617 ha). At peak effectiveness, the VMA successfully counteracted the amount of remnant deforestation during 2010–2012, but this only represents 4.78% of the 371,252 ha of remnant forests cleared in the bioregion since enactment in 1999. Thus, while deforestation rates in the region have substantially reduced since the policy was enacted, our results of positive yet limited direct regulatory impact suggests the policy's effectiveness is strongly confounded by other deforestation drivers, like changing socioeconomic or climate conditions, as well as new social signals provoked by the policy. The mechanisms through which the policy influences deforestation behaviour must be further investigated to ensure real, desirable change is achieved.

4.2 Introduction

Policy evaluation is critical for adaptive management and political development, as it can illuminate the successes of policy instruments and identify areas requiring improvement (Bovens et al. 2006; Pawson 2006). A crucial component of measuring policy effectiveness is impact evaluation, which investigates the direct influence of policy, unconfounded by other rival explanations (Ferraro 2009); yet such analyses are rare due to policy subjectivity, time and resource limitations (McGrath 2010; Perche 2011), and complex biophysical, demographic, and economic implementation contexts (Pfaff & Robalino 2012; Börner et al. 2016). However, naïve before-after or with-without comparisons of impact indicators, such as the amount of remaining habitat or qualitative impact scores, often yield misleading estimates of the intervention's true effects (Ferraro 2009; Miteva et al. 2012; Baylis et al. 2015).

Robust causal inference approaches (Winship & Morgan 1999; Imbens & Wooldridge 2009) are becoming more prevalent in evaluating conservation policy instruments (Miteva et al. 2012), particularly for policies implemented under relatively constrained conditions, such as protected areas (Andam et al. 2008), payments for ecosystem services (Arriagada et al. 2012), and 'hybrid' instruments (Lambin et al. 2014). The few studies aimed at estimating impacts of deforestation policies over more variable landscapes, including those largely under private management, show more variable and contrasting results (e.g. Alix-Garcia et al. 2015; Sills et al. 2015; Bos et al. 2017). For instance, conservation regulations reduced deforestation by nearly 50% in the Amazon (Assunção et al. 2012), but increased pre-emptive habitat destruction resulting from species' listings under the U.S. Endangered Species Act, contrasting with evidence based upon naïve impact indicators (Ferraro et al. 2007). Amidst increasing competition for land and resources around the world, it is critical that the causal impact of conservation policies is robustly evaluated to justify the many direct and indirect costs associated with these interventions and to ensure desirable change is being created for biodiversity conservation and sustainability.

The *Vegetation Management Act (VMA) 1999* is a controversial policy that regulates deforestation on private land to achieve its primary purpose of preserving woody remnant vegetation in a globally-significant deforestation hotspot in Queensland, Australia (McGrath 2010). The policy has been highly criticized since its enactment by landholders and lobby groups, who cite its lack of transparency, inflexibility, and ignorance of potential economic outcomes (Productivity Commission 2004; Senate Inquiry 2010), and was hotly debated as recently as March 2018 when new amendments were put forward by the Queensland Government. Remnant vegetation is defined by the Act as an old-growth native tree or plant (excluding grasses and mangroves) covering "more than 50% of the undisturbed predominant canopy and averaging more than 70% of the vegetation's undisturbed height" (Vegetation Management Act 1999, 2015, sch 5).

The VMA regulates deforestation of remnant vegetation on private land by largely prohibiting broad-scale clearing for agriculture or pasture. The extent of native vegetation clearance is frequently used as an indicator for monitoring the success of the VMA (Evans 2016). This measure, however, is inadequate, as it does not separate the impacts of the policy itself from the confounding effects of changing socioeconomic, climatic, or political conditions. While evaluations of the VMA have indicated that the statute may have design limitations and present significant costs to landholders (Productivity Commission 2004; Senate Inquiry 2010), to date, there has been no robust evaluation of the VMA that directly assesses its effectiveness in achieving its primary purpose of conserving remnant vegetation.

This study provides the first robust quantitative analysis of the policy's ability to reduce deforestation of remnant trees, amidst ongoing intense debate surrounding the policy's effectiveness and concerns over its significant costs to local farmers and graziers (Senate Inquiry 2010; Reside et al. 2017; Simmons et al. 2018b, **Chapter 2**). We illustrate a new application of causal inference techniques to a broad-reaching environmental statute over a temporally dynamic period, using covariate matching to determine how the policy has affected rates of remnant deforestation in the Brigalow Belt South (BBS) bioregion of Queensland, Australia, compared to two counterfactual scenarios—*pre-emptive clearing* (PC) and s*ocial preference* (SP) scenarios—representing the lower and upper impact estimates, respectively, over time. We illustrate how our results compare with associative evidence based upon naïve trend analyses and highlight the importance of future studies to apply counterfactual thinking to evaluating similar policies in both developed and developing countries.

4.3 Methods

4.3.1 Study area

The BBS (21.6 M ha) is an agricultural area consisting largely of extensive pasture grazing by beef cattle (22.7521ºS–28.9991ºS, 145.9432ºE–152.3913ºE) (Fig. 4.1). The study area is a flashpoint for nature conservation and development in Australia. It has significant ecological importance as a national biodiversity hotspot (Ponce-Reyes et al. 2014) and deforestation hotspot (Evans 2016). As of 2016, the area of woody vegetation in the BBS constitutes 11.1 M ha, with remnant areas covering only 38% of the bioregion.

4.3.2 Data

The VMA is defined and assessed in regulation through the use of the Statewide Landcover and Trees Study (SLATS) dataset (QSC 2016h). The SLATS data define woody vegetation clearing outcomes at approximately 25 m resolution according to the type of clearing event (e.g. clearing for pasture, crop, or infrastructure), identifying trees with a minimum foliage projective cover of 8–11% (DSITI 2016), and is considered to be 95% accurate based on field verification (Macintosh 2007; Scarth et al. 2008). In this study, we define 'tree' to represent woody vegetation, and 'deforestation' to

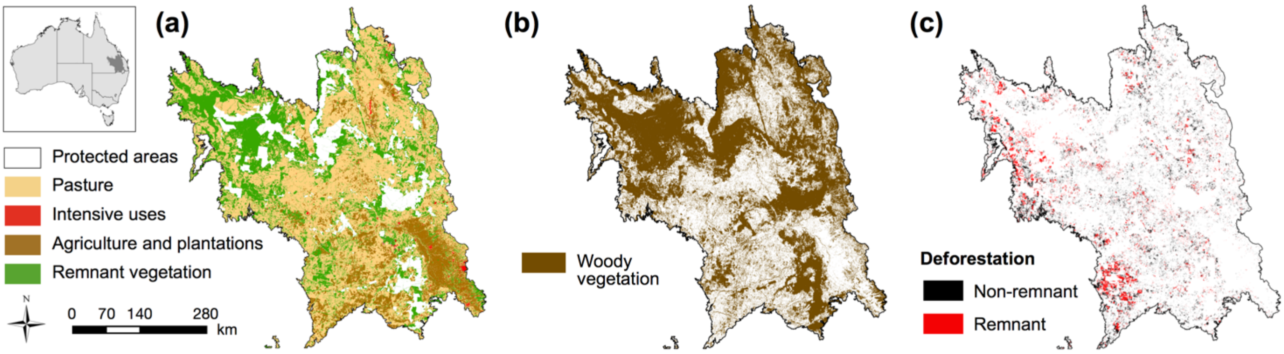

Fig. 4.1. The 2016 extent of (a) remnant vegetation and primary land uses, (b) woody vegetation, and (c) remnant and non-remnant deforestation events during 1997–2016 within the Brigalow Belt South bioregion of Queensland. Protected areas consist of national and regional parks, forest reserves, timber reserves, and state forests. Land uses adapted from the Australian Land Use and Management Classification system.

represent the observed clearance of woody vegetation identifiable by SLATS. We obtained deforestation data for all available time periods from the SLATS dataset: fiscal-year periods between 2000 and 2016 and combined data for 1997–1999. For simplicity, we identify the annual fiscal years by their latest record (i.e. '1999–2000' = 2000, '2000–2001' = 2001, etc.). The earliest map of remnant tree extent was obtained for 1997 from the Queensland Government's spatial catalogue (QSC 2016g) and SLATS deforestation events subtracted from this to produce annual remnant cover maps. Clearing events due to natural tree death or natural disaster damage, which made up less than 1% of SLATS data, were excluded from impact analysis. We also excluded protected areas (national and regional parks, forest reserves, timber reserves, and state forests; QSC 2016f), which made up less than 8% of SLATS data. Only freehold and leasehold lands were included in the analysis, making up 85% of the BBS and 91% of all annual clearing events.

4.3.3 Defining protection status

Regulating the deforestation of remnant vegetation on private land is the main mechanism though which the VMA (1999) attempts to achieve its primary purpose—preserving remnant vegetation. Therefore, we define the 'treatment' as aligning with the spatial extent of remnant vegetation on private land, as defined by the data used by Queensland to support and evaluate the policy (QSC 2016g,h). As nearly all remnant area on private land in the state is effectively treated by the Act, we derive the counterfactual—the assumption of what would have occurred in the absence of policy—from areas of non-remnant tree cover. We define non-remnant trees as all trees that do not meet the aforementioned remnant criteria under the Act. Because the VMA does not regulate deforestation within grassland regional ecosystems, all trees in these ecosystems were assumed to be non-remnant. Our analysis does not distinguish legal and illegal deforestation, as some exemptions from regulation (e.g. clearing for fences, weed control, necessary infrastructure) will be present in the deforestation data.

This represents a simplification of the temporal and thematic coverage of the policy, which has undergone fluctuations in the level of restrictions placed on deforestation (Simmons et al. 2018b, **Chapter 2**), including provisions for 'high-value regrowth', and for remnant vegetation on leasehold lands. High-value regrowth—regrowth that had not been cleared since December 31, 1989—also experienced some deforestation regulation during 2009–2013 from an amendment to the policy, but we excluded these trees from our definition of treatment status since they are not remnant trees. The VMA regulated remnant deforestation on freehold lands since enactment, but deforestation on leasehold lands was not covered by the Act until 2004. Therefore, treated forests for 2000–2004 only consisted of remnant trees on freehold land, and treated forests for 2005–2016 consisted of remnant trees on freehold and leasehold lands. Thus, we emphasize that our analysis measures the effectiveness of the policy's overarching goal of reducing deforestation of remnant vegetation since its enactment.

4.3.4 Scenarios and causal impact estimation

The exposure status of a given forest pixel i is determined by the VMA 1999, which provides regulatory protection to remnant woody vegetation. Remnant woody vegetation thus represents the treatment units of the policy intervention ($D_i = 1$). We assume non-remnant trees can represent the untreated units that do not receive explicit protection ($D_i = 0$). Our outcome variable (Y_i) represents the deforested status of each pixel. For years 2000–2004, only remnant units on freehold land are considered treated, and remnant units on leasehold land are considered treated for 2005–2016. We estimate the average treatment effect on the treated (ATT) over each time period to measure how effective the policy has been at reducing the deforestation of remnant trees on private land:

$$ATT = E(Y_1 - Y_0|D = 1) = E(Y_1|D = 1) - E(Y_0|D = 1) \quad (1)$$

where $E(Y_1|D = 1)$ is the observed remnant deforestation rate under the VMA, and $E(Y_0|D = 1)$ is the counterfactual remnant deforestation rate without the VMA (Imbens & Angrist 1994). We assume that in the absence of the VMA, remnant and non-remnant deforestation rates, conditional upon matched covariates (X), would have followed common trends over time (Lechner 2010). The use of observed non-remnant deforestation under the VMA, $E(Y_0|D = 0)$, thus serves as an appropriate counterfactual approximation, as the underlying structural similarities of treated and untreated forests can account for the processes influencing deforestation (Sills et al. 2015), such that

$$E(Y_0|D = 1, X) = E(Y_0|D = 0, X). \tag{2}$$

Two ATT baselines for the period prior to implementation of the VMA (1997–1999) were generated for remnant forests only on freehold tenures (FO) and remnant forests on freehold and leasehold tenures (FL). The ATTs for this pre-intervention period revealed remnant deforestation rates significantly higher than the counterfactual ($ATT_{1999,FO}$ = 4.46%, $ATT_{1999,FL}$ = 3.29%). Two explanations for this preferential clearing of remnant trees compared to similar non-remnant trees in this period are: 1) that this period shows 'pre-emptive' clearing of remnant trees prior to the Act, evidence of which has been reported in previous analyses (Simmons et al. 2018b,c, **Chapter 2, 3**) and landholder testimonials (Productivity Commission 2004; Senate Inquiry 2010), or 2) that this is a 'social preference' for clearing of remnant trees versus similar areas of non-remnant trees. We developed two assumption scenarios from these: 1) *Pre-emptive Clearing* scenario (ATT_{PC}), assuming that elevated pre-emptive clearing of remnant trees is caused entirely by the Act and that the true difference between our treated and counterfactual samples is zero (ATT_{1999} = 0%), and 2) *Social Preference* scenario (ATT_{SP}), assuming that there is a fixed 'social preference' for clearing remnant over equivalent non-remnant, which is equal to a constant deforestation rate of SP_{FO} = 4.46% for 2000–2004 and SP_{FL} = 3.29% for 2005–2016. In the latter scenario, we use a difference-in-difference approach commonly used in the impact evaluation literature (Lechner 2010; Miteva et al. 2012) to subtract this fixed value from the ATT_{PC} for the calculation of the ATT_{SP}. These two scenarios provide a bound estimate on the ATT of the VMA across time:

$$ATT_{PC,t} = E(Y_t^1|D = 1, X) - E(Y_t^0|D = 0, X) \tag{3}$$

$$ATT_{SP,t1} = ATT_{PC,t1} - SP_{FO} = ATT_{PC,t1} - 0.0446 \tag{4}$$

$$ATT_{SP,t2} = ATT_{PC,t2} - SP_{FL} = ATT_{PC,t2} - 0.0329 \tag{5}$$

where *t* is in {2000, …, 2016}, *t1* is in {2000, …, 2004}, and *t2* is in {2005, …, 2016}.

The sensitivity of the ATT_{PC} estimates to hidden bias due to unobserved confounding factors was tested using Rosenbaum's sensitivity test for binary outcomes (Keele 2010), where Γ represents a relative measure of bias ranging from one (no hidden bias) to infinity. The value of Γ at the moment when the effect of bias begins to significantly affect the ATT estimate (p = 0.05) was compared between years. Significance of the annual ATT estimates was tested by applying the Holm-Bonferroni Method to pairwise Pearson chi-square comparisons and associated odds ratios. The amount of avoided remnant tree loss was calculated annually for each scenario according to the representation of our matched sample within the population:

'Pre-emptive clearing' scenario

$$A(Y_t^0|D = 1) = \frac{ATT_{PC,t}\, n_t\, (Y_{m,t}^1\, A_{n,t-1}|D=1)}{N_t} \tag{6}$$

'Social preference' scenario

$$A(Y_t^0|D=1) = \frac{ATT_{SP,t}\, n_t\, (Y_{m,t}^1\, A_{n,t-1}|D=1)}{N_t} \tag{7}$$

where $A(Y_t^0|D=1)$ is the additional area of remnant trees that would have been cleared in the counterfactual, n is the number of observations in the population within the matched strata, N is the number of observations in the population within all sampled strata, $\left(Y_{m,t}^1|D=1\right)$ is the rate of remnant deforestation within the matched sample, and $\left(A_{n,t-1}|D=1\right)$ is the area of remnant trees within the matched strata that was available to be cleared in the previous year. Under the 'social preference' scenario, ATT_{SP} corresponds to the respective constant for the 2000–2004 and 2005–2016 treatment distinctions (Eq. 4, 5).

4.3.5 Matching

We used the following temporally constant variables—which have previously been shown to explain 54% of the variation in BBS clearing patterns (Simmons et al. 2018b, **Chapter 2**)—to match treated and control observations: remoteness (ALA 2016), slope (QSC 2016d), parcel size, tenure (QSC 2016c), frequency of drought declarations (QSC 2016a), rainfall variability (QSC 2016b), and regional ecosystem (RE) code (QSC 2016e). REs are vegetation communities characterized by unique geology, soil, and landform combinations, defined according to their bioregion, land zone, and vegetation community (Sattler & Williams 1999). Because of the large diversity of vegetation communities in the BBS, we developed an RE code that groups vegetation communities based upon the bioregion code, land zone code, and density of the vegetation community—1 = very sparse, 2 = sparse, 3 = mid-dense, or 4 = dense—according to the Regional Ecosystem Description Database (Queensland Herbarium 2016). Freehold and leasehold tenure was represented as a binary variable.

Data were collated in ArcGIS v10.3.1 for all periods from 1997 to 2016 within the BBS at the 25 m pixel resolution. We constrained the analysis to the estimated extent of woody vegetation outside protected areas as of 1997, which covers approximately 8.9 M ha, or 47% of the unprotected BBS landscape. Trend impact indicators—clearing extent and mean/maximum clearing patch sizes—were calculated for each year based upon SLATS polygons to compare with causal impact estimates. Stratified random sampling was performed in R (R Core Team 2017) on the population dataset separately for treated and untreated pixels for every year using the 'sampling' (Tillé & Matei 2016) and 'data.table' (Dowle et al. 2016) packages. We created annual samples, rather than tracking select observations over time, in order to account for annual changes in deforestation patterns, thus creating samples that would reflect the temporally dynamic clearing behaviours of landholders throughout the bioregion (Simmons et al. 2018b, **Chapter 2**). Strata were defined according to outcome, RE code, and tenure variables to ensure adequate matching of categorical variables and adequate representation of the population's true outcome. Strata that consisted of only remnant or non-remnant trees, as well as those that never experienced deforestation, were excluded from the sampling (3% of study area). For each year, the number of observations randomly selected from each stratum was weighted according to its representation in the true population. The final annual sample distributions mirrored those of the true population.

Covariate matching and subsequent evaluations were performed using R packages 'Matching' (Sekhon 2015), 'rbounds' (Keele 2015), and 'rgenoud' (Mebane Jr. & Sekhon 2015) on the annual sample datasets. Two methods for matching were compared—nearest neighbour (NN) and nearest *k* neighbours (NKN) matching—under multiple caliper conditions. The adequacy of matching methods was evaluated according to multiple empirical and visual match balance estimations (additional details in Appendix G). We selected the NN method using a 0.25 caliper for the causal impact estimation, which produced the best covariate balance (Table H1) and significantly enhanced the comparability of remnant and non-remnant samples across all observed measures (Table H2), but excluded 8–10% of observations due to a lack of insufficient matches (Table I1).

4.4 Results and Discussion

4.4.1 Effectiveness of the Vegetation Management Act

Under the 'pre-emptive clearing' scenario, remnant deforestation rates relative to matched non-remnant deforestation rates have significantly reduced for most years following the enactment of the VMA, with the lowest rate occurring in 2016 at −1.21 ± 0.14% (ATT_{PC} ± *95% CI*), indicating a shift in preference toward non-remnant deforestation (Fig. 4.2a). Overall, the impact of the VMA relative to the counterfactual is negligible; despite reducing the rate of remnant tree clearance by an average of 0.22% during 2000–2016, panic clearing surrounding the VMA's enactment minimized the cumulative amount of remnant forests saved from deforestation, even potentially increasing deforestation (−404 ± 617 ha) (Fig. 4.2b).

The continued deforestation immediately following the passing of the Act in 2000 (1.91 ± 0.23%) reflects reported instances of spikes in pre-emptive deforestation rates ('panic clearing') (Simmons et al. 2018b, **Chapter 2**) and likely arose, in part, due to the delayed proclamation of the VMA in September 2000, when most statutory provisions commenced. This perverse outcome has also been observed during similar deforestation policy changes in the Amazon

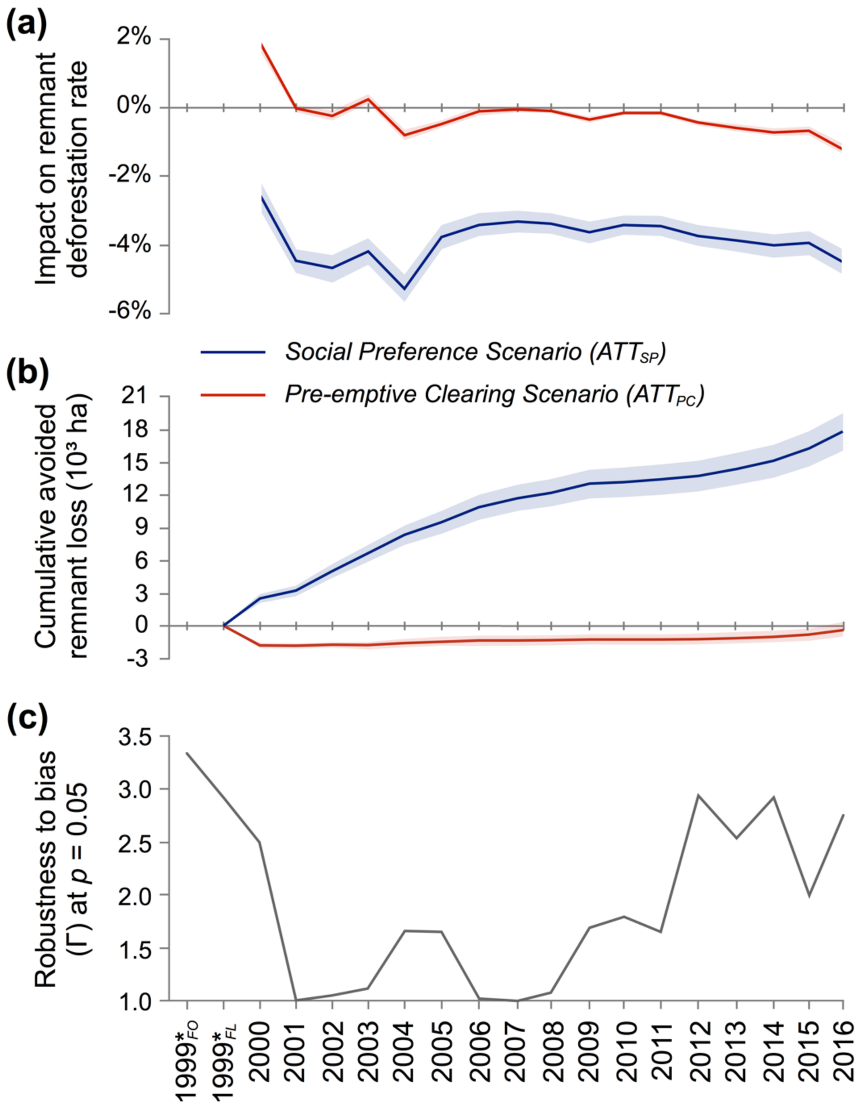

Fig. 4.2. Causal inference results. (a) Annual estimates of the change in remnant deforestation rates due to the *Vegetation Management Act 1999*, according to two scenarios: the average treatment effect on the treated relative to the non-remnant counterfactual deforestation rate (ATT_{PC}), and the impact relative to the fixed social preference rate of deforestation (ATT_{SP}). (b) Cumulative avoided remnant tree loss over time according to the 'pre-emptive clearing' and 'social preference' scenarios. (c) Robustness of annual ATT_{PC} estimates to potential hidden bias at significance (p = 0.05). Shaded areas for (a) and (b) represent the 95% confidence interval. (*) *Period represents all deforestation events during 1997–1999 for only freehold lands (FO) and freehold and leasehold lands (FL).*

(Alston et al. 2000; Aldrich et al. 2012) and in other sectors of environmental policy (Lueck & Michael 2003; Rivalan et al. 2007). Policy effectiveness increased until 2003, when remnant deforestation rates began to increase again (0.26 ± 0.14%), provoking a moratorium issued in the following year (Kehoe 2009). As expected, effectiveness was relatively high while the moratorium was in place (−0.81 ± 0.15%). After the moratorium was lifted, however, the effectiveness of the Act relative to this counterfactual diminished. ATT_{PC} estimates from 2006 and 2007 did not differ significantly from zero, meaning that deforestation rates between equivalent remnant and non-remnant trees were similar, and the impact of the VMA was insignificant (Table I1). This is likely due the government's implementation of a transitional cap of 500,000 ha of broad-scale clearing to be permitted throughout Queensland before the broad-scale clearing ban in 2007 (McGrath 2007). In the years immediately following the ban, the policy displayed limited effectiveness. Negligible changes in policy impact continued through the period of additional protection of high-value forest regrowth on freehold land in 2009–2012 (Simmons et al. 2018b, **Chapter 2**). Since 2012, against the backdrop of rising deforestation rates in both remnant and non-remnant vegetation, the VMA has increased in effectiveness relative to the counterfactual, with non-remnant areas experiencing a greater increase in deforestation rates relative to remnants.

Prior to the introduction of the VMA (1999) under the 'social preference' scenario, the rate of remnant deforestation in the BBS was $4.46 \pm 0.25\%$ higher than similar locations with non-remnant trees on freehold properties, and $3.29 \pm 0.12\%$ higher on both freehold and leasehold properties (Table I1). These rates of deforestation reflect historical incentives for preferentially clearing remnant trees, which targeted intact vegetation likely for economic reasons (e.g. to enhance productivity and expand pastoral lands), practical reasons (e.g. switching from degraded or over-grazed pre-cleared land), and/or cultural reasons (Simmons et al. 2018b, **Chapter 2**). The temporal pattern of the annual ATT_{SP} estimates reflects those of the ATT_{PC} estimates. Given the greater social preference for clearing remnant vegetation specifically on freehold land, however, 2004 represented peak effectiveness, reducing remnant deforestation rates by $-5.26 \pm 0.40\%$ ($ATT_{SP} \pm 95\%\ CI$) (Fig. 4.2a). In this scenario, all ATT estimates following the introduction of the VMA differed significantly and more strongly from the baselines than those of the 'pre-emptive clearing' scenario (Table I2). Under the social preference scenario, the impact of the VMA has been much more effective, reducing the rate of remnant deforestation by an average of 3.86% during 2000–2016 and avoiding a cumulative loss of $17{,}729 \pm 1{,}733$ ha of remnant forest (Fig. 4.2b), roughly equivalent to the combined amount of remnant deforestation during 2010–2012.

4.4.2 Impact robustness

ATT results for most years were moderately robust to potential hidden bias (Fig. 4.2c). For most of the high-impact years, the sensitivity analysis suggests that any potential confounding factor that was excluded from this study would need to exert an influence on the occurrence of remnant trees more than twice that of the other covariates in order to affect the impact estimates (Keele 2010). The years most sensitive to hidden bias coincide with the early years of the VMA timeline, where landholders were subjected to frequent policy uncertainty arising from multiple amendments, a moratorium on clearing permits, withdrawal of Federal Government support for a $150 million structural adjustment package, and implementation of a broad-scale clearing ban (Simmons et al. 2018b, **Chapter 2**). Frequent periods of policy uncertainty have been shown to increase deforestation in Queensland (Simmons et al. 2018c, **Chapter 3**), which could explain the sensitivity of impact estimates during this period. For these years, other unobserved confounders such as additional socioeconomic factors, aesthetic values of nature, or shifts in social or cultural norms could also have a significant effect on the impact of the VMA (Kull et al. 2007; Seabrook et al. 2008; Marcos-Martinez et al. 2017).

The impact estimates of this study are limited by the lack of data on pre-intervention remnant deforestation trends, which would produce a more robust counterfactual. The two scenarios considered in this study, however, represent the potential bounds of policy effectiveness under opposing levels of social influence that could logically represent the true counterfactual. This study also does not distinguish between the most threatened types of vegetation in the landscape. Evidence suggests rarer, threatened forests are still being cleared faster than more common, less threatened forests (Rhodes et al. 2017). Under this definition of effectiveness, the impact of the VMA may differ significantly from the overarching definition used in this study. Assessing the effectiveness of the VMA is inherently complex given its multiple objectives and frequent amendments, but at its core purpose of preserving remnant vegetation, we find the direct regulatory impact of policy has had a small (if any) positive effect, yet these impacts of the policy may be increasing with increasing background deforestation rates recently observed in the state.

4.4.3 Complementing trend impact indicators

Naïve trend analyses of the rate of remnant deforestation (Fig. 4.3a) and the area of trees cleared over time (Fig. 4.3b) show a general decline since the enactment of the VMA until the recent policy relaxations, and this is often used as evidence for the effectiveness of the Act (Evans 2016). When looking at additional indicators of broad-scale clearing, such as mean and maximum patch size of clearing events (Fig. 4.3c), it is evident that landholders are clearing fewer trees and in smaller patches under the VMA. Like other indicators, however, this also increases following the conservative government's policy relaxation during 2012–2013, potentially representing a wider social shift in landholder clearing preferences in the most recent years.

Our causal impact estimates of the VMA differ from these trend impact indicators; we show the continued effectiveness of the VMA against the counterfactual, even amidst concerns over the rising rates of deforestation since 2012. The amount of remnant deforestation in the BBS has increased since 2012, but the amount of non-remnant deforestation has increased faster, with high-

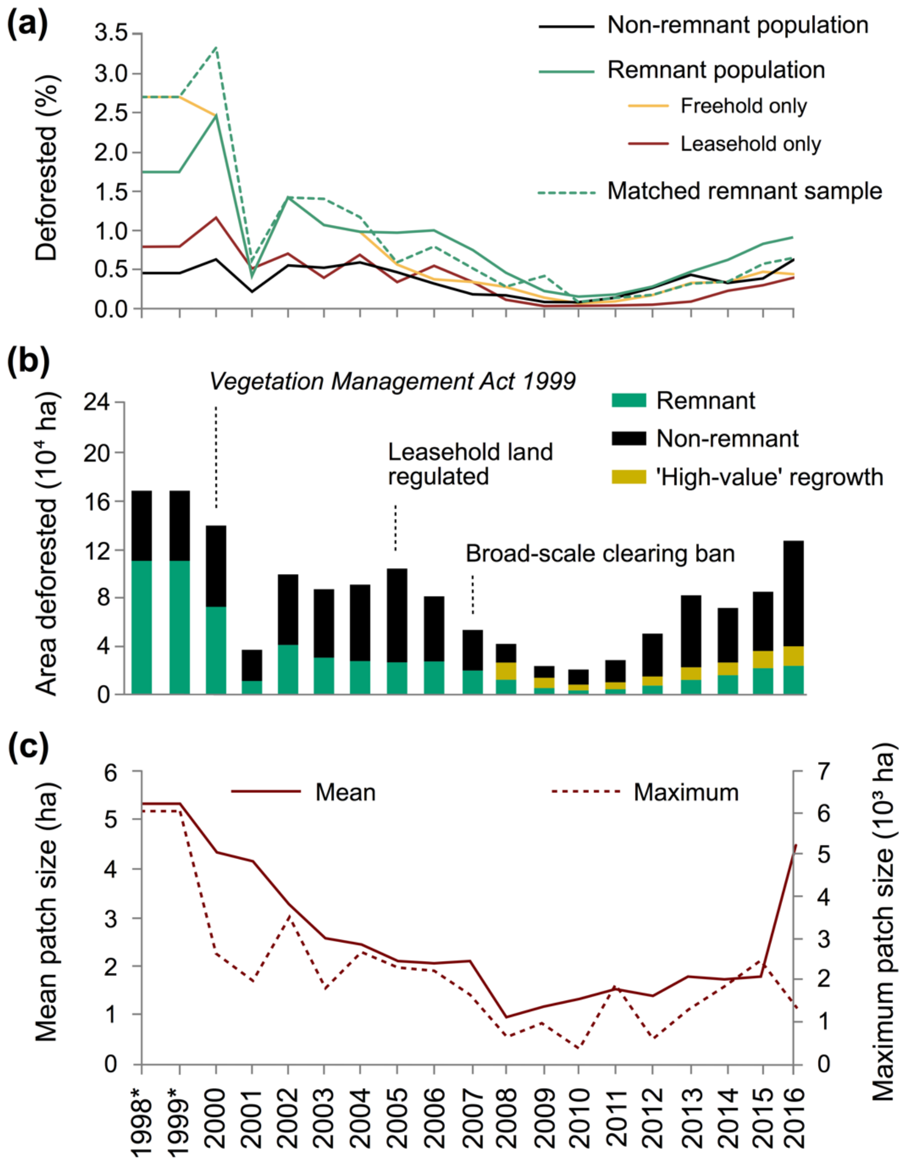

Fig. 4.3. Trend impact indicators. (a) Comparison of deforestation rates between the population and matched samples, with remnant deforestation rates on freehold and leasehold lands distinguished. (b) Trends in deforestation extent relative to the passing of the VMA 1999, inclusion of leasehold lands under regulation, and broad-scale clearing ban in 2007. (c) Changes in the size of deforestation patches over time. Overall trends for 2000–2004 exclude deforestation on leasehold lands. (*) *Deforestation extent represents an average annual estimate for freehold and leasehold lands.*

value regrowth constituting 15–23% of non-remnant deforestation in the last three years (Fig. 4.3b). Additional discrepancies between our impact estimates and those based upon trend indicators include contrasting trends between ATT estimates and absolute clearing areas; for example, 2004 and 2016 exhibit high reductions in remnant deforestation rates (Fig. 4.2a) yet relatively high volumes of remnant deforestation (Fig. 4.3b). This can be explained by examining the differential changes in remnant vs. non-remnant deforestation. In 2004, the amount of non-remnant deforestation increased by 45% from the previous year, but remnant deforestation only increased by 11%. Similarly, non-remnant deforestation increased by 82% in 2016, and remnant deforestation by a mere 9%. Our results highlight an increasing division in the rates at which remnant trees and corresponding non-remnant trees are being cleared in the study region: that is, an increase in the direct effectiveness of the policy. The high effectiveness in 2016, however, may still be confounded by a reduction in remnant clearing due to retrospective (i.e. *ex post facto*) clearing restrictions proposed in a VMA bill introduced that year, which ultimately was not passed in Parliament. Overall, our results show that the perceived effectiveness of the VMA in reducing remnant deforestation rates in the BBS from 2000–2016 is largely due to confounding factors rather than the direct impact of the VMA itself.

4.4.4 Potential mechanisms driving policy effectiveness

It is evident from Fig. 4.3b that the naïve deforestation trends are highly confounded. Clearing of non-remnant trees is unregulated by the VMA; yet, during 2006–2010, remnant and non-remnant deforestation has changed largely in concert. Most interestingly, remnant deforestation has not increased proportionally to non-remnant deforestation since policy relaxations in 2012. Thus, there must be some confounding factor(s) acting upon landholders that has (1) substantially reduced all deforestation during 2006–2010, even for trees that are permitted to be cleared, and (2) largely dissuaded landholders from preferentially clearing remnant trees during 2012–2016, even when given more legal opportunities to clear.

The BBS experienced the greatest rainfall deficit of any bioregion in Queensland during Australia's 'Millennium Drought' of 2001–2009 (van Dijk et al. 2013), and annual rainfall patterns have been identified as a significant driver of remnant and non-remnant deforestation in the region (Simmons et al. 2018c, **Chapter 3**). It is likely that this drought was largely responsible for the reduction of absolute deforestation rates during this period by diminishing the economic incentives to clear, which could explain why the VMA was only marginally effective in those years. Characteristics of landholders' clearing patterns during this period have reflected a preference for maximizing quality over quantity (Simmons et al. 2018b, **Chapter 2**), and this may explain the subsequent increase in the quantity of non-remnant deforestation following the end of the drought. These climate restraints could also have flow-on effects on other socioeconomic drivers of deforestation, such as food prices and potential profitability, which can ultimately diminish the direct impact of the VMA (Marcos-Martinez et al. 2017; Rhodes et al. 2017; Simmons et al. 2018c, **Chapter 3**).

The increased effectiveness of the VMA following the drought may also be a product of the direct or indirect social impacts on landholders. The social preference scenario in this study assumed a norm existed prior to regulation that increased landholders' preference for clearing remnant trees.

It is likely that the VMA, its subsequent amendments, or the broad-scale clearing ban would have diminished the strength of this norm over time by altering social conventions toward appropriate deforestation practices and influencing how landholders expect others to change their behaviours (Ensminger & Knight 1997). This could have been facilitated through changes in personal or social norms. The costs of illegally clearing remnant trees imposed by the VMA can reach 1665 penalty units (AU$202,963.50) (Vegetation Management Act 1999, 2015, s 18); combined with landholders' early protests regarding the accuracy of satellite images used to monitor clearing, limitations on permissible legal defences, and a reversed onus of proof (Productivity Commission 2004), the majority of landholders may not be willing to accept the risks associated with excessive remnant deforestation, necessitating reluctant compliance as a new personal norm. The VMA may have elicited indirect impacts on collective social norms, as well, leading to increased effectiveness in later years. Seemingly in contrast to other deforestation contexts, where deforestation and property rights regulations have induced pro-deforestation shifts in social norms (e.g. Rudel 1995; Schmidt & McDermott 2015), it appears the VMA may have provoked a redirection of landholders' clearing activities toward non-remnant trees. Despite landholders' severe lack of trust in the Queensland Government (Brown 2018), they may have changed their behaviour in accordance to the regulations if they recognize the growing social stigma around deforestation and seek to counteract the public's perception of farmers.

4.4.5 Implications and future directions

Our analysis illustrates how robust causal inference techniques can be used to understand how policy effectiveness changes over time amidst a highly dynamic political, climatic, and social environment. The VMA represents a unique and complex conservation statute, where protections fluctuate, clearing restrictions evolve, and private landholders' behaviour is involuntarily regulated, largely without compensation. We show impact evaluation techniques can still be robust to hidden biases under these complex conditions, and counterfactuals can be developed even when reliable pre-intervention trends are unavailable through the use of bounded counterfactual scenarios. The significant yet limited effectiveness of the VMA reflects previous impact estimates of the broad-scale clearing ban in the BBS (Simmons et al. 2018c, **Chapter 3**), as well as similar deforestation policies around the world, such as the Brazil Forest Code (Azevedo et al. 2017) and numerous international initiatives (Bos et al. 2017), where effectiveness may be limited to a brief period on the policy timeline, or intervention outcomes do not significantly differ from the expected counterfactual.

Policies have the potential to introduce strong social signals into the community (Kinzig et al. 2013). If the VMA has managed to directly or indirectly shift current deforestation norms away from preferentially targeting remnant forest—whether it be due to risk aversion (instrument compliance), re-aligning their collective clearing behaviours (norm-oriented compliance), or merely an obligation to follow the law (legitimacy compliance) (Ramcilovic-Suominen & Epstein 2012)—it is important that future interventions reinforce these new norms and avoid crowding out the incentives for retaining remnants. Policy interventions, however, may not be enough to completely reduce landholders' preferred deforestation regimes. The negative cultural associations with the 'red tape' nature of environmental policy is unlikely to change landholders' underlying clearing preferences and may spur desires to rescind what current command-and-control policies do exist, as is being observed in Queensland (Reside et al. 2017). Sustainable change in deforestation behaviours will need sufficient, stable, and enforceable underlying conservation statutes supplemented with on-the-ground instruments, incentives, and interventions that can target changes in social norms, attitudes, and other psychosocial characteristics (Beedell & Rehman 1999). Given that the effectiveness of these interventions and programs is largely inconsistent and case-dependent (Miteva et al. 2012), ongoing causal inference evaluations will become increasingly valuable for policy development.

4.5 Conclusions

Conservation policies often lack thorough evaluation due to an over-reliance on impact indicators or failures to control for confounding factors. Here we show that more robust quantitative impact evaluation techniques could be used to assess whether policy interventions are producing real, effective, and desirable change. We found that the Vegetation Management Act implemented in Queensland, Australia was successful, on average, at reducing deforestation of remnant vegetation in the Brigalow Belt South bioregion. However, the magnitude of the impact is lower than estimates from less-robust analyses. Nevertheless, the results show that landholders are redirecting their deforestation efforts toward unprotected vegetation—an emergent norm that must be sustained for long-term deforestation behaviour change. Given the growing efforts towards sustainable development, it is ever important that, in addition to robust techniques for conservation policy assessment, the evaluation of unintended policy effects should be undertaken.

4.6 List of Appendices for Chapter 4

Appendix G: Details of the covariate matching methodology and evaluation.
Appendix H: Outcomes of covariate matching.
Appendix I: Full results for the causal inference analysis.

Chapter 5

Simmons BA, Wilson KA, Dean AJ. 2020. Landholder typologies illuminate pathways for social change in a deforestation hotspot. Journal of Environmental Management **254**:109777.

Contributor	**Statement of contribution**
Author BA Simmons (Candidate)	Paper concept (80%), survey design (70%), analysis (90%), wrote and edited the paper (65%)
Author KA Wilson	Paper concept (10%), wrote and edited the paper (10%)
Author AJ Dean	Paper concept (10%), survey design (30%), analysis (10%), wrote and edited the paper (25%)

Chapter 5: Landholder typologies illuminate pathways for social change in a deforestation hotspot

5.1 Abstract

Psychosocial factors determine individual and collective behaviours, and there is growing evidence of their influence on land management behaviours. In Queensland, Australia, the controversial *Vegetation Management Act 1999* was enacted to protect remnant vegetation from globally-significant deforestation rates. Met with considerable opposition from landholders, the success of the policy has been questioned and its impact on landholders debated. As native vegetation management encompasses biophysical, economic, political, and cultural dimensions that are immensely complex, a more thorough understanding of the personal and cultural dimensions of deforestation activity is required. We surveyed landholders across Queensland in order to identify different landholder typologies based upon (1) their recent tree clearing behaviours and (2) their psychosocial characteristics, and determined the unique demographic and psychosocial factors associated with typology membership. The relationship between typology distribution in the landscape and historical deforestation hotspots was also assessed. We identified a heterogeneous mosaic of landholders in the clearing landscape, composed of four clearing typologies and five psychosocial typologies. Social norms, identity, trust, and security played crucial roles in distinguishing different types of landholders. The two most contrasting clearing typologies—*active* and *inactive clearers*—were primarily located in hot- and cold-spots of deforestation, respectively; in contrast, most psychosocial typologies could be found throughout the landscape, highlighting the potential benefit of complementing generalised state-wide psychosocial targets with localised behavioural targets. We discuss how conservation policy instruments can be regionally tailored, and relevant strategies for effective communication and engagement can be developed to create behaviour change by understanding the characteristics and distribution of these types of landholders. If modified top-down efforts (e.g. strategic messages, community-based communication) can be supplemented with more bottom-up approaches (e.g. collective learning, building network support), sustainable land management in this global deforestation hotspot may be achievable.

5.2 Highlights

- Norms, identity, trust, and security are important predictors of landholder typology.
- Clearing typologies occur in clusters, while psychosocial typologies are dispersed.

- Behaviour change strategies will benefit from both state-wide and localised targets.
- Strategic messages and trust-building efforts may successfully reduce tree clearing.

5.3 Introduction

Agricultural expansion is the most commonly cited proximate driver of deforestation (Barbier & Burgess 2001a; Hosonuma et al. 2012), and the resulting land use change is responsible for an estimated 25% decline in global biodiversity (Murphy & Romanuk 2014) and more than 10 Gt of carbon dioxide emissions every year (Kindermann et al. 2008). As countries strive to meet their commitments to the 2030 Agenda for Sustainable Development, it is imperative that conservation interventions deliver effective solutions to the deforestation crisis (FAO 2018). Despite numerous government-led approaches to curbing deforestation, such as command-and-control regulation (Simmons et al. 2018c, **Chapter 3**), payments for ecosystem services (Miteva et al. 2012), and protected areas (Joppa & Pfaff 2011), the success of these policy instruments is often unknown or underwhelming. These interventions may result in no change in target behaviour (Azevedo et al. 2017), displacement of deforestation activities (Meyfroidt et al. 2010), or increases in pre-emptive clearing (Simmons et al. 2018c, **Chapter 3**). The failure of many interventions is likely due to an over-reliance on traditional top-down approaches, such as direct regulation and market-based incentives (Mallampalli et al. 2016; Busch & Ferretti-Gallon 2017). The effectiveness of such approaches are contingent upon high compliance and conventional economic behavioural theory—characteristics that do not adequately reflect the realities of deforestation (Lynne et al. 1988).

Psychosocial drivers of deforestation are not commonly investigated, despite their critical importance in driving individual and collective behaviours (Bamberg & Möser 2007; Meyfroidt 2013; Mastrangelo et al. 2014). For example, the theory of planned behaviour (Ajzen 1985) indicates that attitudes, norms, and perceived behavioural control directly influence behavioural intentions; these factors are, in turn, influenced by factors like values and identity (Fielding et al. 2008; Klöckner 2013). Such frameworks have been used to explain many conservation-oriented behaviours (Armitage & Conner 2001; Kaiser et al. 2005) and shed light on how to design and tailor conservation interventions. In Australia, emerging research identifies the importance of landholder values, attitudes, and social norms in driving on-farm conservation behaviours—from general habitat maintenance to restorative actions like tree planting—which can suppress or complement the influence of economic drivers (Burton 2004; Smith 2008; Farmar-Bowers & Lane 2009; Greiner & Gregg 2011). Different farmers may have distinct values and attitudes, and thus be inclined to adopt different types of land management approaches (Petrzelka et al. 1996; van den Berg et al. 1998; Gosling & Williams 2010). For example, in Australia, different motivation-driven typologies of graziers in northern Queensland were linked to differences in their willingness to participate in general conservation policy interventions and adopt on-farm conservation practices (Greiner & Gregg 2011). In New South Wales, distinguishing farmers according to economic- and conservation-oriented values revealed different program goals and targets necessary to influence farmers' decision-making (Maybery et al. 2005). Different conservation policy instruments may be more appropriate for different sectors of the target population, but identifying relevant behaviour change strategies is contingent upon an understanding of each unique case study, as the psychological profiles and drivers of landholders' behaviours will likely vary substantially from one region to another (Knowler & Bradshaw 2007).

In this study, we investigated how multiple psychosocial drivers of behaviour influence different types of landholders responsible for managing native vegetation, using Queensland, Australia as a case study. A region fraught with intense debate surrounding dynamic and controversial state vegetation management policy, tree clearing in Queensland encompasses biophysical, economic, political, and cultural dimensions that are immensely complex; thus a more thorough understanding of the personal and cultural dimensions of tree clearing is required to illuminate pathways for sustainable vegetation management in this deforestation hotspot. In an effort to understand perceptions of vegetation management policy and why deforestation rates continue to soar despite policy intervention, we surveyed landholders throughout the intensive agricultural regions of Queensland and generate two complementary typologies of landholders: (1) typologies based on recent clearing behaviours, and (2) typologies based on perceptions about tree clearing and vegetation management regulations. For each typology, we identify the key psychosocial, demographic, and socioeconomic factors associated with group membership. Finally, we examine the spatial relationship between the distribution of landholder typologies and deforestation hotspots throughout the study area, and conclude with recommendations for strategic targeting of landholders to provoke sustainable land management behaviour change.

5.4 Methods

5.4.1 Study area

5.4.1.1 Regulatory context

Over the last 40 years, the State of Queensland, Australia has lost 60% of its forests due to the rapid replacement of remnant (i.e. primary) vegetation for pasture expansion (Evans 2016), resulting in severe habitat fragmentation and biodiversity decline (Cogger et al. 2003; McAlpine et al. 2011). In response, the Queensland Government enacted the controversial *Vegetation Management Act (VMA) 1999*, which placed clearing regulations on all remnant woody vegetation on private lands. The Act has since been the focus of heated political debate, with landholders and agricultural lobby groups arguing that the policy lacks transparency, accuracy and relevance to the landscape, and disregards the financial consequences on farmers (Productivity Commission 2004; Senate Inquiry 2010). As a result, the VMA has undergone multiple amendments in its nearly 20-year lifespan, with regulations tightening, loosening, and tightening again in recent years (Simmons et al. 2018b, **Chapter 2**). Despite some forest gains in the last decade, this volatility of the VMA has elicited unintended 'panic clearing' from landholders, diminishing the potential benefits of regulatory intervention (Simmons et al. 2018c, **Chapter 3**). Particularly, in the Brigalow Belt South bioregion of Queensland—an extensively cleared national biodiversity hotspot—the direct effectiveness of the VMA has been limited, but its most significant impact may lie in its ability to alter social norms of tree clearing, as more landholders are redirecting their clearing efforts away from protected vegetation (Simmons et al. 2018a, **Chapter 4**).

5.4.1.2 Data

All postcodes within Queensland that were listed as the participant's place of residence and/or the location of their production property (for land managers) were mapped, and the amount of clearing within the last five years—relative to the postcodes' area—was calculated for all woody vegetation and remnant woody vegetation only (Fig. 5.1). We used clearing data from Queensland's Statewide Landcover and Trees Study (SLATS), and intersected the clearing polygons with remnant vegetation maps generated from the Queensland Spatial Catalogue (QSC 2016g,h). The final map of remnant and total tree clearing was aggregated to a 400 km^2 resolution and represented as the proportion of the pixel cleared during 2013–2016. The amount of clearing within each postcode was calculated, and each postcode's standard deviation (SD) from the mean of all postcode clearing rates was used to identify hotspots of clearing. The following clearing categories were generated based upon each postcode's amount of clearing per km^2, relative to the average amount of clearing for all postcodes: *low* ($SD < -0.50$), *moderate* ($-0.50 \leq SD \leq 0.50$), and *high* ($SD > 0.50$). The average degree of remoteness for residence and property postcodes was calculated using the Accessibility/Remoteness Index of Australia (ALA 2016).

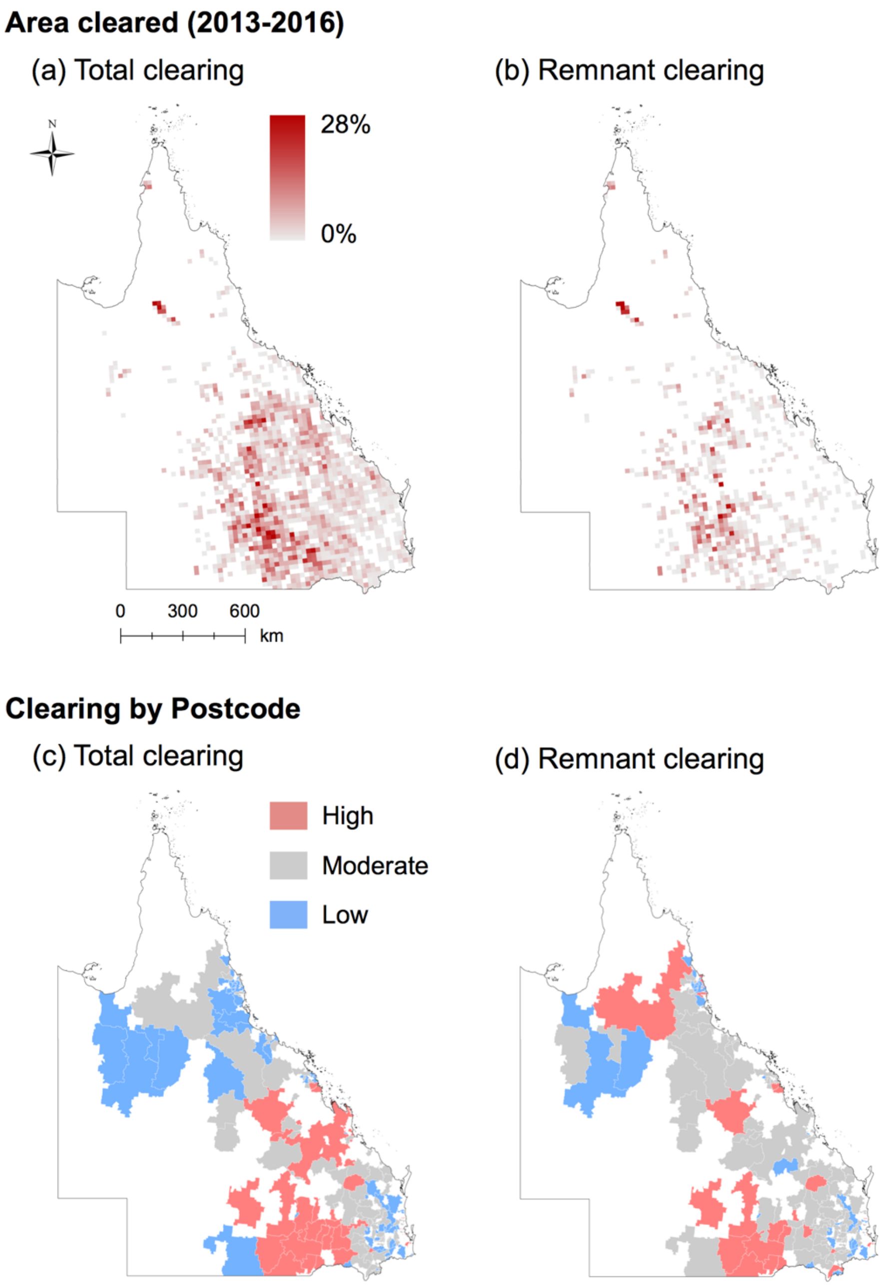

Fig. 5.1. Clearing hotspots within participants' postcodes. Land clearing rates of (a) all woody vegetation and (b) remnant woody vegetation during 2013–2016 as percent of 400 km^2 pixel area. (c) Total clearing and (d) remnant clearing rates for residential and property postcodes reported in survey.

5.4.2 Participants

Farmers/graziers, landowners, and/or members of farming families who lived in Queensland, Australia were recruited by a social research company to complete an anonymous telephone interview (or equivalent online survey, if preferred). The study received ethical clearance prior to commencement (Approval #2017001054). All participants provided informed consent and were surveyed during May 2018. The final sample (N = 265) consisted of predominantly male participants

(72%), 80% of which managed one or more production properties, and the remainder largely represented members of farming families. Of the 211 land managers, 72% were the primary decision-maker in the family; most others made joint decisions with other family members. The average participant was 62 years old. Land managers had been managing their current production property for an average of 34 years. Most participants lived in moderately remote regions of Queensland, typically within proximity to rural towns. The sample comprised a variety of education and income levels (Appendix M).

5.4.3 Survey

5.4.3.1 Variables for land clearing typologies

Five variables were used to generate clearing typologies for land managers (Table 5.1). Four items measured the frequency with which land managers had cleared trees in the last five years for relevant (i.e. permitted) purposes, and two items for non-relevant (i.e. prohibited) purposes, as defined by the most recent 2018 amendment of the VMA (0 = '*never*' to 4 = '*very often*'). The same scale measured their frequency of clearing the following amounts of trees (including tree regrowth): single trees, <1 ha, 1–5 ha, 5–10 ha, >10 ha. A weighted value of 0.10, 0.50, 2.50, 7.50, and 15.0 was attributed to each clearing amount, respectively, and multiplied by their respective score (0 to 4). The final continuous scale for *clearing amount* represented the sum of each land manager's weighted clearing scores (0 to 102.4). Land managers' perception of their clearing amount relative to other farmers was measured on a five point scale (1 = '*much less than others*' to 5 = '*much more than others*'). Their intentions to clear trees during the next six months was measured on a six point scale (1 = '*strongly disagree*' to 6 = '*strongly agree*') adapted from Fielding et al. (2008).

5.4.3.2 Variables for psychosocial typologies

The following variables were used to generate psychosocial clusters: attitudes toward tree clearing and VMA regulations, relative threat of the VMA, negative emotions to the VMA, and social norms for tree clearing and VMA disobedience (Table 5.1). Most items were scored on a six point scale (1 = '*strongly disagree*' to 6 = '*strongly agree*'). The *relative threat of the VMA* was calculated based on participants' response to the prompt, "To what degree do the following pose a threat to the land in your area/the property you manage?" (1 = '*no threat*' to 6 = '*severe threat*') for a list of relevant potential threats, such as drought, pest species, and vegetation management regulations. The final continuous score was calculated by taking the average difference in threat level of 'vegetation management regulations' from all other threats (−5 = '*lowest threat*' to 5 = '*highest threat*').

Table 5.1. Description of the survey items including the scale and Cronbach's alpha (α) of single scores generated for multi-item scales. Complete table with all survey items in Table K1.

Variables	Items	Scale	α
Clearing Purposes *	In the last 5 years, how often have you cleared trees from your property for the following purposes?		
Relevant	Restorative purposes (e.g. thinning) Necessary maintenance (e.g. regrowth or weed removal) Infrastructure (e.g. fences, barns or sheds) Fodder development or expansion	[0, 4]	0.758
Not Relevant	High-value agriculture development or expansion Pasture development or expansion	[0, 4]	0.709
Clearing Amount *	In the last 5 years, how often have you cleared the following amount of trees from your property?	[0, 102.4] ‡	
	Single trees	[0, 4]	
	Less than 1 hectare (ha)	[0, 4]	
	1 - 5 ha	[0, 4]	
	5 - 10 ha	[0, 4]	
	More than 10 ha	[0, 4]	
Clearing Amount Relative to Others *	Compared to other farmers/graziers in your community, do you think you clear trees more or less than they do?	[1, 5]	
Clearing Intentions (next 6 months) *	"I intend to engage in tree clearing on my property during the next 6 months."	[1, 6]	
Attitudes **			
Pro-Clearing	I am concerned about the rate of tree clearing in Queensland † Tree clearing should be stopped † People are clearing too many trees † People who clear trees from their property do not care about the environment †	[1, 6]	0.819
Anti-VMA	In my opinion, vegetation management regulations… Are a burden to me Are fair to farmers † Are necessary † Should be more strict †	[1, 6]	0.648
Relative threat of the VMA **	To what degree do the following pose a threat to the property you manage?	[−5, 5] ‡	
	Drought and extreme weather	[1, 6]	
	Pest species (e.g. feral cats, pigs, foxes, rabbits)	[1, 6]	
	Mining activities	[1, 6]	
	Your personal health and well-being	[1, 6]	
	Escalating costs of running the business	[1, 6]	
	Changing prices for agricultural products	[1, 6]	
	Vegetation management regulations	[1, 6]	
	Chemical and pesticide use regulations	[1, 6]	
Emotions to Regulations **	When you think about vegetation management regulations in Queensland, do you feel…		
Negative	Angry Depressed Anxious Exhausted	[1, 6]	0.859
Social Norms **			
Tree clearing	Most of the farmers in my community clear trees	[1, 6]	
Disobeying regulations	Most of the farmers in my community follow the vegetation management regulations †	[1, 6]	

* Variables used for clearing clusters
** Variables used for psychosocial clusters
† Scores reversed for analysis
‡ Scale of computed score differs from items' scale; see main text for calculation

5.4.3.3 Variables describing both typologies

Additional psychosocial variables described the resulting clusters for both typologies (see Table K1 for survey items). *Perceived behavioural control* was measured using items of controllability and self-efficacy (Cronbach's α = 0.669) adapted from Rhodes and Courneya (2003). Two items measured participants' *trust* in the Queensland Government (α = 0.712), and two distinct measures of *security* represented the perceived threat of the VMA to their lifestyle ("I am confident that I can enjoy a comfortable lifestyle while following vegetation management regulations") and livelihood ("Vegetation management regulations are a threat to my business or livelihood"). Participants' *definition of a 'good farmer'* was measured according to five qualities: profit-maximizing, altruistic, law-abiding, productivity-maximizing, and lifestyle-focused. *Awareness of norms* was measured for land managers based on two items, "I know how most farmers in my area manage their land" and "Most farmers in my area know how I manage my land" (α = 0.797), while those who did not manage a property received only the former item. *Financial strain* was measured by three items (α = 0.712) from Ullah (1990). *Life satisfaction* was measured using an 11 point scale developed by IWG (2013). A single score for *participation in voluntary programs* was calculated based on their average rate of participation in programs, such as land management agreements and conservation covenants. Respondents who had participated in at least one of these programs were asked which *incentives for participation* were their main reasons for participating (select top three choices), with five suggested items based on results from Kabii and Horwitz (2006). Similarly, those who had not participated in at least one program were asked about their main *barriers to participation* from a list of five items.

Some psychosocial variables were most relevant to land managers and thus were only presented to this group (N = 211). Three items from Maybery et al. (2005) measured relevant *economic values* (α = 0.747), *lifestyle values* (α = 0.748), and *conservation values* (α = 0.743), and two items from Gosling and Williams (2010) measured *place attachment* (α = 0.644). Land managers' *self-identity* as a 'good farmer' was measured based on their score for "I think of myself as a 'good farmer.'" Four items adapted from De Baets and Buelens (2012) measured different types of *loss aversion* relevant to land managers: possessions, profits, autonomy, and land. Two measures of *social capital* relevant for Queensland farmers—agricultural and community group membership—were adapted from ESS (2016). Demographic characteristics recorded in the survey included age, gender, education, income, postcode of main place of residence, and the number of years they have lived at their current residence. For those identifying as a land manager, we also recorded the postcode(s) their property is located in, the number of years they have managed their current property, if they currently (or within the last four years) have trees on their property, and if they are primarily responsible for making land management decisions on this property.

5.4.4 Analysis

A total of 180 participants (68%) met the following criteria to be included in the clearing typology analysis: (1) manages a production property, (2) currently has trees on their property *or* had trees on their property in the last four years, and (3) answered all questions that were used to generate clusters. This excluded 14% of land managers from the analysis. Ward's method for hierarchical agglomerative clustering (Ward 1963) using squared Euclidean distance produced the strongest clustering of the data compared to other methods (agglomerative coefficient, *ac* = 0.973). The 'elbow' (Ketchen Jr. & Shook 1996) and gap statistic (Tibshirani et al. 2001) methods for determining cluster cut-offs identified a three- and five-cluster solution to be optimal, respectively. The three-cluster solution over-represented participants in the second cluster (45%), while the five-cluster solution produced a cluster containing only 13% of land managers. The four-cluster solution was chosen as a compromise between cut-off methods, cluster representation, and conceptual relevance.

Psychosocial typologies were created for all participants (N = 265). Following the same cluster methodology above (Ward's *ac* = 0.963), the 'elbow' method and gap statistic identified a four-cluster solution to be optimal. This solution, however, grouped 47% of participants into the first cluster. The five-cluster solution split this cluster into 26% and 21% of participants and produced a conceptually important distinction between the two new clusters; thus the five-cluster solution was selected for further analysis. Differences between clusters were first identified using the Kruskal-Wallis H test (Kruskal & Wallis 1952). A series of logistic regression models were developed using the significant variables identified in the K-W tests in order to identify significant drivers of individual cluster membership (Dean et al. 2016). To identify the most parsimonious model explaining cluster membership, the model with the lowest Akaike information criterion (AIC) resulting from sequential parameter reduction was selected for each cluster (Fig. L1). For the psychosocial typologies (land managers and non-managers), the following variables differed significantly between typologies but were excluded from further analysis due to their relevance for land managers only: values, self-identity, loss aversion, barriers to program participation, and most measures of clearing behaviour. Model fit was assessed using McFadden's pseudo R-squared (McFadden 1974).

5.5 Results

5.5.1 Participant characteristics

Overall, participants scored highly on pro-clearing and anti-VMA attitudes (Fig. 5.2). Most participants did not view tree clearing or disobedience of VMA regulations to be the norm in their community, and they generally agreed that they were aware of how others manage their land. Participants largely felt a diminished sense of security from the VMA, but the severity of the VMA threat was relatively equal to other threats facing farming communities. A diminished sense of behavioural control and strong lack of trust in the Queensland Government was also common amongst participants. While most did not express positive emotions toward the VMA, the majority did not express very strong negative emotions. Land managers scored highly on economic values and very high on lifestyle and conservation values, as well as place attachment. Most managers stated that they occasionally clear for VMA-relevant purposes and rarely for non-relevant purposes. The reported amount of clearing varied between participants, with an average clearing rate of similar magnitude to frequently clearing 1–5 ha or occasionally clearing 5–10 ha of trees. The majority believed that they clear trees almost as much as others in their community and do not anticipate clearing any trees within the next six months. Additional characteristics of participants can be found in Tables L1 and L2.

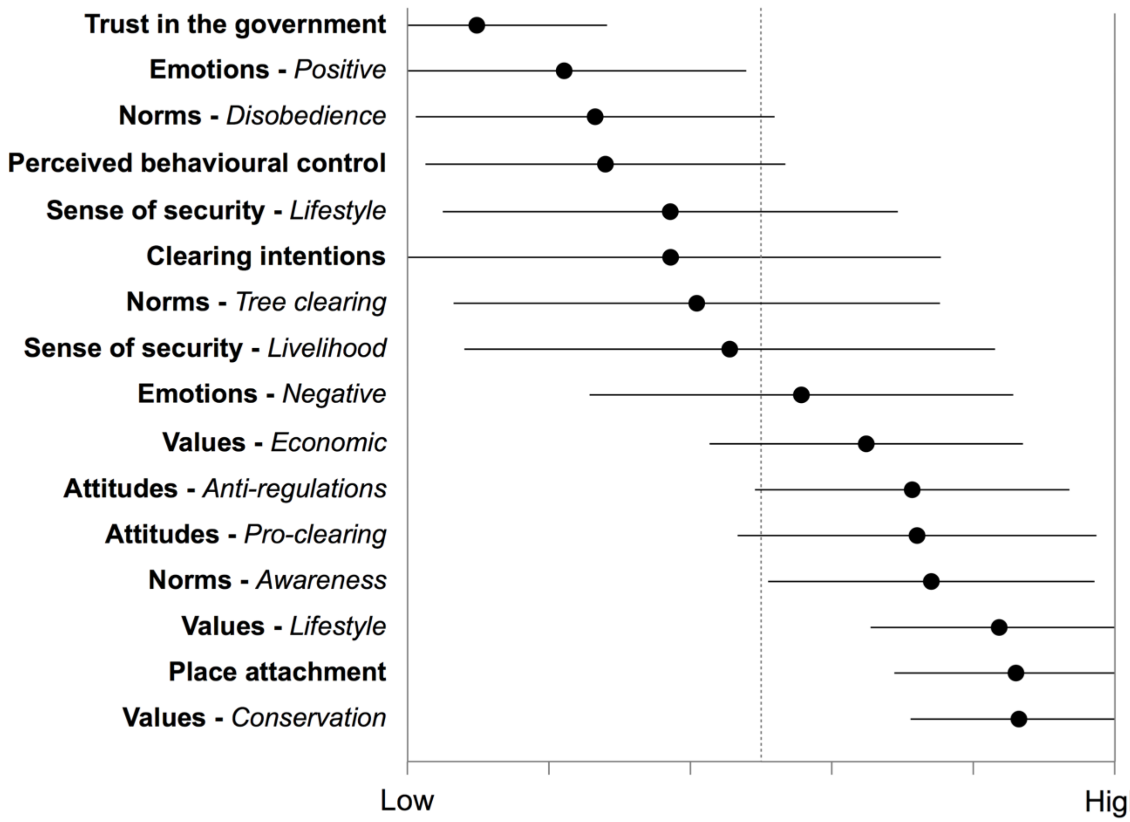

Fig. 5.2. Mean and standard deviation of landholders' scores across select variables. All variables were scored on a 1 to 6 scale. See main text for scale descriptions for each variable. Complete summary statistics for all variables included in the analysis are available in Tables L1 and L2.

5.5.2 Clearing typologies

Throughout this section, we refer to 'land managers' as those participants meeting the aforementioned criteria for inclusion in the clearing typology analysis. The following clearing typologies were identified (Fig. 5.3):

- ***Inactive Clearers***: land managers clear less frequently than all other typologies for relevant and non-relevant purposes, clear a minimal amount of trees, believe they clear less than others in their community, and do not intend to clear in the next six months;
- ***Irregular Clearers***: land managers clear for relevant and non-relevant purposes more frequently than the average participant, yet they clear fewer trees than the average participant, and they recognise that they clear less than others in their community;
- ***Perceived Active Clearers***: land managers tend to rank their relative clearing behaviour higher than other clusters and are more likely to clear in the next six months;
- ***Active Clearers***: land managers clear more often for relevant and non-relevant purposes, clear a much larger amount of trees, tend to rank their relative clearing behaviour higher than other clusters, and have very strong intentions to clear in the next six months.

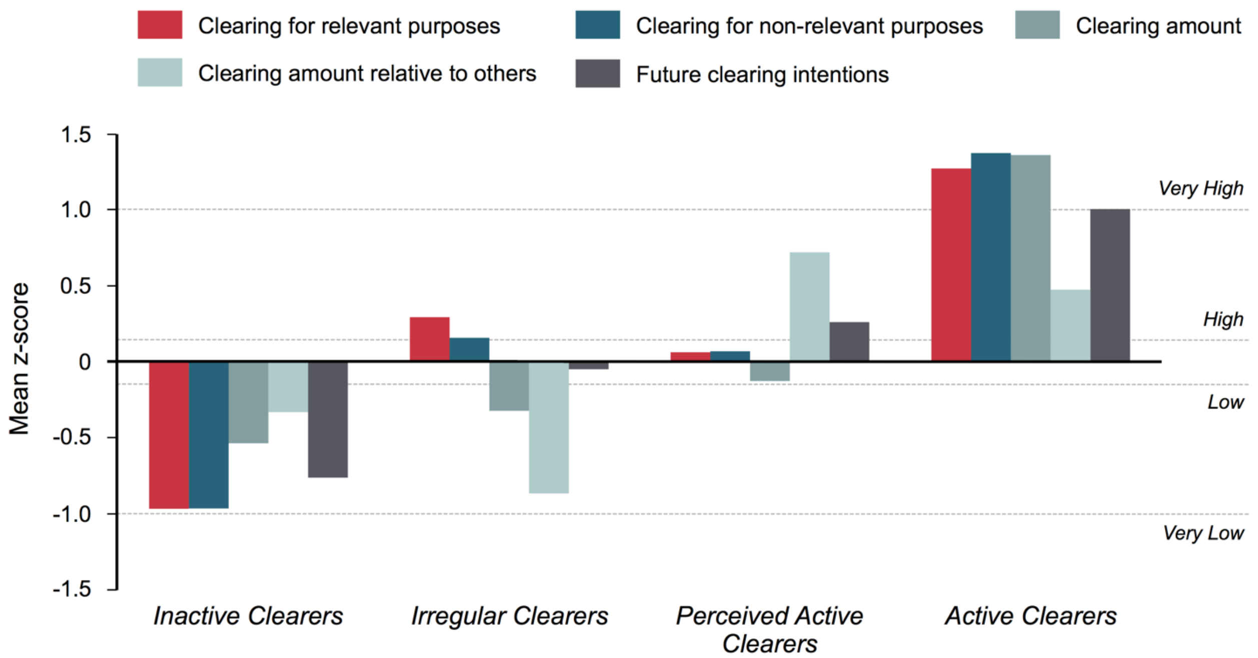

Fig. 5.3. Composition of the four clearing typologies identified for land managers. Mean standardized z-scores for variables outside the confidence interval of the mean (CI = 0.146) were considered *high/low*, and those exceeding one SD were considered *very high/very low*. Number of land managers within each typology: inactive clearers (n = 62), irregular clearers (n = 35), perceived active clearers (n = 46), active clearers (n = 37).

Significant differences between clearing typologies were identified for the following variables: values, attitudes, relative VMA threat, emotions, social norms, awareness of norms, life satisfaction, clearing influences, voluntary program participation, age, and remoteness (Table M1). Membership within the *active clearers* typology had the greatest explanatory power (AIC = 126.35, McFadden R^2 = 0.390) (Table 5.2). *Active clearers* were uniquely characterised as younger landholders, with strong anti-regulation attitudes and strongly influenced by droughts and the aesthetic value of trees. *Inactive clearers* had stronger pro-regulation attitudes and were less influenced by the costs attributed to clearing. The contrast between *irregular* and *perceived active clearers* is most pronounced in the strength of their economic values and local clearing norms, with *irregular clearers* having weaker economic values despite living in a normative clearing environment. Interestingly, where clearing is perceived to be the norm, *active* and *irregular clearers* are found, and where clearing is not the norm, *inactive* and *perceived active clearers* are found. For more detailed descriptions of the typology characteristics, see Appendix N.

Table 5.2. Coefficients* of the variables included in the models of clearing typology membership.

Variable†	Inactive Clearers	Irregular Clearers	Perceived Active Clearers	Active Clearers
Age	0.03 (0.02)			−0.06 (0.02)‡
Voluntary Program Participation	−0.84 (0.28)‡	0.41 (0.29)		0.46 (0.35)
Life satisfaction		−0.30 (0.11)‡	0.15 (0.11)	
Awareness of Norms	−0.27 (0.17)			
Values				
Economic	−0.26 (0.19)	−0.43 (0.20)‡	0.49 (0.19)‡	0.52 (0.28)
Social Norms				
Tree clearing	−0.30 (0.12)‡	0.30 (0.13)‡	−0.33 (0.13)‡	0.55 (0.18)‡
Remoteness				
Residence postcode	0.06 (0.06)	0.03 (0.07)	−0.15 (0.07)‡	
Emotions to Regulations				
Negative		0.32 (0.17)		−0.25 (0.22)
Attitudes				
Pro-clearing		−0.32 (0.20)		
Anti-regulations	−0.40 (0.20)‡			0.62 (0.31)‡
Clearing Influences				
Aesthetics		−0.30 (0.14)‡		0.48 (0.15)‡
Droughts			−0.37 (0.15)‡	0.42 (0.15)‡
Costs	−0.32 (0.11)‡		0.17 (0.12)	
Profitability			0.19 (0.14)	
Regulations			0.21 (0.12)	
Policy uncertainty				0.15 (0.14)
Sample size	170	172	172	173
AIC	187.50	157.28	182.85	126.35
McFadden pseudo R^2	0.218	0.172	0.166	0.390

* Coefficients, *mean (SD)*, represent the percent change in membership probability per 1% change in the explanatory variable.
† Variables not retained in the final models: relative VMA threat, influence of agricultural prices on clearing.
‡ $p < 0.05$

5.5.3 Psychosocial typologies

The following psychosocial typologies were identified (Fig. 5.4):

- ***Refusers***: participants have very strong pro-clearing and anti-regulation attitudes, stronger negative emotions toward the VMA, view VMA regulations as a more severe threat to their area, and tend to believe more people in their community may not be following these regulations;
- ***Reluctant Acceptors***: participants have very strong pro-clearing and anti-regulation attitudes, stronger negative emotions toward the VMA, view VMA regulations as a more severe threat to their area, yet they believe most people in their community follow these regulations;
- ***Neutrals***: participants view VMA regulations as a less severe threat to their area and believe most people in their community abstain from tree clearing and follow the regulations;
- ***Acceptors***: participants have weaker pro-clearing and anti-regulation attitudes, weaker negative emotions toward the VMA, yet they believe most people in their community are clearing trees and more people may be disobeying regulations;
- ***Supporters***: participants have very strong anti-clearing and pro-regulation attitudes, minimal negative emotions toward the VMA, view VMA regulations as a much lower threat to their area than others, and despite believing most people are abstaining from tree clearing, they tend to believe people in their community are disobeying regulations more than the average participant.

Significant differences between psychosocial typologies were identified for the following variables: 'good farmer' definition, trust, security, emotions, perceived behavioural control, norm awareness, and remoteness (Table M2). According to the most parsimonious model, membership within the *supporters* typology had the greatest explanatory power (AIC = 125.71, McFadden R^2 = 0.444) (Table 5.3). Perceptions about the impact of vegetation management regulations on lifestyle or livelihoods were strongly associated with most psychosocial typologies. Expectedly, landholders with a greater sense of security (*neutrals* and *supporters*) viewed clearing to be atypical in their community, and they were the only ones who did not view the VMA as a substantial threat. Those with the strongest anti-regulation attitudes (*refusers* and *reluctant acceptors*) were more likely to perceive that the VMA threatened their livelihood and lifestyle. Landholders who reported being aware of others' land management behaviours (*reluctant acceptors* and *neutrals*) tend to agree that farmers are obeying regulations, and abstaining from tree clearing is the norm. In contrast, those who reported being least aware of others' behaviours (*refusers* and *acceptors*) have a greater tendency to believe that people are more disobedient and more likely to be clearing trees. For more detailed descriptions of the typology characteristics, see Appendix N.

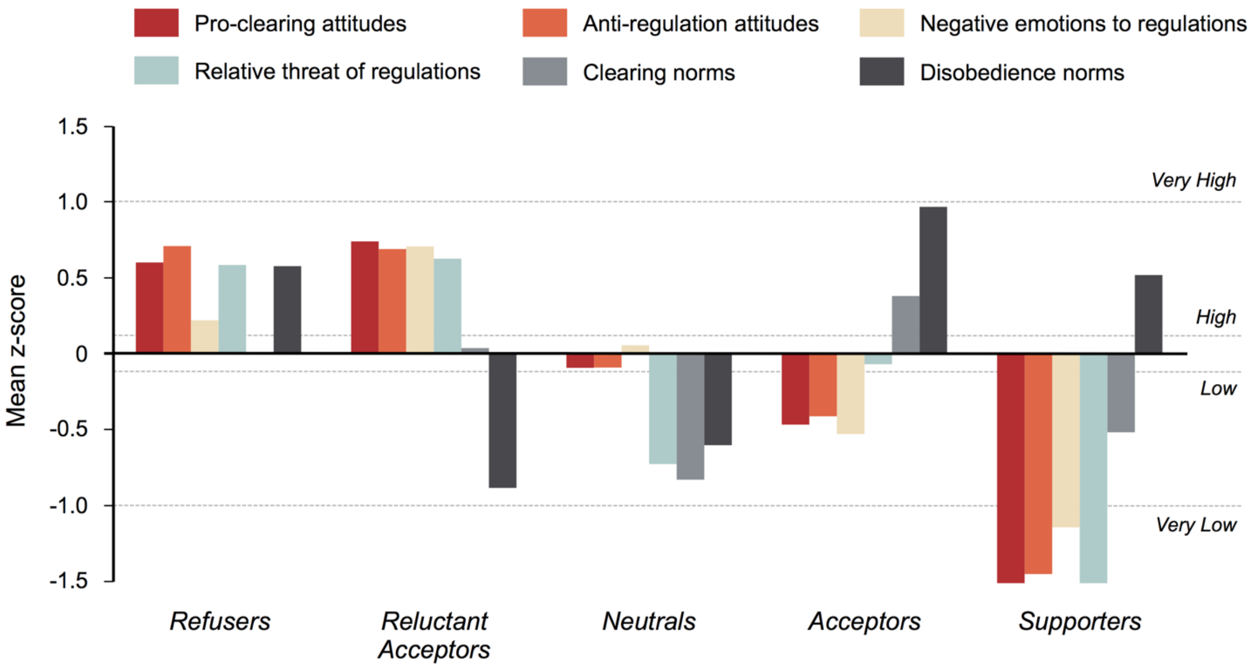

Fig. 5.4. Composition of the five psychosocial typologies identified for participants. Mean standardized z-scores for variables outside the confidence interval of the mean (CI = 0.120) were considered *high/low*, and those exceeding one SD were considered *very high/very low*. Number of participants within each typology: refusers (n = 55), reluctant acceptors (n = 69), neutrals (n = 49), acceptors (n = 57), supporters (n = 35).

Table 5.3. Coefficients* of the variables included in the models of psychosocial typology membership.

Variable†	Refusers	Reluctant Acceptors	Neutrals	Acceptors	Supporters
Awareness of Norms	−0.35 (0.15)‡	0.48 (0.18)‡	0.42 (0.16)‡	−0.45 (0.13)‡	−0.33 (0.20)
Perceived Behavioural Control	0.32 (0.17)	−0.31 (0.18)	−0.24 (0.16)	0.09 (0.16)	0.51 (0.21)‡
Trust in the Government	−1.61 (0.64)‡			0.20 (0.20)	
Sense of Security					
Lifestyle	−0.30 (0.15)‡	−0.31 (0.14)‡	0.12 (0.12)	0.05 (0.12)	0.57 (0.18)‡
Livelihood		−0.42 (0.11)‡	0.27 (0.10)‡		0.58 (0.18)‡
Emotions to Regulations					
Positive	−0.34 (0.19)	−0.39 (0.18)‡		0.22 (0.13)	0.37 (0.19)‡
Remoteness					
Residence postcode		0.09 (0.05)	−0.05 (0.05)	0.02 (0.04)	−0.21 (0.09)‡
Good Farmer Identity					
Law-abiding	−0.37 (0.12)‡	0.40 (0.14)‡			
Sample size	264	257	257	257	257
AIC	234.92	216.56	236.47	257.50	125.71
McFadden pseudo R^2	0.174	0.325	0.071	0.096	0.444

* Coefficients, *mean (SD)*, represent the percent change in membership probability per 1% change in the explanatory variable.
‡ $p < 0.05$

5.5.4 Typologies in the landscape

Supporters were the only psychosocial typology to differ significantly from statistical expectation within the clearing landscape, with a disproportionately low number residing in high clearing postcodes for all woody vegetation (Pearson's $\chi^2 = 16.37$, df = 8, $p = 0.037$) (Fig. O1). No significant relationship between psychosocial typology and remnant clearing hotspots was observed (Fisher's exact test, $p = 0.451$). Membership of clearing typologies was associated with residential postcode clearing hotspots (Fig. O2): a disproportionately high number of *inactive clearers* resided in low clearing postcodes, and the majority of participants residing in high-clearing postcodes were *active clearers* ($\chi^2 = 23.20$, df = 6, $p < 0.001$) (Fig. 5.5). In contrast, no significant relationship between clearing typology and remnant clearing hotspots was observed ($p = 0.229$). Similar relationships were observed when considering the postcodes of managers' production properties: most managers within high total clearing postcodes were *active clearers* ($\chi^2 = 18.78$, df = 6, $p = 0.005$), and no relationship was found according to remnant clearing postcodes ($p = 0.307$). The majority of land managers classified as *supporters* were also classified as *inactive clearers* ($\chi^2 = 21.58$, df = 12, $p = 0.043$). Surprisingly, no other relationships were identified between typologies. *Inactive* and *irregular clearers* could be found in most psychosocial clusters in relatively equal densities, and *active clearers* were often *reluctant acceptors* or *acceptors* (Fig. P1).

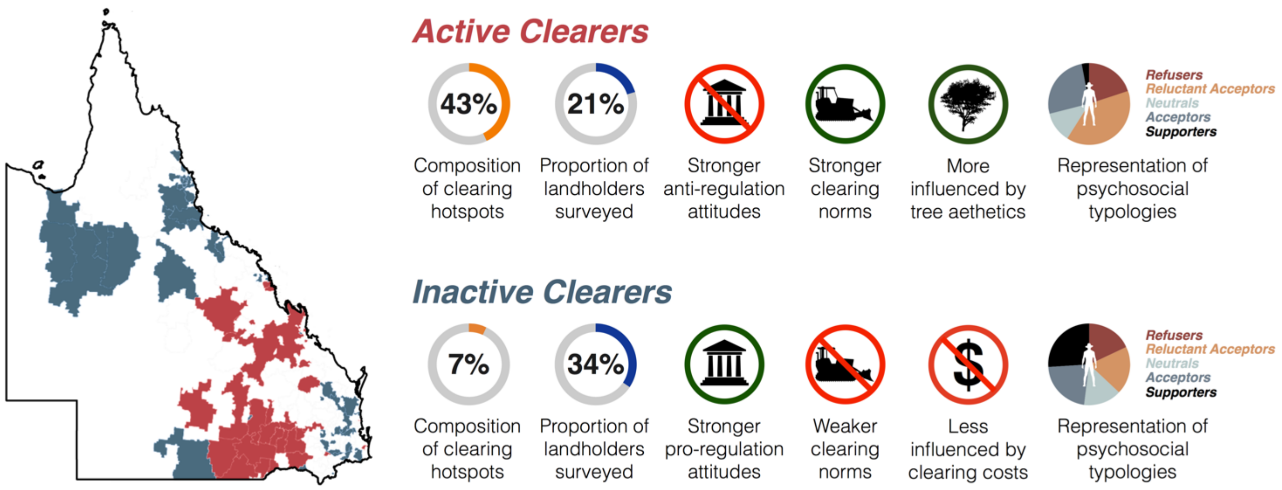

Fig. 5.5. Concentration of clearing typologies within the landscape. Characteristics of the two most contrasting clearing typologies are displayed, including unique drivers of typology membership and their prevalence throughout post codes included in the study area.

5.6 Discussion

The results of this study highlight the heterogeneity of landholders throughout Queensland, as well as the inherent complexity in determining distinct farmer typologies in such dynamic agricultural landscapes, as has been identified in previous studies (e.g. Emtage et al. 2007). The psychosocial typologies are reflective of the spectrum of farmer typologies previously identified in the Wet Tropics of Queensland (Emtage & Herbohn 2012), which was based on potential adoption of 'best management practices.' Interestingly, Queensland landholders differ from those in the neighbouring state of New South Wales, where landholders were distinctly separated into economic, lifestyle, and conservation value-oriented typologies (Maybery et al. 2005), unlike most landholders in this study. This emphasises the uniqueness of farmer typologies and the need to investigate the personal and cultural dimensions of land management behaviour on a case-by-case basis. The range of psychosocial drivers of typology membership investigated in this study extends our understanding of what influences tree clearing, with social norms, identity, trust, and security playing crucial roles. In the remainder of this discussion, we expand upon the role of these social drivers, highlight the major issues that must be addressed, and describe mixed-method approaches to promote sustainable vegetation management behaviours across Queensland.

5.6.1 Challenges and opportunities: the role of social drivers

5.6.1.1 Clearing typologies

The intricacies of defining clearing typologies are most apparent in the intermediate typologies: *irregular clearers* and *perceived active clearers*. Values have been known to act as broad, underlying determinants of behaviour (Stern et al. 1999; Roccas et al. 2002), and their influence on self-perceptions of clearing is apparent in *irregular* and *perceived active clearers*. Situated in a normative clearing environment, the significantly weaker economic values of *irregular* clearers may contribute to their disproportionately low perception of their own clearing behaviours, particularly if they clear primarily for maintenance or necessity, which would explain their frequent small-scale clearing efforts. In contrast, *perceived active clearers* have stronger economic values and perceive themselves to be clearing much more than others, despite clearing as much as the average participant in this study; because these landholders are situated within more urban areas, this inflated self-perception may be indicative of a different reference point from landholders in more remote areas where clearing is more common. If they are aware of clearing norms, the relatively strong clearing intentions of *perceived active clearers* indicates two potential roles for them within their community: (1) they are ‘lone-wolf’ *active clearers* situated in areas under-represented in this survey, where their minimal amount of clearing is, in fact, very high in their community; (2) they represent up-and-coming *active clearers* that may have recently began clearing greater areas of trees, whose clearing history has yet to reflect future clearing behaviours.

The lack of influence of economic values, potential profitability of clearing, and financial strain on the two most contrasting clearing typologies (*active* and *inactive clearers*) is an important result. Despite some studies, and farmer testimonials, highlighting the importance of financial motivations and incentives for driving environmental behaviour (Productivity Commission 2004; Maybery et al. 2005; Sorice et al. 2013), the characteristics of these contrasting clearers are driven primarily by other psychosocial factors. It is possible that for landholders in Queensland, financial incentives are necessary but not sufficient for change, and they may need to be accompanied by psychological approaches for meaningful change in clearing behaviours (Burton et al. 2008). Characteristics of our clearing typologies appear to lend support to the influence of attitudes and norms as indicated by psychological theories (Ajzen 1985; Klöckner 2013), but the lack of influence of control or security—in contrast to the psychosocial typologies—is surprising. This missing component, encompassing measures of security, self-efficacy, and controllability (Bandura 2001), may be an underlying issue that affects all types of clearers. If these core issues can be addressed, it may have beneficial flow-on effects into the more direct drivers of clearing typology membership.

While *active* and *inactive clearers* do not tend to overlap as often in the landscape (consistent with their reported clearing norms), *irregular* and *perceived active clearers* are present throughout low- and high-clearing regions. The interaction between land managers’ perceptions of tree clearing norms and their own clearing behaviours relative to this norm is important for defining clearing typology characteristics. For example, *inactive clearers* are situated in communities where clearing is atypical, which may provoke or enhance their anti-clearing and pro-regulation attitudes, but the prevalence of tree clearing in *active clearers*’ communities with stronger clearing norms may strengthen anti-regulation attitudes and spur more vested interests in protesting ongoing changes to the VMA—especially given the influence of recent droughts for making clearing decisions, which was a significant point of argument from rural farmers during recent Parliamentary debate (Bond & Bhole 2018). *Active clearers* were also the only typology to be strongly influenced by the aesthetic value of trees in making clearing decisions. While this has been previously identified as a key driver of tree retention in the Brigalow Belt bioregion of Queensland (Seabrook et al. 2008), it is surprising that this characteristic is unique to the most prevalent clearers. If these landholders are located in communities with high rates of tree loss, this may result in positive environmental feedbacks, whereby the aesthetic value of trees becomes increasingly important as native vegetation becomes scarce.

5.6.1.2 Psychosocial typologies

The most prominent characteristics distinguishing psychosocial typologies from one another —their sense of security—reflect previous reports from farmers most opposed to ongoing VMA regulations regarding the perceived threats to local livelihoods and autonomy (Productivity Commission 2004; Senate Inquiry 2010). Previous research has shown that people with greater degrees of security and self-determination are more likely to engage in environmentally-friendly behaviours because they believe they have a greater degree of choice (Villacorta et al. 2003; de Groot & Steg 2010). Given the significance of security to psychosocial typology classification, tackling the broader issues of security, autonomy, and flexibility may promote the transition of more *refusers* or *reluctant acceptors* into *neutrals* or *supporters*, though trust will be a significant barrier, particularly for *refusers*.

It is interesting that landholders who state they are more aware of others' land management behaviours believe there are few behavioural issues (i.e. farmers are obeying the laws and tree clearing is relatively uncommon), while those who state they are less aware tend to believe the opposite is occurring. Landholders' perceptions can play a critical role in modifying environmental behaviour (Fielding et al. 2005), as they provide a benchmark for comparison of their own behaviours relative to those of the community (Schultz et al. 2007; Kinzig et al. 2013). There appears to be an important interaction between landholders' perceptions and awareness of these norms that is influencing their membership into the psychosocial typologies. For example, *acceptors* were the only typology to consider tree clearing to be normative behaviour, yet their diminished awareness of norms—the lowest of all typologies—may skew their perception of reality, potentially leading to a rationale that government intervention is a justifiable solution to a normalised problem.

It is possible that perceived norms may influence landholders' sense of security. For example, *neutrals* see the burden of regulations on landholders, yet they may have a greater sense of security because they do not perceive clearing or disobedience to be a significant issue. Additionally, in more urban areas where clearing is less the norm, perceptions of rural farmers' outrage over the VMA may influence *supporters*' greater sense of sense of security and behavioural control from government intervention. Numerous studies have highlighted this interplay between norms, attitudes, and perceived control or security on environmental behaviours, though the directionality of influence is often case-specific (Fielding et al. 2005; Price & Leviston 2014; Zeweld et al. 2017). Moreover, it is likely that social norms and 'good farmer' identity work synergistically, playing a crucial role in distinguishing the two typologies of landholders that should be prioritised for conservation efforts: *refusers* and *reluctant acceptors*. Despite large similarities between the two, *reluctant acceptors* primarily distinguish themselves from *refusers* due to their unique emphasis on defining 'good farmers' as law-abiding citizens. Because identity theory posits that individuals will act in accordance with their self-identity (Tajfel 1981; Fielding et al. 2008), landholders' identity is thus an important component to target for conservation interventions (Seabrook & Higgins 1988; Sulemana & James Jr. 2014).

5.6.2 Pathways to change

This study has identified two complementary sets of landholder typologies across Queensland based upon numerous psychosocial and demographic factors. Identifying the types of landholders present, and the factors that influence their clearing behaviours, can highlight different strategies for promoting change in clearing behaviours. Characteristics and aggregation of the typologies in the landscape can allow regional natural resource management (NRM) organizations to tailor local extension programs for specific landholder groups (Emtage et al. 2007; Greiner 2015). It has been argued that collective change in vegetation management requires effective communication and engagement at both localized, community-based scales, and larger population scales (Siepen & Westrup 2002). Communicating for behaviour change—sometimes referred to as 'nudging' (Michalek et al. 2015; Reddy et al. 2016)—involves targeting psychological drivers of behaviour. For example, experimental studies show that communicating positive social norms can strengthen landholder intentions to continue in environmental schemes (Kuhfuss et al. 2016). Below, we outline a number of top-down and bottom-up strategies that could be used within both localized engagement and large-scale communication activities to tackle the key factors driving membership into *refusers*, *reluctant acceptors*, and *active clearers* (Fig. 5.6).

While *refusers* were most untrusting of the Queensland Government, trust was exceptionally low for most landholders; this raises the challenge of how to best improve trust in the government in the context of these contested spaces. When coupled with a reduced sense of security, control, and autonomy provoked by policy intervention, it is likely that most attempts at intervention will fail if these barriers are not targeted for immediate change (Moon & Cocklin 2011; Sorice et al. 2013; Price & Leviston 2014). Combatting this lack of trust will require long-term relationship building between the farming community and government. Some surveyed landholders expressed disappointment that their relationship with the former Department of Primary Industries has been dissolved, stating that the help they received from this resource was "quite amazing," and its amalgamation into other departments has had negative effects on the community. Such relationships need to be cultivated across Queensland once again, as personal communication is most successful at building trust between actors (Siepen & Westrup 2002). Several landholders also suggested more on-the-ground projects, including educational programs, community-led projects, and land clearing forums with

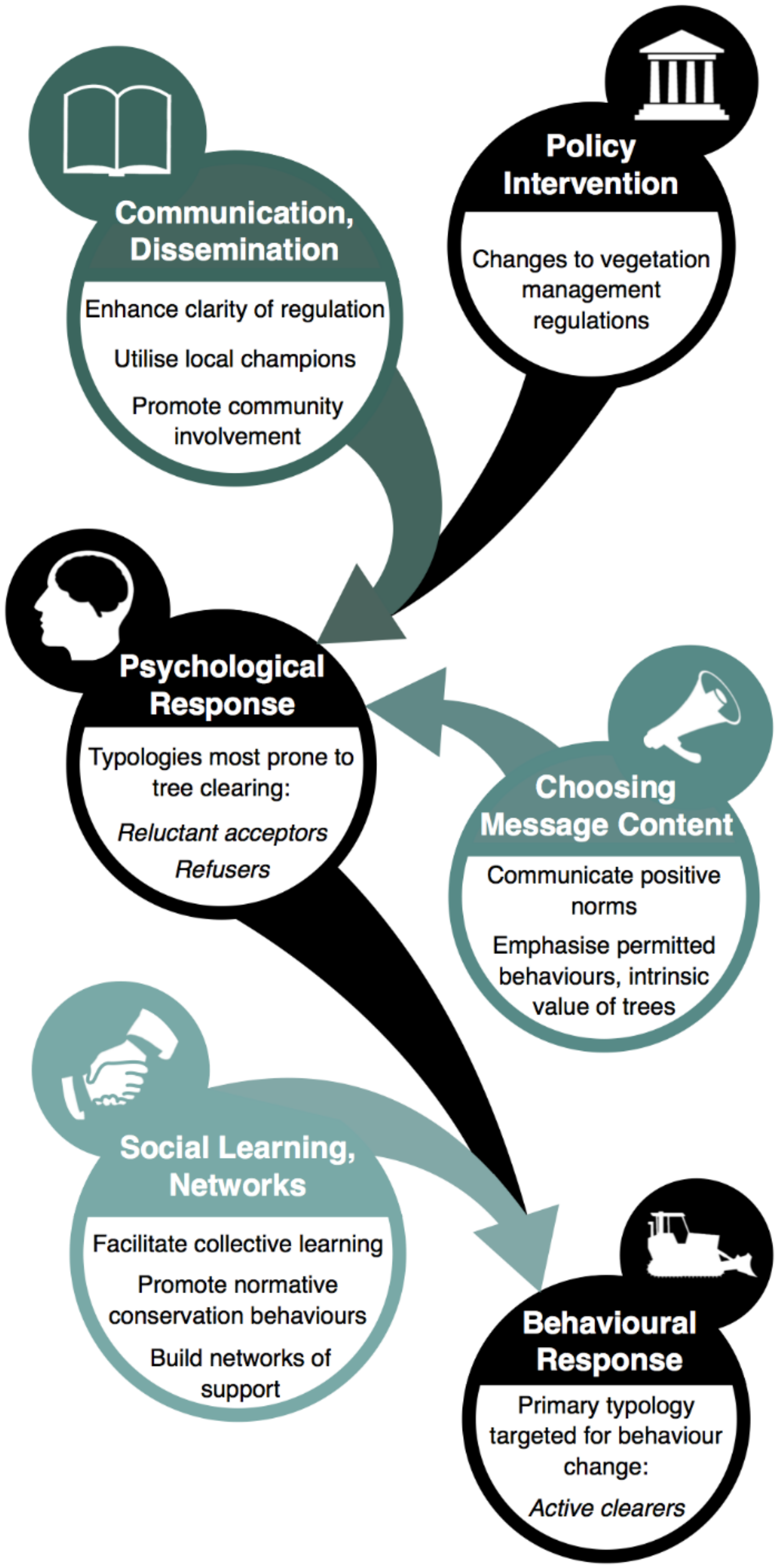

Fig. 5.6. Proposed path of influence for targeted behaviour change strategies. This mix of top-down and bottom-up approaches for behaviour change represent overarching strategies for Queensland landholders (*communication*, *dissemination*), strategies targeting psychosocial typologies (*choosing message content*), and strategies targeting tree clearing typologies (*social learning*, *networks*).

diverse stakeholder representation, and many indicated that they occasionally used the advice of industry experts, agronomists, or 'best practice' articles to inform their land management decisions. It is important to highlight that learning about *how to respond* to a problem (procedural knowledge) is more likely to support new behaviours than factual-based learning about a problem (Kaiser & Fuhrer 2003; Dean et al. 2018). Particularly, if farmers do not have extensive experience working under such heavy regulatory conditions, facilitating the development of their adaptive skills in this context may make it easier to adjust to top-down interventions. As one landholder stated, "The farmers want to be left alone *unless* they can be convinced they are genuinely being helped" (emphasis added). Thus, the most successful bottom-up approaches to trust building (and progressive behaviour change) will likely need to promote local knowledge exchange, strengthen adaptive capacity, identify and prioritise solutions to local issues, and increase community involvement in managing these issues.

Regarding the VMA regulations, landholders have criticized its transparency, scientific legitimacy, spatial accuracy of vegetation maps, and underlying agenda (Productivity Commission 2004; Senate Inquiry 2010). Most recently, farmers in the Mulga Lands have issued a call to Parliament to clarify whether they are allowed to harvest fodder to feed cattle during drought under the 2018 VMA amendments (Queensland Times 2018). Effective communication is critical here. As one landholder stated in the survey, "communication with all the community and cooperation are the two most important things." The use of personal communication, community involvement, and promotion of trusted mentors or local champions to disseminate political and scientific information can be effective tools to engage landholders at multiple levels (Siepen & Westrup 2002; Haq et al. 2013), as was observed after the enactment of the VMA, when the government implemented the short-lived Vegetation Management Extension Framework to promote knowledge exchange between landholders and policy-makers (Westrup 2001). Changing clearing norms, and simultaneously enhancing landholders' awareness of these norms, will require emphasising normative pro-environmental behaviours, while promoting communication via social groups, advice and support networks, and collective learning (Bandura 2001; Price & Leviston 2014; Mills et al. 2017).

The majority of landholders held high lifestyle and conservation values. Despite the agreement of these results with those observed in graziers of northern Queensland (Greiner & Gregg 2011), many landholders report frustration at what they believe are misconceptions about farmers and rural life, where they are portrayed as villains in the vegetation management story. Many survey participants emphasized this issue: e.g. "recognition for conservation works on the farm goes unnoticed," "people have to remember the good work that has been done […] they are good people and attached to the land and want to do the right thing on conservation issues." Importantly, *active clearers* are also highly influenced by the aesthetic values of trees. The key to effective communication here lies in promoting these stewardship values and identities of landholders.

Conservation policy instruments promoting positive norms, positive perceptions, and greater awareness of issues and impacts are more likely to promote behaviour change and increase program participation (Moon et al. 2012; Bennett 2016; Kuhfuss et al. 2016). Previous studies have argued that framing messages of agricultural conservation around land stewardship behaviours (rather than anti-environmental behaviours) and the role of farmers as stewards of the land will be most successful in creating change (Greiner & Gregg 2011; Price & Leviston 2014; Greiner 2015). Behaviour change strategies should thus be targeted toward the most prolific clearers, emphasise landholders' intrinsic values and support for nature, and highlight the successes and rewards of farmers making significant strides to improve the natural environment. As one landholder put it, "What would make a massive difference is if rural producers were rewarded and applauded for their current commitments and the true story of the good [that] ordinary people are doing every day to make a difference to themselves, the health of their land, their produce and the greater community and environment."

Importantly, there are a number of factors excluded from this study that should be considered when developing these conservation targets. First, the questions in our survey did not distinguish remnant (protected) and non-remnant (typically unprotected) trees, but rather addressed tree clearing as a whole. This was done to avoid soliciting information of potentially illegal clearing behaviours from landholders, which could diminish participant trust in our survey, leading to false or incomplete results. Given landholders' responses and their situation in the landscape, there is a high likelihood that participants answered honestly to clearing questions, but these typologies may change if only illegal clearing behaviours were studied. Second, some factors driving environmental behaviour that have been identified elsewhere were not measured in this study, such as subjective norms (van Dijk et al. 2016), farm size (Seabrook et al. 2008), political identity (Unsworth & Fielding 2014), and tree planting behaviours (Gosling & Williams 2010). The typologies created in this study, however, are based upon relevant characteristics that can be useful to researchers, practitioners, NRM organizations, and government representatives for identifying targets for behaviour change (Emtage & Herbohn 2012). Finally, additional data should be collected from Queensland farmers in other clearing hot- and cold-spots to create a larger representative map of typologies across the state. Given the reliability of identifying our *active* and *inactive clearers* in the clearing landscape, it is important that behaviour change interventions target proximate drivers of tree clearing (drivers of clearing typology membership), knowing that successful strategies will have positive flow-on effects to changing the underlying social drivers of clearing (drivers of psychosocial typology membership).

5.7 Conclusions

Native vegetation management has become deeply embedded into the moral framework of farming culture in Queensland, transforming tree clearing codes into profound issues surrounding property rights, trust, and economic and environmental sustainability. Diverse approaches are needed to capture a thorough understanding of the myriad of internal and external drivers of landholders' tree clearing decision-making. We have identified a number of opportunities for engagement and communication strategies to target key underlying psychosocial issues provoked by command-and-control policy in order to create sustainable behaviour change. If new top-down and bottom-up approaches can be developed that (1) emphasise the roles, knowledge, and concerns of landholders, (2) are open and adaptable to new information and two-way learning, and (3) can adequately capture the complex human dimensions of tree clearing, then it is likely that landholders will become more responsive to vegetation management policy instruments.

5.8 List of Appendices for Chapter 5

Appendix J: Ethics approval letter.
Appendix K: Full list of survey items included in the analysis.
Appendix L: Results of model selection for all typologies.
Appendix M: Summary of participants' responses to all variables.
Appendix N: Detailed typology descriptions.
Appendix O: Results of the relationship between typologies and clearing hotspots.
Appendix P: Results of the relationship between clearing and psychosocial typologies.

Chapter 6: Discussion

6.1 The dimensionality of tree clearing: a synthesis

The chapters of this thesis have illuminated critical drivers of tree clearing across multiple dimensions of land management decision-making that are often singularly considered, if they are considered at all. The findings are both timely and crucial for the development of future vegetation management policy interventions. By examining historical clearing behaviour trends, providing evidence and rationales of intervention successes and failures, and generating more comprehensive frameworks of behavioural influence through a multi-dimensional lens, this thesis fills an important gap in our understanding of how environmental regulations like the Vegetation Management Act can directly and indirectly influence the compliant and non-compliant responses of landholders targeted for behaviour change. Although it may be impossible to completely disentangle the linkages between these dimensions of decision-making, it is important to understand the key driving factors within each dimension so that potential feedback effects can be accounted for when adapting vegetation management policy instruments.

6.1.1 Biophysical factors

Chapter 2 verified the standard assumptions regarding aggregate tree clearing patterns of landholders across Queensland: areas that are most suitable for pasture development and expansion are the primary targets for landholders' clearing regimes. These various spatial characteristics defining the agricultural suitability of the landscape accounted for more than 50% of the variance observed in clearing patterns in most regions of the state. **Chapter 3** confirmed the influence of climate characteristics on both metrics of forest cover dynamics across spatial scales, highlighting both the importance of ecological characteristics and stochastic events, such as long periods of drought, in driving clearing regimes. However, at more localised scales, important nuances in the selection of these clearing locations were detected, indicating different underlying drivers of selective clearing (**Chapter 2**). This includes differences between pasture *expansion* (i.e. extending current pastoral regimes into less favourable areas, as observed in the Brigalow Belt South) and pasture *growth* (i.e. developing new pastures, as observed in South Eastern Queensland). Ultimately, these differences in biophysical characteristics of clearing events shed an important light on how landholders' have responded to changes in vegetation management policy. Landholders in the Brigalow Belt South appear to be consistently driven by the availability of potentially profitable uncleared areas, regardless of policy changes. In contrast, landholders in the Great Barrier Reef catchment and South Eastern

Queensland responded more opportunistically to policy changes, directing their clearing efforts to more favourable locations during panic clearing and policy relaxation periods.

6.1.2 Political factors

The characteristics and absolute amounts of tree clearing were influenced by significant policy regime changes. For the first time, detailed characteristics of perverse responses to policy change (i.e. panic clearing) were identified and described across spatial scales (**Chapter 2**), and the effects resulting from these peak periods of policy uncertainty were quantified (**Chapter 3**). While responses to frequent policy uncertainty negated the potential benefits of the broad-scale clearing ban—by up to 4 M ha of remnant forests during 2007–2014—the clearing ban still exhibited positive spill-over effects onto secondary forest cover gains. These results reveal important distinctions between metrics of reforestation and deforestation that can assist policy-makers in determining what environmental indicators should be used to assess policy effectiveness and how policy instruments can differentially impact these indicators. Instruments like the broad-scale clearing ban, for example, may be best suited to deter deforestation of atypical or relatively intact landscapes, as they introduce new disincentives (both politically and socially) to undertaking new clearing regimes. In the Brigalow Belt South, however, the broad-scale clearing ban was found to be consistently ineffective at preventing deforestation. **Chapter 4** investigated this curious case further by presenting the first robust impact evaluation of the VMA in this historical clearing hotspot. Under the best-case counterfactual scenario, the Act managed to prevent nearly 20,000 ha of remnant clearing—a figure that represents less than 5% of all remnant clearing since the policy's enactment. Under the worst-case scenario, the Act may have even made the situation slightly worse due to the perverse effects of panic clearing following enactment. Today, the absolute trends in tree clearing are still the basis for politicians' and environmental advocates' claims that the Act was supremely effective during the height of policy restriction (2006–2011). This thesis, however, shows that these simple impact proxies are highly confounded by other drivers of clearing, including many of the biophysical characteristics identified in this thesis.

6.1.3 Cultural factors

Fortunately, the impacts of vegetation management policy are not all doom and gloom. Despite increasing clearing rates following regulatory relaxations (2012–2016), **Chapter 4** identified increasing effectiveness of the VMA in the Brigalow Belt South. That is, even when given more opportunities to legally clear remnant vegetation, landholders are no longer targeting these protected trees at the same rate before the Act was introduced. Thus the Act may have elicited new social signals in the agricultural community, whereby landholders are more inclined to direct their management efforts to clearing unprotected regrowth vegetation on their properties. Evidence of this potential cultural effect is presented in **Chapter 5**, which identifies different types of landholders across Queensland according to cognitive and behavioural profiles. *Active clearers*, more so than any other typology identified, stated that they were more strongly influenced by the aesthetic value of trees when making tree clearing decisions on their property. This surprising result could explain recent departures from targeting remnant vegetation: the VMA may have introduced this intrinsic valuation of nature into the clearing community, or the VMA may have activated this existing intrinsic value in landholders. Nevertheless, potentially long-lasting damage from landholders' experiences of vegetation management regulation presents a significant hurdle to provoking sustainable behaviour change. Issues of trust in the government were consistent across all landholders, and landholders' sense of security, self-identity, and perceptions of normative clearing behaviours in their community are critical to shaping their classification into these different cognitive and behavioural typologies. Such psychosocial characteristics, however, can be malleable and potentially re-aligned to reflect vegetation management goals. Combined with an increased understanding of the biophysical and political dimensions of tree clearing, this chapter offers the most comprehensive recommendations to date for promoting change in tree clearing behaviour, outlining targeted communication strategies emphasising trusted and transparent information exchange, collaborative networks, social learning, and message framing.

6.2 Creating change: contributions to conservation research and policy

6.2.1 An interdisciplinary focus on conservation behaviour

This thesis has illustrated how interdisciplinary thinking can be applied to conservation science and that complex, multi-dimensional factors contribute to environmental decision-making, which is the first step researchers must recognise in seeking to solve the global environmental crisis. Using theories, techniques, and variables characteristic of fields like political science, economics, and social psychology, the chapters of this thesis have addressed the *what*, *where*, *when*, *who*, and *why's* of the tree clearing story in the most comprehensive analysis of deforestation behaviour in Queensland to date. Better integration of these disciplines in conservation research, as well as better collaboration between researchers in these disciplines, is crucial for understanding environmental behaviours and targeting pathways for sustainable change (Bennett et al. 2016; Reddy et al. 2016). In this section, I outline how this thesis has enhanced our understanding of conservation behaviour, referencing the important connections these contributions have in the interdisciplinary decision-making space. In the following section (6.2.2), I translate the conclusions of the thesis into important implications for environmental policies attempting to regulate private land management behaviours and provide recommendations to improve policy intervention in the Queensland tree clearing context.

Investigating the impacts of command-and-control policy instruments is critical to ensuring desirable change is created by conservation efforts. **Chapter 2** provides the first characterisation of panic clearing events, **Chapter 3** is the first to quantify the perverse effects of policy uncertainty on remnant forest loss, and **Chapters 3** and **4** are the first to apply robust counterfactual thinking to assessing the impacts of the broad-scale clearing ban and the Vegetation Management Act, respectively. These results reflect important theories from political science and economics. Due to complex positive feedback effects (Jordan & Matt 2014), more regulations do not necessarily provoke more intentional outcomes (Knill et al. 2014); in fact, the norm signals introduced by regulations are highly susceptible to perverse outcomes or 'boomerang effects' (Byrne & Hart 2009) if the signals provoke reactance (i.e. resistance) responses from landholders due to emphases on lost freedoms (Cornforth 2009) or crowding out common-interest behaviours in favour of self-interest behaviours (Kinzig et al. 2013). Strict regulation is not always going to work, and indeed, it has been marginally effective for tree clearing in Queensland. Counterfactual thinking is critical for conservation research, as ecological indicators cannot separate intervention impacts from simple correlations, as is the case in Queensland.

The chapters of this thesis also reveal the heterogeneity of these impacts, providing the first investigations into the spatial and temporal heterogeneity of clearing behaviours (**Chapter 2**) and the first investigation into the behavioural, cognitive, and spatial heterogeneity of landholders across Queensland in the tree clearing context (**Chapter 5**). Together, these results highlight the importance of considering multiple scales and units of environmental decision-making, as landholders respond differently to policy intervention changes given the conditions of the natural, political, and social environments in which they make land management decisions. Social science, and particularly social psychology, has a lot to offer to conservation. In a similar way that corporations implement strategic marketing tactics to influence consumers' purchases, conservation scientists must also realise that many pro-environmental behaviours will need to be 'sold,' for example, through social marketing (Haq et al. 2013) and normative messages (Schultz et al. 2007). The identification of different types of landholders in the tree clearing context reveals important qualities that have yet to be considered (or utilised) by researchers, advocacy groups, and politicians in Queensland. Such market-segmentation approaches must be used to target policy interventions to landholders where impacts can be greatest (Mills et al. 2017), utilising methods outside of the natural sciences, like message framing and priming (Cornforth 2009; Crompton 2010; Unsworth & Fielding 2014).

6.2.2 Pitfalls and recommendations along the policy intervention cycle

With a greater understanding of the interdisciplinary nature of conservation behaviours, we can build a more comprehensive understanding of the intricate pathways of influence that environmental policy instruments exert on behaviour. Politicians, scientists, lobbyists, campaigners, journalists, and neighbours can all play a role in influencing the success of policy interventions. While these pathways of influence typically exist in disciplinary silos, the lessons learned from this thesis highlight the important roles of these actors within the policy intervention cycle, allowing for a more complete and inclusive picture of behavioural influence to be drawn. Throughout this section, I describe the roles of various stakeholders along a dynamic policy intervention cycle, punctuated by four key components influencing intervention success: (1) design and implementation, (2) monitoring and enforcement, (3) impact evaluation, and (4) communication. Figure 6.1 outlines the roles of these different components along both the direct intervention path of influence and the feedback paths of influence that shape adaptive management and behaviour. Using evidence from this thesis, and supported by the interdisciplinary literature, I identify the pitfalls and failures of each component within the Queensland vegetation management context (Fig. 6.2) and provide recommendations for each component that can reduce perverse policy outcomes and facilitate positive tree clearing behaviour change (Fig. 6.3). Recognisably, a number of additional factors and stakeholders play an important role in influencing intervention success, and these are discussed further in Section 6.3.

6.2.2.1 Design and implementation

From the outset, the potential for intervention success rests in the hands of policy-makers through the design and implementation of their policy instruments. Targets and minimum standards are established, appropriate policy instrument(s) are selected, and the spatial (i.e. local, state, national) and temporal (i.e. timing, sequencing) scales of implementation are determined. A significant degree of Queensland landholders' distrust stems from this component. Direct regulation is inherently unfavourable for most landholders (Cocklin et al. 2007), so issues surrounding the consistency and validity of these instruments and their underlying rationales will only strengthen mistrust and provoke perverse outcomes (Schmidt & McDermott 2015). As observed in Queensland, a lack of transparency regarding regulations, disagreements around a 'one size fits all' approach to vegetation management, frequent changes in the restrictions and objectives of the VMA, and the unpalatable nature of command-and-control regulation propelled panic clearing behaviours.

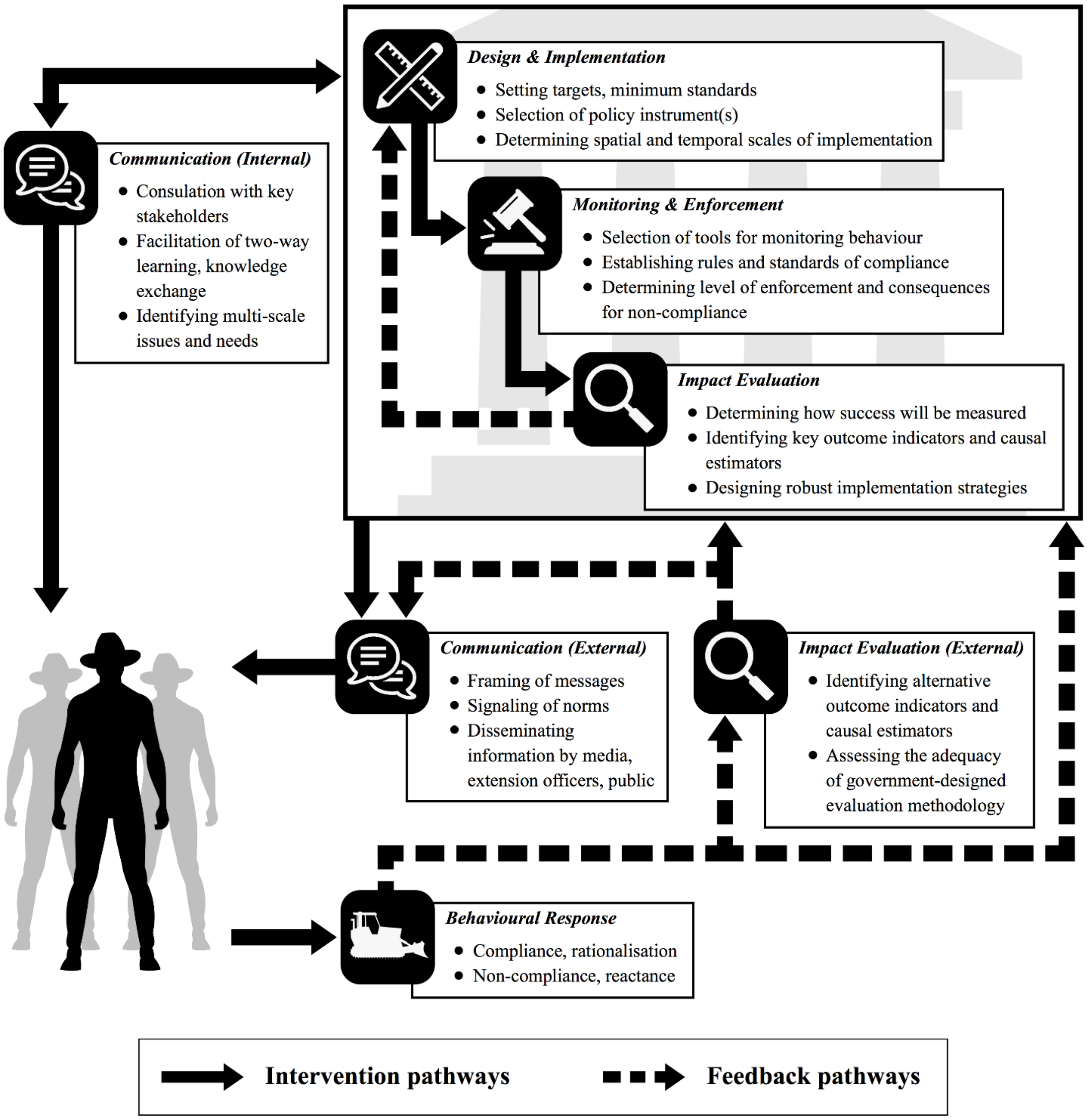

Fig. 6.1. Key components punctuating the various stages of the policy intervention cycle. Influences of additional factors, such as climate, personal circumstances, market forces, and non-governmental organisations and their instruments, are excluded.

As vegetation management policy adapts in the future, it is imperative that its objectives remain consistent and abrupt changes to restrictions are minimised. Many landholders expressed frustration and confusion over the lack of consideration of the heterogeneity of land management requirements across the variable landscape. While it is important for baseline standards and targets to be established at state or national levels, environmental decision-making is a multi-scale process, and greater consideration should be given to regional and local conditions and proposing relevant standards that can account for considerable heterogeneity of landscapes (Anderson et al. 2009).

Despite a role for Local Government Areas to apply VMA regulations within their jurisdictions, greater flexibility and subjectivity of state-level rules to be interpreted and implemented by local governments could be beneficial; this is only the case, however, if they have the resources and capacity to enforce adequate applications of the law to fit the economic and ecological needs of their communities, and if this does not generate more uncertainty or ambiguity around legal and illegal activities for landholders. Examples of similar decentralised regulations, like those within the Brazil Forest Code, have indicated that these tactics can be quite favourable to stakeholders (Bauch et al. 2009).

This could also be facilitated by implementing a greater mix of extension-based approaches to curb tree clearing rates, which can greatly complement regulatory intervention (Santos et al. 2006; Lambin et al. 2014). It is currently unclear, however, what instruments may prove successful in curbing tree clearing in Queensland. Some market-based incentives have been suggested as alternative instruments, such as carbon farming (e.g. Evans 2018), but these tactics may have perverse psychological outcomes (Agrawal et al. 2015) or marginal large-scale impacts (Cooke & Moon 2015). And although some previous voluntary instruments have been well-received by landholders in the past (e.g. Landcare, Caring for Our Country), evidence suggests they have minimal conservation effects beyond the property level and may reinforce resistant attitudes toward top-down controls (Lockie & Higgins 2007). In response, some scholars have argued that environmental cooperatives may be able to effectively generate widespread support and participation of landholders while delivering environmental benefits at the necessary landscape level (Cooke & Moon 2015). In the end, increased government recognition of the potential value of more incentive-based instruments (whether financial or non-financial), could at the very least improve landholder attitudes toward intervention efforts at all levels, and more research will need to examine the potential effectiveness of different incentive-based instruments (cf. Section 6.3.4).

6.2.2.2 Monitoring and enforcement

Informed by the design and implementation of the intervention, policy-makers must determine what tools will be used to monitor compliance, the standards of compliance, the level of enforcement of these standards, and the consequences for non-compliance. While Queensland employs the most detailed and accurate monitoring system of tree clearing in the country (SLATS) (Macintosh 2007), a number of surveyed landholders argued that the vegetation maps employed by the state are inaccurate, and the use of satellite surveillance techniques is largely unfavourable to landholders, citing concerns about privacy (Bartel 2005). Additional issues have risen stemming from high-profile cases where oversight at the state level resulted in permitting up to 32,000 hectares of remnant clearing (Willacy & Solomons 2015; Slezak 2017). Strict enforcement of regulations is important for ensuring effectiveness (Ferraro et al. 2013; Arima et al. 2014), but inconsistencies or inadequacies in persuading compliance and punishing non-compliance are a hindrance to tree clearing regulation (Bartel 2008).

Importantly, despite annual SLATS reports of tree clearing across the state, the consideration of multi-scale spatial and temporal patterns of clearing is lacking. The results of this thesis highlight the importance of identifying regional-scale patterns across multiple facets of tree clearing, as we observed heterogenous patterns in terms of the extent, frequency, timing, and characteristics of clearing events. Given ecological and social conditions are spatially and temporally heterogenous, using coarse or incomplete measures to monitor behavioural responses can overlook micro- and meso-level drivers of clearing and, subsequently, micro- and meso-level intervention impacts (Pfaff & Robalino 2012; Bos et al. 2017; Carlson et al. 2018). Decentralising enforcement may also be beneficial for Queensland. Local governments and communities can play a greater role in monitoring and enforcing compliance, which can improve adaptive management (Bauch et al. 2009) and may be more effective at reducing forest loss than state-level governance (Cardenas et al. 2000; Corrigan et al. 2018).

Future policy development would benefit from an improved understanding of state- and regional-level responses surrounding clearing regulation and its evolution, as goals and targets (cf. Section 6.2.2.1) can be adapted to reflect the relevant clearing dynamics across the state. This should also include a broader suite of impact indicators and outcomes to monitor (cf. Section 6.2.2.3), beyond the mere amount of clearing, which only describes a piece of the tree clearing situation. For example, Rhodes et al. (2017) tracked bioregional trends in tree clearing between threatened and unthreatened vegetation, arguing that improved monitoring and spatially-targeted enforcement regimes could address the disproportionate clearing pressures facing vegetation in different parts of the state. Queensland's Department of Environment and Science is currently in the process of improving the technology used to generate maps of vegetation in the state (D. Vandenberg, personal communication), which will hopefully minimise future conflicts with landholders and facilitate greater trust—though this will be heavily dependent on the communication of these surveillance techniques to landholders. Recognising the financial limitations for complete monitoring and enforcement on behalf of the state (Albers 2010), the role of neighbours in monitoring and reporting tree clearing activities may also be important for promoting voluntary compliance norms, which are an important complement to coercive compliance methods (Arias 2015, cf. Section 6.2.2.4).

6.2.2.3 Impact evaluation

Policy instruments must have some reflective capacity to ensure the interventions are eliciting the desired behaviours; after selecting the necessary tools to monitor behavioural responses, policy-makers must outline their methodology surrounding impact evaluation—how success will be measured, the outcome indicators and causal estimators of relevance, and how to implement the instrument to facilitate causal inference. The continued reliance of impact indicators, such as the amount of clearing, by politicians, scientists, and lobbyists as justification for the effectiveness of previous VMA regulations is both inadequate and a hindrance to policy reflection and adaptation. Like Queensland, this reliance on impact indicators has overestimated avoided deforestation resulting from command-and-control instruments across the globe (e.g. Andam et al. 2008; Joppa & Pfaff 2011). Additionally, this perceived effectiveness by politicians, scientists, and environmental advocates does not align with landholders' perceptions based on their lived experience, further jeopardising trust and validity in the intervention, and therefore policy support and compliance.

The government must change its current associative measures of impact evaluation to more causal measures to ensure real behaviour change is occurring, controlling for the influence of confounding factors. This is crucial for guiding changes in the design and implementation of policy instruments (Arriagada et al. 2012; Azevedo et al. 2017), as simply increasing the number or intensity of regulations may not create the desired impacts (Knill et al. 2012). Furthermore, it would be beneficial to design robust methods that can evaluate the VMA's effectiveness across all of its stated objectives (e.g. avoiding land degradation, preventing biodiversity loss, reducing greenhouse gas emissions) to understand where improvements can be made and how tree clearing affects the environment at grander scales (Reside et al. 2017). However, I must assert that impact indicators do serve an important purpose for monitoring the current state of the environment. The government should not abandon monitoring the extent of tree clearing, species abundances, carbon emissions, etc. These indicators are important for guiding environmental protection policies, monitoring global environmental commitments, and identifying early warnings of perverse outcomes (Ferraro 2009; Larrosa et al. 2016). In isolation, however, they cannot inform us of the success of current or historical interventions.

Impact evaluations from outside Parliamentary walls are also important for adaptive management. While it is generally good practice to have independent organisations evaluate the effectiveness of policy instruments, the potential additionality or indirect effects of these interventions can reveal important outcomes that are relevant to other organisations or stakeholders, such as poverty (Ferraro et al. 2011), well-being (Arriagada et al. 2015), and social capital (Zammit 2013). The results of these external evaluations can be directly communicated to policy-makers, allowing for necessary changes to the design or evaluation protocols, as well as to the stakeholders, potentially modifying their current behaviours more directly. Such evaluations need not only come from scientists, and the implementation of external evaluations from non-governmental organisations should be encouraged. Given complaints from landholders and agricultural lobby groups, evaluations of the impacts of vegetation management regulations on landholders' economic situations could be particularly beneficial for informing future policy debate, guiding adaptation, and introducing new market-based policy instruments.

6.2.2.4 Communication

Governments need not (and should not) make all of the aforementioned decisions in isolation. Communication between policy-makers, scientists, industry experts, and other key stakeholders during the design and implementation stage of the policy intervention cycle can be highly influential on the relevancy and potential success of policy instruments, as it can facilitate two-way learning and knowledge exchange, strengthen networks and social capital, and identify specific issues and needs at various spatial scales, which often increase landholders' acceptance and engagement in policy interventions (Schenk et al. 2007; Blackmore & Doole 2013; Zammit 2013; Halbrendt et al. 2014). Admittedly, the Queensland Government has attempted to accomplish this task in the past, yet the failures of their approaches far outweigh any potential benefits. For instance, shortly after the enactment of the VMA in 2000, the Vegetation Management Extension Framework was implemented to allow landholders to provide feedback to policy-makers regarding the minimum standards needed in their community to sustain ecological function (Westrup 2001). Despite their claims, however, the government decided it would be too difficult to establish and monitor such diverse standards across the landscape, and landholders' recommendations were dismissed in favour of one standard benchmark for maintaining all remnant vegetation to at least 30% of its pre-clearing extent (Lockie & Higgins 2007). For many landholders, this signalled the government's lack of consideration of their knowledge, as well as scientific inaccuracies forming the basis of the Act's regulations. During debate of proposed bills in more recent years, the government has held community forums and allowed for stakeholders to submit comments on the proposed legislative changes, but the dates and deadlines of these events were given with very short notice and held in a few select towns, which limits the amount of knowledge exchange that can occur with many stakeholders (Siepen & Westrup 2002).

During this thesis, many landholders expressed an openness to sharing their issues and experiences with vegetation management, with a number of those surveyed even inviting me to stay at their home for a few days so they could give me a tour of their community. It has become apparent that landholders are open to a dialogue, provided they believe others are listening rather than lecturing and that their voices are valued. Comerford (2014) also found that communicating with natural resource management groups or environmental non-governmental organisations was not a deterrent for landholders' participation in covenant programs. These exchanges are important, especially for natural resource management (Lynam et al. 2007), as opinions between landholders and experts can vary substantially (Tudor et al. 2015), and in some cases landholders' predictions may outperform those of experts (Halbrendt et al. 2014). Future policy changes should be designed with a greater emphasis on community participation, which will be important for re-building landholders' sense of trust in the government and can re-establish valued relationships between landholders and extension officers (Santos et al. 2006; Blackmore & Doole 2013).

Communication of the resulting policy instrument(s) through various information channels by actors like journalists, industry experts, extension officers, and the general public is a critical component for provoking behaviour change; face-to-face communication, in particular, may be most successful for engaging landholders (Mills et al. 2017). Depending upon the content and framing of these messages, as well as the source disseminating the information, norm activation can provoke rationalisation or reactance behaviours (Proudfoot & Kay 2014). Despite great dismissal from conservation scientists in the tree clearing space, the results of this thesis provide evidence that landholders' cognitive and behavioural characteristics are deeply affected by a number of communication failures surrounding tree clearing (e.g. the villainous portrayal of landholders, perceptions of clearing norms, lack of recognition of conservation efforts on farms, poor translation of ongoing policy restrictions). The resulting disengagement from these failures can have significant consequences for intervention effectiveness, particularly if highly disengaged landholders inhabit areas of high conservation value (Raymond & Brown 2011).

Owing to landholders' high conservation values, appreciation of aesthetic values of nature, and disengagement with top-down controls, future policy changes should be communicated more clearly to landholders by extension officers and trusted leaders in the community (local champions). Since many landholders have a tendency to view supporters of the VMA outside of their in-group, utilising trusted peers to communicate these messages can promote stronger support and rationalisation of regulations through enhanced trust, credibility, and perceived similarity (Burchell et al. 2013; Torabi et al. 2016). These messages should also shift from a focus on emphasising large-scale remnant clearing (which is not reflective of the majority of landholders' clearing behaviour) to emphasising stewardship values and highlighting positive environmental behaviours of landholders to activate conservation-oriented norms. Utilising more common-interest frames over self-interest frames can enhance landholders' intrinsic—and potentially subconscious (Sherren et al. 2011)—valuation of remnant trees, while simultaneously enhancing other environmentally-friendly behaviours (Crompton 2010). If these approaches are successful, they may also effectively improve landholders' sense of control and security, trust in the government, and reinforce the benevolent stewardship identities of farmers, which would likely reduce the number of active clearers in the landscape and minimise potential boomerang effects (Kinzig et al. 2013).

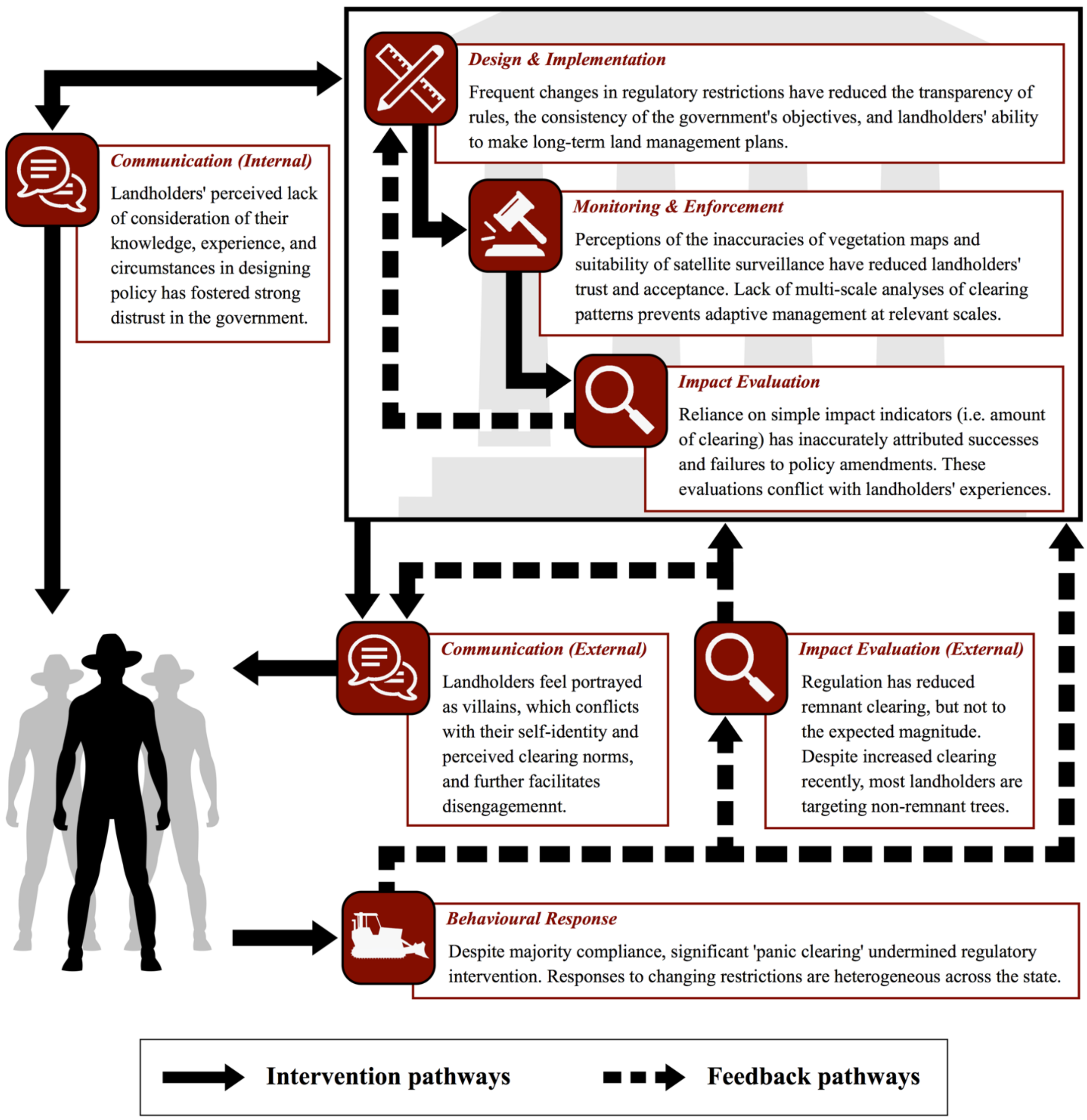

Fig. 6.2. Pitfalls identified along the stages of the policy cycle of the Vegetation Management Act 1999. Influences of additional factors, such as climate, personal circumstances, market forces, and non-governmental organisations and their instruments, are excluded.

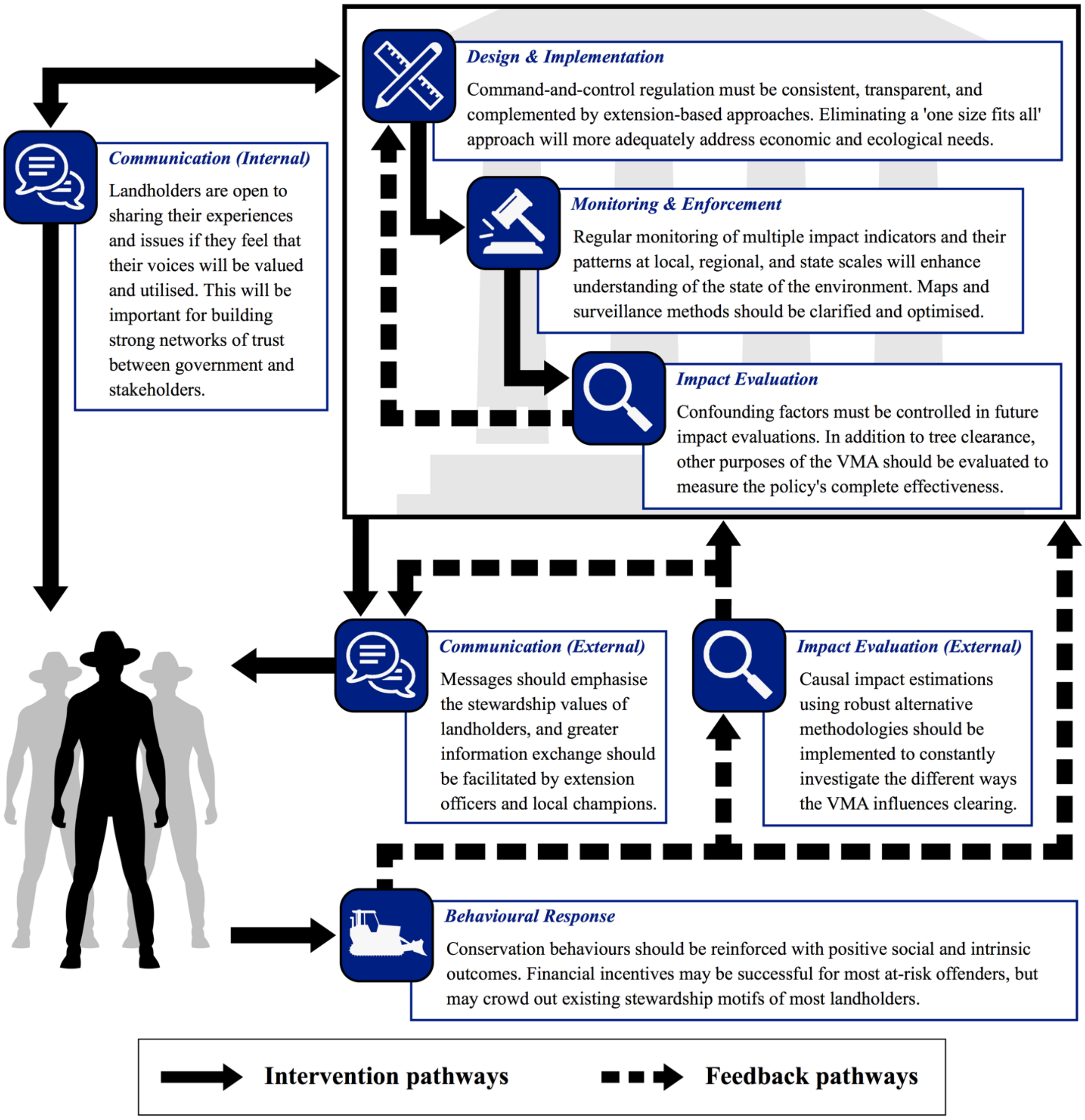

Fig. 6.3. Recommendations along the stages of the policy cycle of the Vegetation Management Act 1999 to promote sustainable tree clearing behaviour change. Influences of additional factors, such as climate, personal circumstances, market forces, and non-governmental organisations and their instruments, are excluded.

6.3 Completing the tree clearing puzzle

6.3.1 Data limitations

Despite the relative accuracy and precision of the SLATS datasets, clearing data prior to 2000 were aggregated into multi-year epochs (i.e. 1988–1991, 1991–1995, 1995–1997, 1997–1999), which impeded our ability to track finer-scale temporal changes in clearing characteristics (**Chapter 2**), as well as our ability to construct a more reliable counterfactual of clearing in the Brigalow Belt South (**Chapter 4**). Additionally, the extent of remnant clearing was only (reliably) monitored since 1997–1999, which further limited the development of a proper counterfactual in the causal inference analysis. While the two counterfactual scenarios we created to account for the range of potential trends, the final results undoubtedly have a greater degree of uncertainty without more pre-intervention data. Similarly, the extent of high-value regrowth was monitored beginning in 2007, thus eliminating any potential for reliably estimating impacts on this important vegetation. With more time, however, and perhaps with the aid of the Queensland Herbarium, more accurate historical maps could be estimated and utilised for future research. Admittedly, the NCAS dataset used in **Chapter 3** has been criticised for its imperfections at monitoring tree cover (Macintosh 2007). This is the best dataset that provides a consistent and long-term measure of forest cover across Australia, and thus is most relevant when considering how Australia reports on the state of its forests. While it is possible that such remote-sensed datasets suffer from uncertainty due to issues of image misclassification (Martínez et al. 2011), our approach attempted to minimise these uncertainties by controlling for unreasonable changes between years. Inherent differences between NCAS and SLATS, therefore, imply that the deforestation rates obtained by each cannot be directly compared. It is encouraging that the results of **Chapter 3** showed similar relationships between the drivers of deforestation and the different metrics of forest cover, but trends in remnant tree clearing are best estimated from the SLATS dataset. Luckily, the limitations of the NCAS data are well-known to stakeholders and its classification algorithms are constantly being improved, so a more reliable dataset may be available in the near future, such as those implemented in Brazil (Diniz et al. 2015).

As with most freely available data from the government, I encountered some issues with other variables, such as the property and tenure spatial data (**Chapters 2, 3, 4**). I uncovered a number of instances where some parcels of land did not have a property assigned to them, or multiple tenure classifications were overlayed on a single parcel (e.g. freehold and leasehold). After making side-by-side comparisons of the potential outcomes from selecting either tenure classification, I found the differences to be noticeable yet relatively minimal. I therefore made my best judgements for each property as to which tenure classification would be most logical. Thus it is possible that some tenure properties were incorrectly labelled. This could have potentially been remedied by purchasing a more accurate, cleaned dataset from the government, but this was not feasible given the budget during the early stages of this thesis. The lack of some property information also made it unreliable to state which parcels of land jointly made up one property; therefore, I decided to represent properties as individual parcels of land, which could mask the influence stemming from properties with multiple parcels of land that should be treated as one unit for decision-making processes. It would have also been valuable to obtain a spatial dataset outlining the market values of these properties, which could be an important driver of clearing (e.g. Rhodes et al. 2017). However, this dataset also must be purchased from the government, and even still, it represents a fixed value as of 2012, which may provide limited usefulness in understanding dynamic clearing patterns. I have now been gifted this dataset from colleagues, and it would be useful to incorporate this variable into future investigations.

Finally, the dataset obtained from surveyed landholders (**Chapter 5**) has a recognisably limited sample size (N = 265). I had initially aimed to obtain this same sample size solely for the Brigalow Belt South, but it became clear during the recruitment process that it was not feasible to reach that many landholders in such a remote region. After exhausting recruitment efforts in this bioregion (obtaining approximately 130 responses), it was decided that other bioregions would also be targeted. To maximise relevancy, these efforts were targeted toward regions with relevant clearing histories, but the final sample size is small relative to the distribution of landholders surveyed across the state. This sample also has a relatively high median age (62 years) compared to the 2017 census data of the greater Darling Downs area (41 years, ABS 2018). This may have been influenced by the higher likelihood that older landholders would be home to answer the phone and have the time to answer the questions. The results of our analysis indicate that *active clearers* were significantly younger (median 54 years); had a greater number of younger landholders been obtained, this may have illuminated even more meaningful differences between landholders within this typology. Given more time and funding, a greater sample size could have been obtained through other solicitation methods, such as radio advertisements, posting ads in community centres or town halls, or mail-out surveys. It is also important to recognise the responses of this dataset represent a single snap-shot of the current social dimensions surrounding the tree clearing space. Under more ideal circumstances, these surveys would be carried out more frequently over time to produce longitudinal datasets that reflect the dynamic nature of these social systems (Stidham et al. 2014). While some comparisons could be made between the results of this chapter and that of the small-scale investigation into farmers' motivations to retain trees by Seabrook et al. (2008), statements regarding how these psychosocial drivers have evolved over time (and thus influenced clearing dynamics) cannot be made just yet.

6.3.2 Important assumptions and caveats

Although the analyses performed throughout this thesis are designed to be robust to potential biases, they rely on a number of assumptions. The conclusions drawn from **Chapters 2**, **3**, and **4**, assume that changes along the policy timeline are due to the most pronounced and observable changes in the Vegetation Management Act. However, it is important to recognise that these changes are not the only changes occurring in this sphere. Changes were also likely occurring beyond the VMA, including changes in legislative processes, relationships between stakeholders, and other state and national environmental policies, which could have significant effects on tree clearing and subsequent impact estimations of the VMA (Capano 2009). Given more time, all of these underlying changes could be mapped and assessed against changing clearing patterns, though I hypothesise most will only have marginal or indirect effects compared to the VMA, which is the primary instrument used to regulate clearing. Further, the purposes of the VMA have also changed over time. Throughout this thesis, we made all assumptions of VMA effectiveness with reference to the original primary purpose of the Act, which was to "preserve" remnant vegetation. Today, however, the primary purpose is to "conserve" remnant vegetation; thus there has been a shift in phrasing from implying remnant trees be *untouched* to *sustainably managed*, which is an important distinction, however subtle the change may be. We also do not consider the effectiveness of the Act against its other stated objectives. Given more time and better data, however, it would be prudent to investigate all of these measures of effectiveness.

The analyses also do not explicitly consider the potential interactions between policy instruments (e.g. protected area designations, market-based or voluntary incentive schemes) on the impact of the broad-scale clearing ban (**Chapter 3**) or the VMA (**Chapter 4**). Despite the robustness of these models, these unobservable interactions could have complementary, substitutive, or antagonistic effects on command-and-control impacts (Lambin et al. 2014), as well as on one another (Bryan 2013), which would be difficult to disentangle without more complex modelling techniques and detailed spatiotemporal datasets of household-level participation in these instruments. Although the tenure dataset included in this study does identify some conservation covenant lands, which have seen a rapid increase in uptake in Queensland (Fitzsimons 2015), it does not indicate when these lands were enrolled, and there are many other voluntary, non-binding schemes that may not be sufficiently captured in these databases (Curtis & Lockwood 2000). Further, the impact analysis in **Chapter 4** attempts to control for potential moderators of impact, but does not investigate the effects of mechanisms of impact—variables that are affected by the intervention and subsequently affect its impact on the treated units (Ferraro & Hanauer 2014). Given the newfound understanding of the different dimensions of clearing, however, it could be possible to estimate the effects of potential mechanisms in future impact analyses, but this will require more intensive and comprehensive mind mapping of the different interactions between landholders and all of the available policy instruments.

The potential for spill-over effects is also an assumption that could be violated. As **Chapter 3** identified, a potential positive spill-over may have occurred from the broad-scale clearing ban, which had a significantly positive influence on secondary forest cover gains. As this ban does not have any direct bearing on secondary forests, this could mean that this temporal indicator is reflecting some other hidden change in reforestation efforts, or that new social signals were elicited to reforest areas. For **Chapter 4**, the analysis assumes no spill-over effects are present. A number of studies have identified significant spill-over effects, such as higher deforestation in properties adjacent to neighbouring properties where deforestation is occurring (e.g. Andam et al. 2008; Robalino & Pfaff 2012). In most cases, however, these effects are prominent in the context of protected area establishment, which will be influenced by different mechanisms than broad command-and-control regulations on private properties. Nevertheless, it would be beneficial for future impact evaluations of the VMA to consider the possibility of these spatial interactions, perhaps by using more explicit spatial matching techniques (e.g. Honey-Rosés et al. 2011).

I must also recognise potential caveats or biases surrounding the design, implementation, and responses of the survey in **Chapter 5**. Given the timing of the survey solicitation—immediately following the passing of the new VMA amendments—it is possible that some degree of participation bias may exist, where landholders who were strongly pro- or anti-regulation would be most inclined to express their opinions. In a similar vein, responses to some survey questions may also be biased due to the political environment or the questions presented to them. For example, Proudfoot and Kay (2014) found that when participants' attitudes were directly assessed, they were more likely to provide reactance-based responses (i.e. strongly opposed to regulation). Thus it is possible that some of the questions presented may have unintentionally influenced landholders' responses. The analysis for this chapter also assumes the participants were honest and accurate in their responses, that they understood and interpreted all questions as intended, and that the sample adequately reflected the true population of graziers in the region. While it appears that the self-reported clearing behaviours of *active* and *inactive clearers* align with recognised hot- and cold-spots of total clearing, there was no correlation between typologies and remnant-specific clearing hotspots. Thus it may be that landholders were honest about their clearing behaviours and there was simply not enough prolific remnant clearers in the sample, or they may have intentionally underestimated their amount of remnant clearing in their total clearing accounts. All survey questions had undergone initial pilot testing, and the final questionnaire reflects adaptations based on prior feedback from the test audience to ensure no problematic items were present. Future studies would benefit from explicitly asking landholders about their remnant clearing behaviours, but as this may largely constitute illegal behaviours, we avoided asking this question to promote more trusting attitudes toward the survey. Finally, landholders' responses to the various psychosocial and behavioural measures are assumed to accurately reflect their recent history. Some evidence has shown, however, that landholders' stated farming objectives and behaviours does not reflect their past behaviours (e.g. Guillem et al. 2012). Additionally, some typologies identified may be experiencing false consensus effects (Mannarini et al. 2015), whereby they inaccurately assume most people in their community behave and share the same perceptions as they do. Given more time and resources, these responses could be tested against past clearing observations, but this would only be possible for those landholders that provided more detailed spatial information regarding their place of residence, which was an even smaller sample size.

6.3.3 Strengthening causal linkages between variables and behaviour

This thesis has identified a number of tree clearing drivers across multiple analyses, but confirming causal pathways of influence is exceptionally difficult. Ultimately, understanding the relationships and interactions of moderators and mechanisms of policy impact requires identifying the relevant scales at which tree clearing patterns are defined, using robust experimental designs for impact evaluations, and investigating all potential variables that could affect decision-making. Despite the relevance for recognising household- or intrahousehold-level decision-making (McGregor et al. 2001), this was not the unit of analysis for most chapters of this thesis. This was primarily due to the lack of reliable household identification information in the property dataset, but it also would have been difficult to estimate how many different properties were under the control of a single landholder. **Chapters 2** and **3** thus considered clearing patterns at 100 m and 1 km resolutions, respectively, to reflect relevant biophysical scales, and **Chapter 4** considered a 25 m pixel resolution to identify discrete treated and untreated plots of vegetation, relevant to the scale of SLATS measurement. Given better property-level data, different impact estimations and important management implications could appear if individual properties were used as the unit of analysis, which would be beneficial for future investigations. Ideally, utilising a range of scales will be most informative for understanding decision-making processes.

Though grounded in the literature, the design and analysis of some chapters also presents some limitations to identifying causal pathways of influence. In an ideal, proactive setting, causal impact evaluations should be constructed following robust experimental designs; that is, treated and untreated units are selected randomly in the landscape and are identical across observable characteristics except the treatment status (Ferraro 2012). For **Chapter 4**, however, we had to implement a quasi-experimental design, as is common for most environmental policy impact analyses. Although controlling for a number of confounding factors created sufficient match balance between remnant and non-remnant trees, there are inherent differences between the two types of vegetation. For example, remnant trees are under greater clearing pressures than non-remnant trees, and this is why the VMA was enacted to begin with. In fact, this issue is often present in conservation impact estimations (e.g. Alix-Garcia et al. 2015), but as long as the control units have "some underlying structural similarity to the treated unit in terms of the processes that generate the outcome"

(Sills et al. 2015), robust matching methods can minimise this potential bias. It is also worth noting that high-value regrowth could also have been considered 'treated' by the VMA during 2009–2013. Ultimately, however, high-value regrowth was excluded from treatment status as it was not part of the original primary purpose of the Act, and there was minimal pre-intervention data on the extent of this vegetation category. It would be interesting to evaluate how effective the 2009 amendment to the VMA was at protecting high-value regrowth given more time and consideration of the different policies relevant to this vegetation. The identification of the psychosocial and behavioural typologies in **Chapter 5** can also be criticised, as defining landholder typologies is both difficult and subjective due to the changing status and identity of farmers over time (Burton & Wilson 2006). While these typologies were chosen based upon hypotheses derived from the literature and previous chapters, it is possible that other typologies could be distinguished that better reflect the interplay of psychosocial and behavioural characteristics on landholders. Due to time constraints, however, more explorations into different typology orientations were not feasible, but it will be an important investigation for future analyses.

Understanding *why* landholders decide to clear trees is a challenging task, as the literature is overflowing with potential political, socioeconomic, and psychosocial drivers of decision-making that vary on a case-by-case basis. Due to limitations in model parameterisation, data availability, and survey length, the following variables were not investigated in this thesis but could be relevant in the Queensland tree clearing context: (1) political factors, such as the influence of campaigns and activist groups (Whelan & Lyons 2005), and the number, intensity, and direction of policy changes (Knill et al. 2012); (2) socioeconomic factors, such as land prices (Armsworth et al. 2006), assets and farming resources (Arriagada et al. 2015, Dayer et al. 2018), training experience (Seabrook et al. 2008), debt (Hamblin 2009), and economic reliance on farming (Raymond & Brown 2011; Comerford 2013); (3) psychosocial factors, like habits (Klöckner 2013), farming motivations or goals (Farmar-Bowers & Lane 2009), knowledge and awareness of environmental issues (Schirmer et al. 2012), connectedness to nature (Gosling & Williams 2010), injunctive or subjective norms (Smith et al. 2012; Niles et al. 2016), political or occupational identity (Groth et al. 2014; Unsworth & Fielding 2014), and media influences (Ryffel et al. 2014). Finally—and perhaps most importantly—it may be that the most relevant question is not, 'Why do landholders clear trees?' but rather, 'Why do landholders *not* clear trees?' (Seabrook et al. 2008; Schirmer et al. 2012). This important distinction may be necessary for understanding a different perspective on the tree clearing story, or at least to complement our understanding of clearing behaviours. Although it is unrealistic to expect all of these factors could be measured and analysed to investigate drivers of tree clearing, the current understanding of how these different dimensions influence tree clearing can inform the development of future studies seeking to complement the current findings of this thesis with other select variables. Perhaps the most logical approach for future research would be to present as many of these variables as possible to landholders in a mind-mapping exercise to eliminate the most unlikely drivers in this context. There are certainly no shortages to the possibilities for further research on landholders' decision-making, and the results of this thesis provide a crucial foundation for solving the tree clearing puzzle.

6.3.4 Future directions

While a number of potential drivers of behaviour exist, it is important to recognise that each case study system will require its own investigation to eliminate rival explanations that may be relevant elsewhere (Knowler & Bradshaw 2007). An important next step to understanding tree clearing behaviours is constructing and testing models of behaviours that can make more direct, quantifiable linkages between social-ecological feedback mechanisms affecting decision-making (Meyfroidt 2013). Future studies could benefit from investigating well-established frameworks of environmental decision-making, such as the value-belief-norm framework (Kaiser et al. 2005), theory of planned behaviour (Klöckner 2013), and theory of interpersonal behaviour (Feola & Binder 2010), as well as unique modifications or combinations of decision-making models that may be more relevant for the tree clearing context (Mastrangelo et al. 2014; Price & Leviston 2014). In some cases, these models have been used to explain 64–95% of people's conservation behaviours (Kaiser et al. 2005) and can provide important insights into the relationships and potential feedbacks occurring as landholders interpret and evaluate their clearing behaviours.

The large variety of psychosocial variables measured in **Chapter 5** would allow for many of these established theories to be tested and many potential pathways of influence to be investigated. For example, structural equation models could be designed to analyse the (in)direct relationships of landholders' clearing and regulation attitudes, perceived behavioural control, self-identity, and perceived norms on their clearing intentions (i.e. a test of the theory of planned behaviour), which could then be assessed against their actual clearing behaviours in the last five years. Alternatively, the results of **Chapter 5** indicate that the following variables may have greater significance on clearing behaviours in the Queensland context: sense of security, clearing influences, 'good farmer' definition, and awareness of norms. Ultimately, a number of models will need to be designed and compared. In addition, time limitations prevented me from analysing the importance of different types of media on informing landholders' decisions, and this should be incorporated in future analyses to identify the relevant information channels influencing behaviour.

This thesis has focused on a singular command-and-control policy instrument, but a number of other instruments may be influencing tree clearing behaviours, such as direct payment schemes for conservation (Hajkowicz 2009), conservation covenants (Fitzsimons 2015), and heritage agreements

(Leaman & Nicolson 2014). It will be important to consider the potential participation rates and effectiveness of these various approaches, which require a greater understanding of the motivations driving landholders' willingness to engage with these instruments (Greiner & Gregg 2011). For example, some instruments rely on financial incentives to encourage greater participation and uptake of conservation practices, yet the literature is inconsistent in its support for this approach; despite the importance for using monetary incentives to increase uptake for some of the most resistant types of farmers (Kabii & Horwitz 2006; Kusmanoff et al. 2016), the interactions of multiple financial incentives can affect environmental outcomes (Bryan & Crossman 2013) and may crowd out the intrinsic, environmental motivations for conservation (Agrawal et al. 2015). Alternatively, an increasing number of studies are arguing that the use of non-financial incentives are most likely to promote participation from landholders, such as increased social recognition (Greiner & Gregg 2011), social learning (Selinske et al. 2015), and stronger relationships with extension officers (Selinske et al. 2017). In some cases, however, capacity-building incentives like increased education, support, and training can result in a boomerang effect, whereby participation rates decline as landholders feel they no longer need assistance (Blackmore & Doole 2013).

The survey designed in **Chapter 5** also included a subset of questions asking participants, "Which option is most important to you when considering bush management schemes?" They were presented with ten unique pairs of hypothetical contract attributes for preservation schemes from which they could choose only one attribute per pair. This included one direct financial attribute (*financial compensation per hectare*), two indirect financial attributes (*option to certify produce as 'bush friendly'*, *extra public funding for community-based projects*), and seven non-financial attributes (*most farmers in the region being involved*, *regular updates on the scheme's outcomes*, *training in best management practices*, *flexibility to choose the length of the program*, *flexibility to choose the areas of land to be included*, *low compliance monitoring*, *low paperwork*). The results of this small choice experiment are currently in preparation for submission to an environmental economics journal, but they reveal that landholders' sense of security is strongly related to whether they prefer financial or non-financial incentives, which is an important extension to the results in this thesis.

Extending this research into incentive preferences further, it would be interesting to measure the potential usefulness of the different policy instruments available (e.g. protected areas, carbon farming, covenants). This could come from the design of a similar series of choice experiments, but the preference for these hypothetical instrument options would be measured under various social, political, and economic contexts. Similar strategies have been employed to understand the effects of regulatory crowding out on optimal economic decision-making (Cardenas et al. 2000), what types of motivations drive willingness to participate in conservation programs (Greiner 2015), and how attitudes affect landholders' willingness to pay for conservation benefits (Hoyos et al. 2015). This would also present more opportunities to investigate how landholders perceive and cope with varying levels of risk (Levin et al. 1998; Mase et al. 2015), which could provide a more direct measure of the effects of (e.g.) policy uncertainty, droughts, and message framing on regulatory compliance, their interaction with different policy instruments, and overall tree clearing decision-making.

Finally, it would be wise to use this new knowledge to identify areas where different interventions would be most successful. Future research endeavours could utilise this greater understanding of relevant drivers of tree clearing to estimate optimal configurations of the landscape for biodiversity, identify areas prone to heterogeneous intervention impacts, and determine the most cost-effective locations or land management practices for future conservation investments. For example: (1) would interventions be more successful under a land-sharing or land-sparing mosaic (e.g. Balmford et al. 2012), or targeted preferentially toward marginal lands rather than productive lands (e.g. Batáry et al. 2015)? (2) which areas are more likely to experience smaller or larger impacts based upon the local deforestation pressure (e.g. Rhodes et al. 2017) or habitat characteristics (e.g. Carlson et al. 2018)? (3) which areas would be most cost-effective for intervention efforts (e.g. Kalcic et al. 2015) or for certain market-based incentives (e.g. Evans et al. 2015)? These various applications of spatial planning and prioritisation are crucial to understanding the trade-offs between engaging landholders and maximising environmental returns (Raymond & Brown 2011; Sorice et al. 2013).

It will be important for researchers to consider how social factors vary across the landscape, as they will inevitably impede or facilitate intervention success (Bryan et al. 2010; Knight et al. 2010). An interesting avenue for future research could utilise the spatial psychosocial data from **Chapter 5** to map areas of Queensland where landholders are most likely to engage in conservation efforts, which could then be compared with a map of the most important areas for biodiversity conservation. Promising results in the literature indicate that conservation planning software, such as Marxan and Zonation, can combine important social and ecological data to produce optimal planning solutions that deliver high conservation benefits (Troupin & Carmel 2014; Whitehead et al. 2014). The results would then inform which locations are more likely to succeed with minimal or maximal persuasion, perhaps in the form of financial versus non-financial incentives. Ultimately, if the different biophysical, political, and cultural drivers of tree clearing can be identified, quantified, mapped, and manipulated, sustainable land management change may finally be achieved in Queensland.

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Appendices

Appendix A. Details of the principal component analyses

Prior to analysis, two tests were applied to each case study to assess the usefulness of principal component analysis for the datasets. Bartlett's test of sphericity assesses the degree of collinearity in the dataset (Bartlett 1950). We reject the null hypothesis of zero correlation between variables at a significance level $\alpha = 0.05$ and determine that there is sufficient collinearity between variables for analysis. In addition, the Kaiser-Meyer-Olkin (KMO) test of sampling adequacy is applied to all datasets, which measures the adequacy of the correlation matrices by estimating the degree of common variance among variables (Kaiser 1970). The number of principal components selected was based upon the commonly used Kaiser Criterion (Kaiser 1958) and verified by a scree test (Cattell 1966). The Kaiser Criterion retains principal components with eigenvalues—the variance captured within a component, E—that extract at least as much variance as one original variable ($E \geq 1$). To compliment this selection method, we use a scree test to visually identify large breaks in principal component eigenvalues; when the difference in eigenvalues between components begins to level off, we select the leftmost component before this break. For all case study regions, the scree test identified few potential breaks in component eigenvalues, with the largest break appearing to occur around the Kaiser Criterion eigenvalue of 1.0 (Fig. C1). Some components were observed with an eigenvalue $0.98 < E < 1.0$ for QLD, SEQ, and GBRC, and were still selected. Thus all principal components with $E > 0.98$ were selected for rotation. All final datasets used in the PCAs were found to be adequate according to Bartlett's test of sphericity ($p < 0.001$) and the Kaiser-Meyer-Olkin test of sampling adequacy (KMO > 0.50).

When variables produced significant contributions to more than one principle component, we applied varimax rotation to the selected principal components using the R package 'psych' (Revelle 2017). Rotation of the principal components enhances the interpretability of the components by producing a "simple structure," where variables have high loadings—correlations with the component—on one component and near-zero loadings on the remaining components. We chose the orthogonal varimax method for rotation to produce simplified, uncorrelated rotated components (RCs) that maximize column variance in the RC pattern matrix (Kaiser 1958; O'Rourke & Hatcher 2013). Here, we use the term 'rotated components' in lieu of the more traditional term 'factors' in order to eliminate confusion between principal components and factors. In cases when variables exhibit cross-loading—significant loadings on two or more rotated components—the variable(s) were removed from the dataset and the analysis was performed again until rotation produced the desired simple structure. A loading value of ±0.32 is typically regarded as a standard threshold, beyond which variables are significantly represented in a given component (Tabachnick & Fidell 2001). The final selection of RCs was made based upon interpretability and variable representation. While an RC with at least three high-loading variables is generally satisfactory (Costello & Osborne 2005), we selected RCs with two high-loading variables when the variables represented a similar conceptual construct, thus enhancing the interpretability of the components. The variables chosen for interpretation of each selected RC were based upon the strength of their loading according to the scale provided by Liu et al. (2003): strong (> 0.75), moderate (0.50−0.75), weak (0.30−0.49). We thus interpreted each RC according to all variables with moderate or strong loadings.

The initial varimax rotations of each case study yielded one or more variables cross-loading into more than one rotated component (i.e. exhibited loadings > |0.32| on multiple rotated components). Thus those variables with loadings greater than 0.32 on more than one rotated component were removed from the dataset and the analysis performed again. For most cases, this resulted in no further cross-loadings in the final rotated components, though CYP and SEQ regions had one variable loading at −0.34 and 0.33, respectively. After multiple attempts to remove different combinations of variables and multiple alterations in the number of selected components, however, these results for CYP and SEQ proved to capture the most variance in the data with the minimal amount of cross-loadings. Therefore, we set the threshold for cross-loading at 0.34 for this analysis, recognising that this is still considered a “weak” loading (Liu et al. 2003).

Appendix B. Additional spatial and temporal characteristics of clearing across Queensland

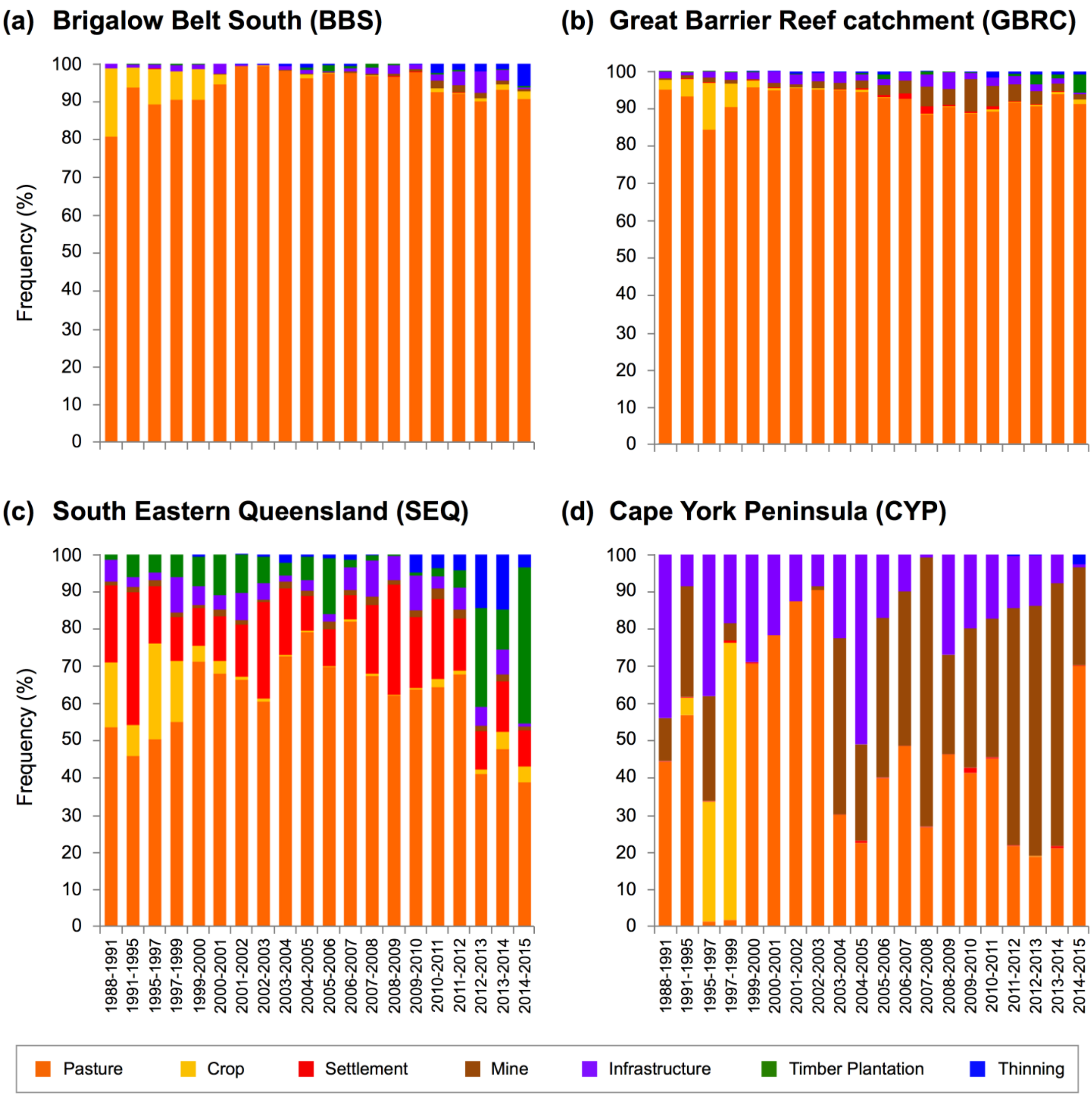

Fig. B1. Proportion of annual land clearing area devoted to seven anthropogenic purposes. Clearing within protected areas, natural tree losses, and unidentified clearing purposes are excluded.

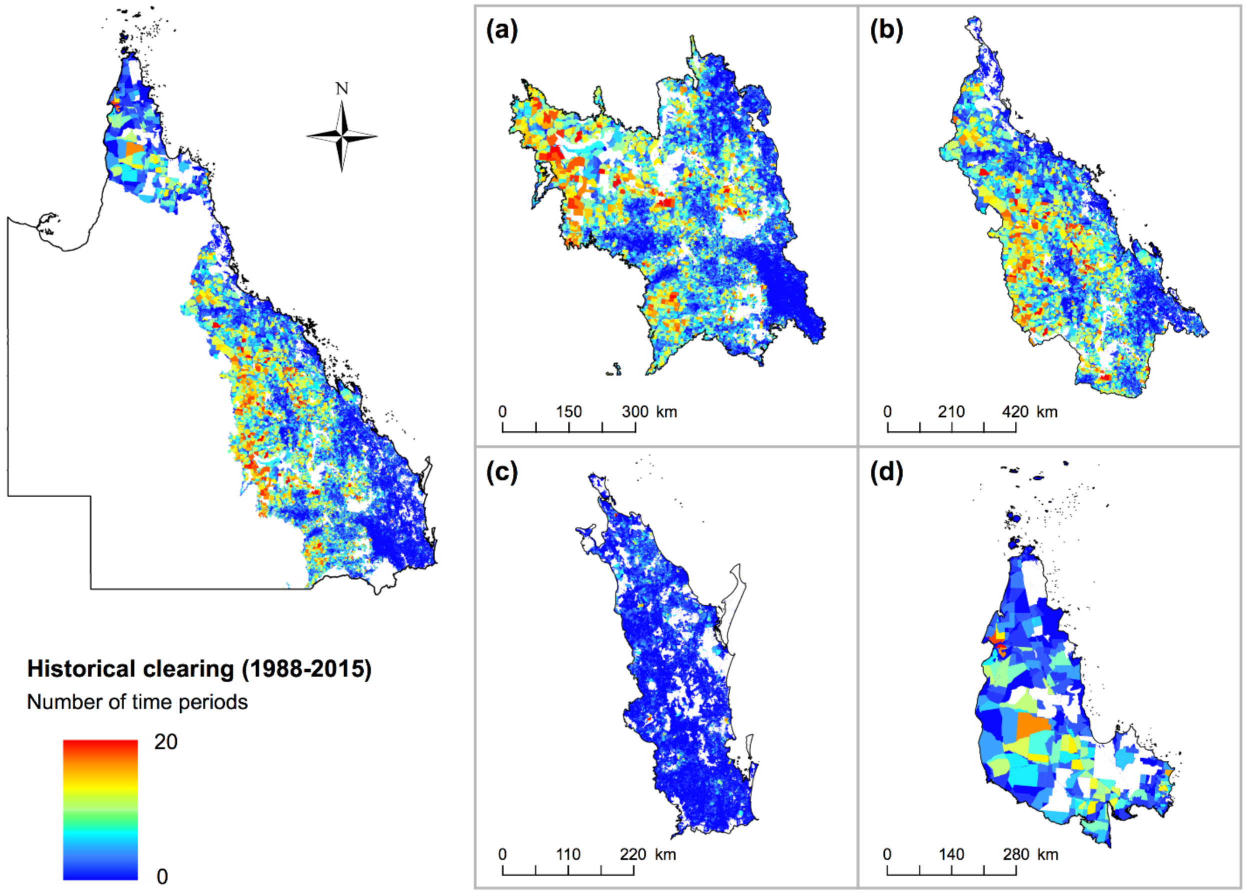

Fig. B2. Frequency of clearing events per parcel of land across the twenty time periods monitored by the Statewide Landcover and Trees Study (SLATS) for (a) Brigalow Belt South (BBS), (b) Great Barrier Reef catchment (GBRC), (c) South Eastern Queensland (SEQ), and (d) Cape York Peninsula (CYP). Parcels within protected areas and natural tree loss events are excluded.

Appendix C. Full results for the principal component and cluster analyses

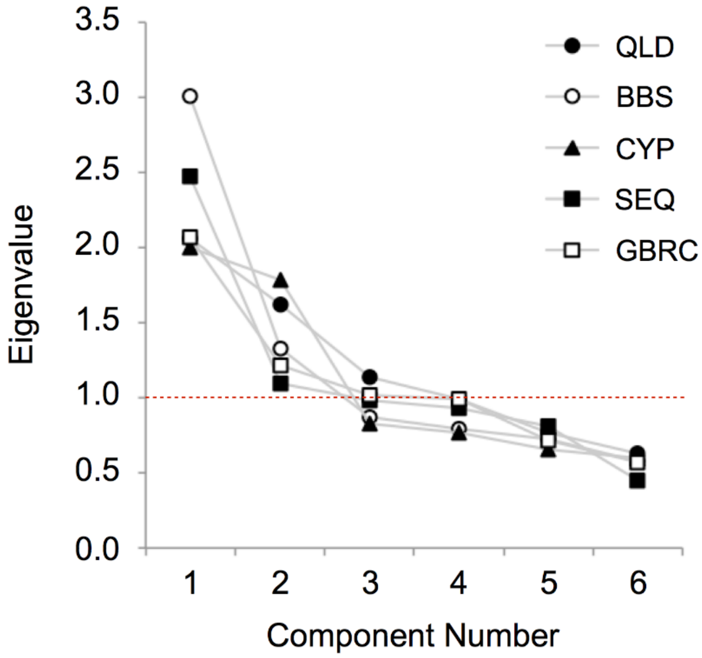

Fig. C1. Scree plot from the final principal component analyses for each case study: Queensland (QLD), Brigalow Belt South (BBS), Cape York Peninsula (CYP), South Eastern Queensland (SEQ), and Great Barrier Reef catchment (GBRC). Most regions exhibited an observable break around the Kaiser Criterion (*red dotted line*) used for component selection. Only the first six principal components shown.

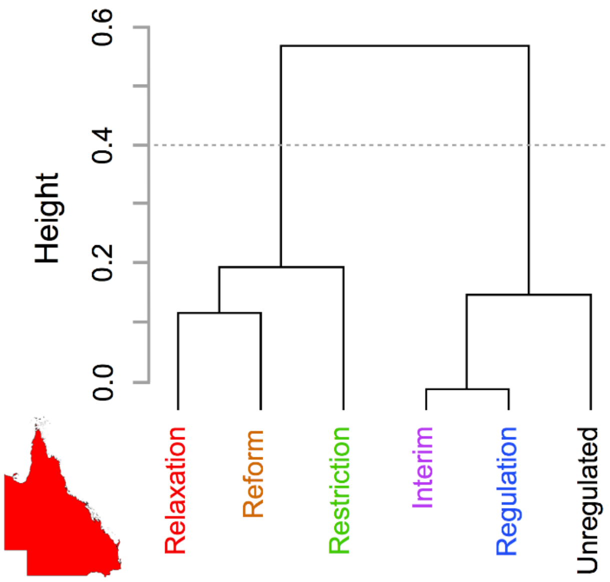

Fig. C2. Ward's hierarchical clustering of aggregated policy periods based on the mean component scores across the *Property*, *Climate*, and *Terrain Components* for the State of Queensland.

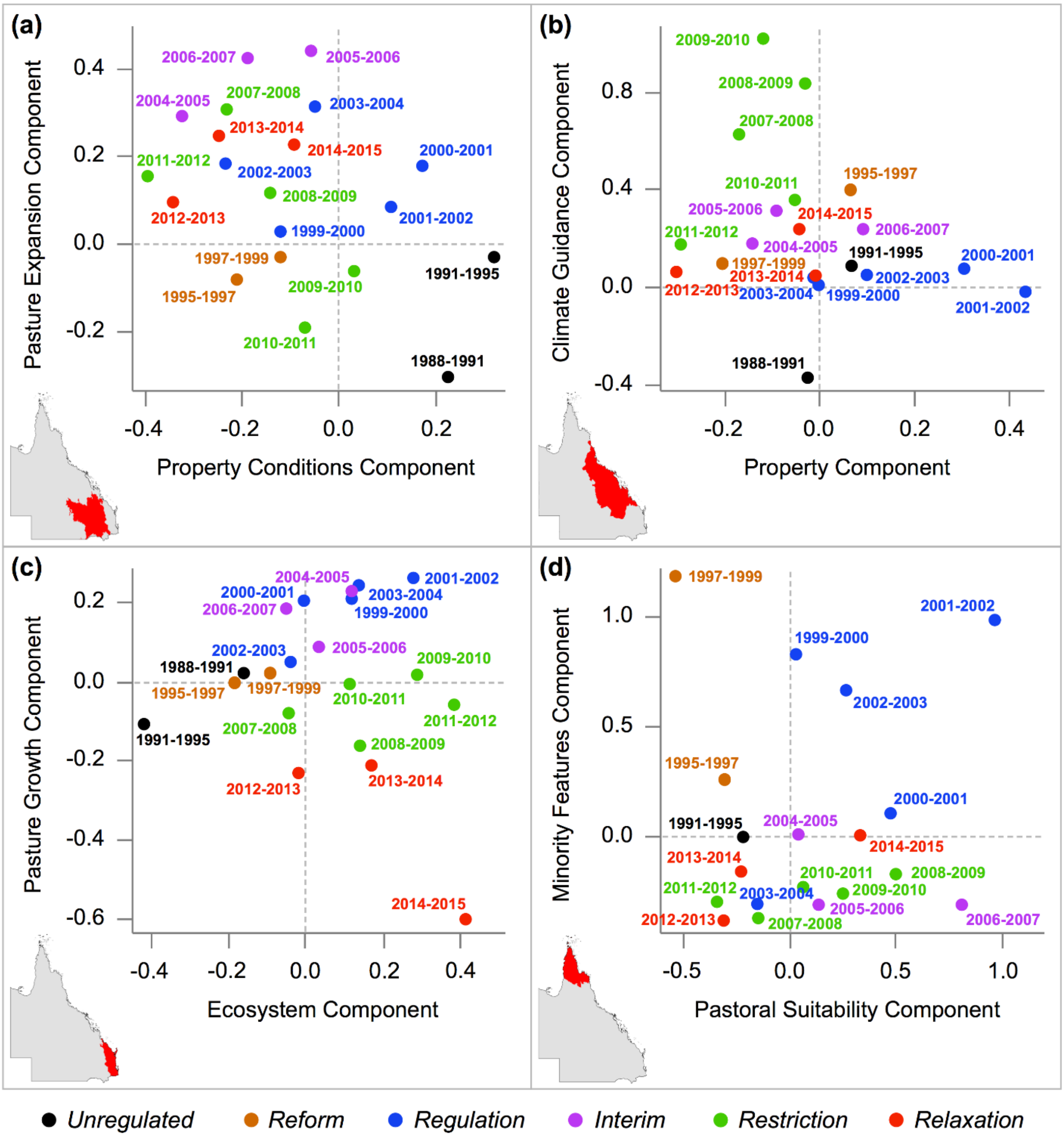

Fig. C3. Mean component scores by year, coloured according to policy period, across the final rotated components for (a) Brigalow Belt South (BBS), (b) Great Barrier Reef catchment (GBRC), (c) South Eastern Queensland (SEQ), and (d) Cape York Peninsula (CYP).

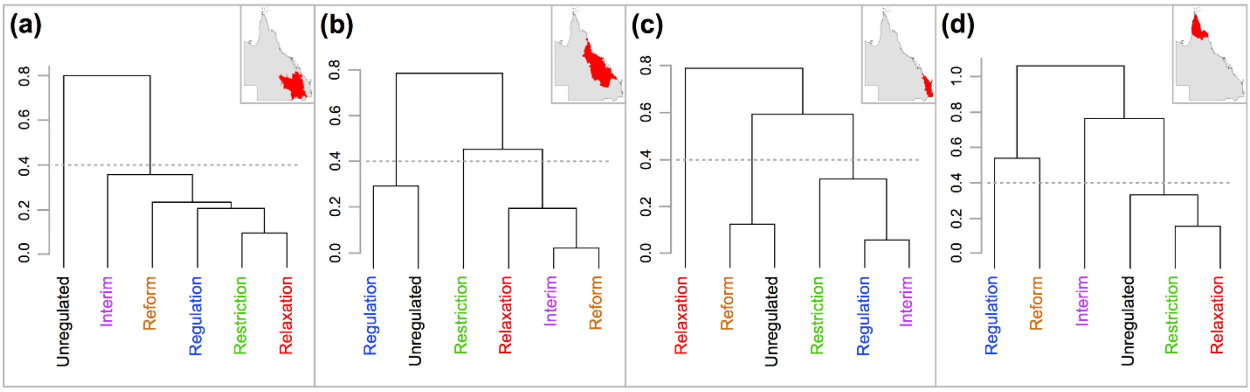

Fig. C4. Hierarchical clustering of policy periods based on the mean component scores across the selected rotated components for (a) Brigalow Belt South (BBS), (b) Great Barrier Reef catchment (GBRC), (c) South Eastern Queensland (SEQ), and (d) Cape York Peninsula (CYP).

Table C1. Selected components' eigenvalues (*E*), individual variance captured (*v*), and the cumulative variance for all components (*Vc*) for unrotated and varimax-rotated principal component analyses for each region.

Region	Rotation	Component 1		Component 2		Component 3		Component 4		*Vc*
		E	*v*	*E*	*v*	*E*	*v*	*E*	*V*	
QLD	Unrotated	2.06	26%	1.62	20%	1.14	14%	1.00	12%	73%
	Rotated	1.90	24%	1.60	20%	1.28	16%	1.04	13%	73%
BBS	Unrotated	3.01	38%	1.32	17%	-	-	-	-	54%
	Rotated	2.97	37%	1.36	17%	-	-	-	-	54%
CYP	Unrotated	2.00	29%	1.79	26%	-	-	-	-	54%
	Rotated	1.97	28%	1.82	26%	-	-	-	-	54%
SEQ	Unrotated	2.48	35%	1.10	16%	0.99	14%	-	-	65%
	Rotated	2.41	34%	1.13	16%	1.01	14%	-	-	65%
GBRC	Unrotated	2.07	30%	1.22	17%	1.02	15%	1.00	14%	76%
	Rotated	2.00	29%	1.25	18%	1.04	15%	1.02	15%	76%

Table C2. Rotated component (RC) loadings for variables within each case study region. Loading parameters include communality, measured by the squared cosine (*h2*), uniqueness (*u2*), and loading complexity (*com*). Variables without a loading in a given region were excluded due to significant cross-loadings on previous rotation attempts.

Region	Variable	Rotated variable loadings				*h2*	*u2*	*com*
		RC 1	RC 2	RC 3	RC 4			
Queensland (QLD)	Clearing type	-	-	-	-	-	-	-
	Drought declarations	−0.12	0.76	−0.17	0.31	0.71	0.29	1.50
	Elevation	0.32	0.15	0.82	−0.12	0.82	0.18	1.40
	Parcel size	0.73	−0.05	−0.09	0.10	0.55	0.45	1.10
	Rainfall variability	−0.09	−0.89	−0.08	0.17	0.83	0.17	1.10
	RE status	0.20	0.04	0.05	0.91	0.87	0.13	1.10
	Remoteness	0.78	0.32	0.02	0.07	0.72	0.28	1.30
	Slope	−0.29	−0.28	0.73	0.22	0.74	0.26	1.90
	Tenure	−0.71	0.17	−0.18	−0.06	0.57	0.43	1.30
Brigalow Belt South (BBS)	Clearing type	0.19	0.51	-	-	0.30	0.70	1.30
	Drought declarations	−0.71	0.05	-	-	0.51	0.49	1.00
	Elevation	0.79	0.28	-	-	0.70	0.30	1.30
	Parcel size	0.71	0.03	-	-	0.50	0.50	1.00
	Rainfall variability	-	-	-	-	-	-	-
	RE status	−0.20	0.70	-	-	0.53	0.47	1.20
	Remoteness	0.88	−0.09	-	-	0.78	0.22	1.00
	Slope	0.09	0.71	-	-	0.51	0.49	1.00
	Tenure	−0.69	−0.13	-	-	0.50	0.50	1.10
Cape York Peninsula (CYP)	Clearing type	0.61	0.27	-	-	0.45	0.55	1.40
	Drought declarations	-	-	-	-	-	-	-
	Elevation	0.68	0.28	-	-	0.54	0.46	1.30
	Parcel size	0.68	−0.34	-	-	0.57	0.43	1.50
	Rainfall variability	-	-	-	-	-	-	-
	RE status	0.08	−0.74	-	-	0.56	0.44	1.00
	Remoteness	0.78	−0.31	-	-	0.70	0.30	1.30
	Slope	0.23	0.67	-	-	0.50	0.50	1.20
	Tenure	−0.09	0.67	-	-	0.46	0.54	1.00
South Eastern Queensland (SEQ)	Clearing type	0.33	0.60	−0.13	-	0.49	0.51	1.60
	Drought declarations	0.90	0.04	0.09	-	0.82	0.18	1.00
	Elevation	0.79	0.22	0.15	-	0.69	0.31	1.20
	Parcel size	0.08	−0.02	0.98	-	0.96	0.04	1.00
	Rainfall variability	−0.83	−0.06	0.02	-	0.69	0.31	1.00
	RE status	−0.40	0.17	0.04	-	0.19	0.81	1.40
	Remoteness	-	-	-	-	-	-	-
	Slope	-	-	-	-	-	-	-
	Tenure	−0.19	0.83	0.08	-	0.73	0.27	1.10
Great Barrier Reef catchment (GBRC)	Clearing type	0.19	−0.77	0.20	0.16	0.69	0.31	1.30
	Drought declarations	−0.09	0.00	0.96	−0.02	0.93	0.07	1.10
	Elevation	-	-	-	-	-	-	-
	Parcel size	0.78	−0.04	0.11	−0.07	0.62	0.38	1.20
	Rainfall variability	0.08	0.81	0.18	0.19	0.73	0.27	1.10
	RE status	-	-	-	-	-	-	-
	Remoteness	0.85	−0.03	−0.05	−0.03	0.73	0.27	1.10
	Slope	−0.08	0.02	−0.02	0.97	0.95	0.05	1.00
	Tenure	−0.78	0.05	0.18	0.00	0.65	0.35	1.40

Appendix D. Details of the design and selection of the econometric models

An iterative spatial Hausman test was applied to all four models to determine if random or fixed effects were most appropriate for the analysis (Hausman 1978). Results of the Hausman test from 400 samples containing 4,000 observations per model, tracked over the corresponding periods of analysis, indicated that random effects were acceptable on average for all models except the FCI-BBS model (Table D3). However, the *p*-value histograms of the samples indicated that a fixed effects approach would be more suitable for 59% of samples at a significance of $\alpha = 0.05$ (Fig. D2). We confirmed that results for all four models using random effects and fixed effects were largely consistent, with the statistically significant variables having the same sign and roughly equivalent magnitudes. Thus we focus the results and discussion of our analysis to the fixed effects model but note the significance of several time-invariant variables in the random effects models (Tables E1, E2).

To compute predictions for each model for all study periods, we followed the fixed effects spatial maximum likelihood estimation (FE-MLE) described by Baltagi et al. (2012), where the best linear unbiased predictor (BLUP) of FCI or RCI for observation i at time $T + \tau$ is represented as:

$$\hat{y}_{i,T+\tau} = X_{i,T+\tau}\hat{\beta}_{MLE,FE} + \hat{\mu}_i \tag{D1}$$

with

$$\hat{\mu}_i = \bar{y}_i - \bar{X}_i\hat{\beta}_{MLE,FE} \tag{D2}$$

and

$$\bar{y}_i = \sum_{t=1}^{T} y_{i,t}/T \tag{D3}$$

where $\hat{y}$ is the estimated FCI or RCI value (BLUP), $X\hat{\beta}$ is the change explained with the observed data, $\bar{y}$ is the overall mean FCI or RCI, $\bar{X}$ is the mean value of the time series variables, and $\hat{\mu}$ is the estimate of the fixed effect. As a goodness-of-fit measure, we generated pseudo R-squared averages for each year, as well as global R-squared averages per model, by using the square of the correlation coefficient between predicted and observed FCI or RCI values described by Elhorst (2014):

$$corr^2(Y,\hat{Y}) = \frac{\left[(Y-\bar{Y})^T(\hat{Y}-\bar{Y})\right]^2}{[(Y-\bar{Y})^T(Y-\bar{Y})][(\hat{Y}-\bar{Y})^T(\hat{Y}-\bar{Y})]} \tag{D4}$$

Table D1. Variables included in the econometric model. (Continued on next page.)

Variable	Description	Unit	Type	Resolution	Source
Forest Cover Index (FCI)	Proportion of 1-km cells with designated forest status	Score (0–1)	Spatial time series	1 km	
Remnant Forest Cover Index (RCI)	Proportion of 1-km cells with designated remnant forest status	Score (0–1)	Spatial time series	1 km	
Biophysical characteristics					
Elevation	Meters above sea level	m	Spatial	90 m	QSC 2016d
Slope	Slope gradient	Degrees	Spatial	90 m	QSC 2016d
Soil pH	pH in the upper 30 cm soil layer	-	Spatial	250 m	ACLEP 2014
Soil clay content	Percent of clay content in the upper 30 cm soil layer	%	Spatial	250 m	ACLEP 2014
Soil bulk density	Bulk density in the upper 30 cm soil layer	Mg m^{-3}	Spatial	250 m	ACLEP 2014
Rainfall	Five-year moving averages of annual rainfall	mm	Spatial time series	0.05 deg.	BOM 2015
Rainfall variability	Standard deviation of average rainfall during 1890–2013	mm	Spatial	5 km	QSC 2016b
Maximum temperature	Five-year moving averages of annual maximum temperature	°C	Spatial time series	0.05 deg.	BOM 2015
Drought frequency	Percentage of time during 1983–2011 where the Local Government Area was declared in drought by the State	%	Spatial	1 km	QSC 2016a
Socioeconomic characteristics					
Food price index	Average of 5 commodity group price indices, weighted with the average export shares of each group for 2002–2004	Point Index	Annual time series		FAO 2018
Potential agricultural profit	Highest profit per hectare for agricultural land uses in 2005–2006	AU\$ ha^{-1} (2013)	Spatial	1 km	Marinoni et al 2012
Distance to protected areas	Euclidean distance from each pixel to the nearest pixel under protection status	km	Annual spatial time series	1 km	Department of the Environment 2014

Accessibility and Remoteness Index of Australia (ARIA)	Measure of a location's proximity to the nearest urban centre	Score (0–19)	Spatial	1 km	ALA 2016
Property characteristics					
Parcel size	Area within a property's cadastral boundaries as of 2016	km^2	Spatial	100 m	QSC 2016c
Tenure					
Freehold	Dummy variable for land under freehold tenure as of 2016		Spatial	100 m	QSC 2016c
Leasehold	Dummy variable for land under leasehold tenure as of 2016		Spatial	100 m	QSC 2016c
Other	Dummy variable for land that is not freehold or leasehold land as of 2016		Spatial	100 m	QSC 2016c
Political characteristics					
Broad-scale clearing ban	Dummy variable for the years during enforcement of the clearing ban		Annual time series		
Policy uncertainty	Dummy variable denoting policy uncertainty		Annual time series		

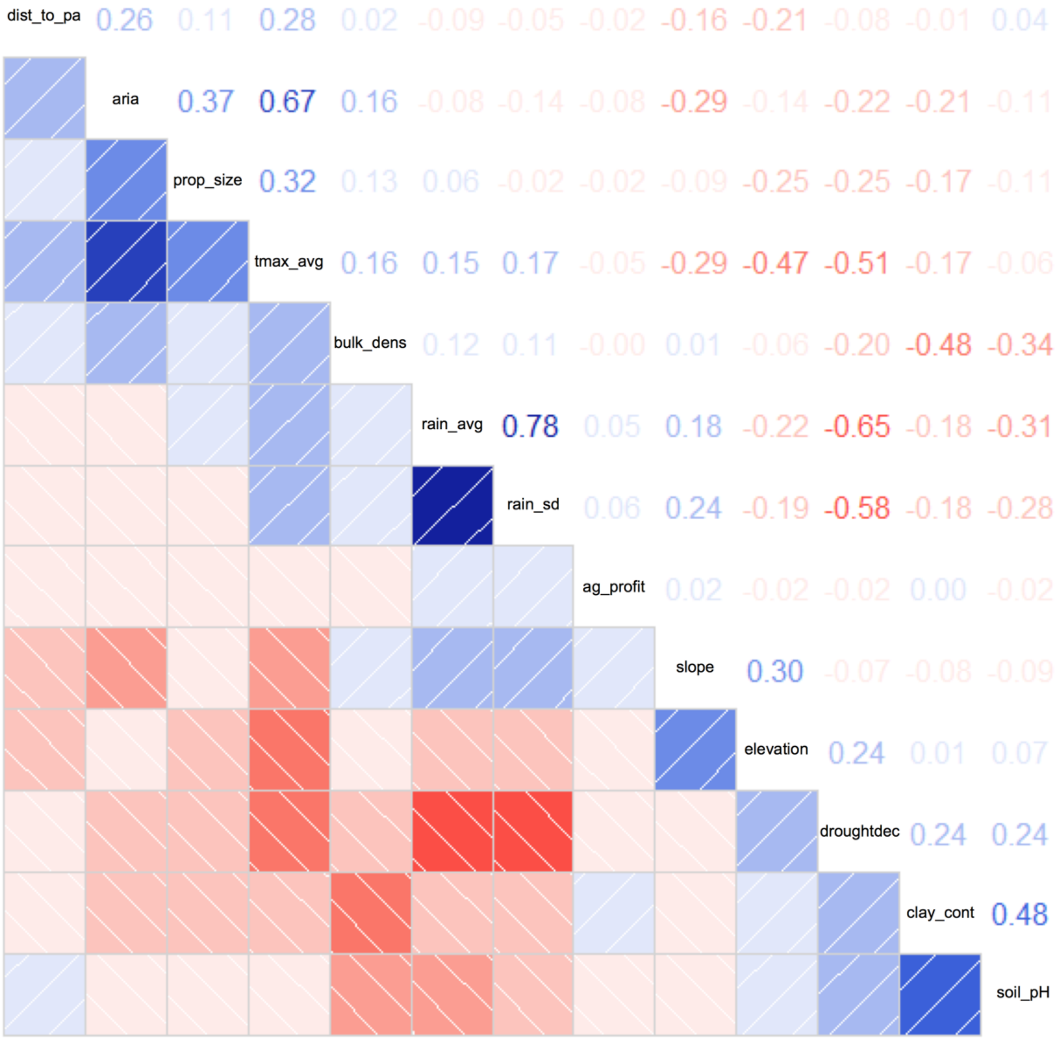

Fig. D1. Collinearity of variables included in econometric model. (Lower panel) Correlogram of all continuous variables included in the complete random effects model. (Upper panel) Correlation matrix displaying Pearson's correlation coefficient (*r*). Colour intensity corresponds to strength of correlation.

Table D2. Individual variable multicollinearity diagnostics. Collinearity is undetectable when the variable inflation factor (VIF) < 1.50, present but acceptable when VIF < 5, and high when VIF > 10.

Variable	VIF(β)
Potential agricultural profit	1.011
Distance to protected areas	1.138
Remoteness (ARIA)	2.671
Slope	1.319
Elevation	1.708
Soil pH	1.462
Soil clay content	1.599
Soil bulk density	1.344
Rainfall	3.288
Rainfall variability	2.936
Maximum temperature	3.580
Drought frequency	2.744
Parcel size	1.289
Tenure	1.421

Table D3. Mean *p*-value of the iterative spatial Hausman test for each model.

Model	Mean *p*-value	Recommended approach
FCI-QLD	0.2084	Random effects
FCI-BBS	0.0409	Fixed effects
RCI-QLD	0.1194	Random effects
RCI-BBS	0.3947	Random effects

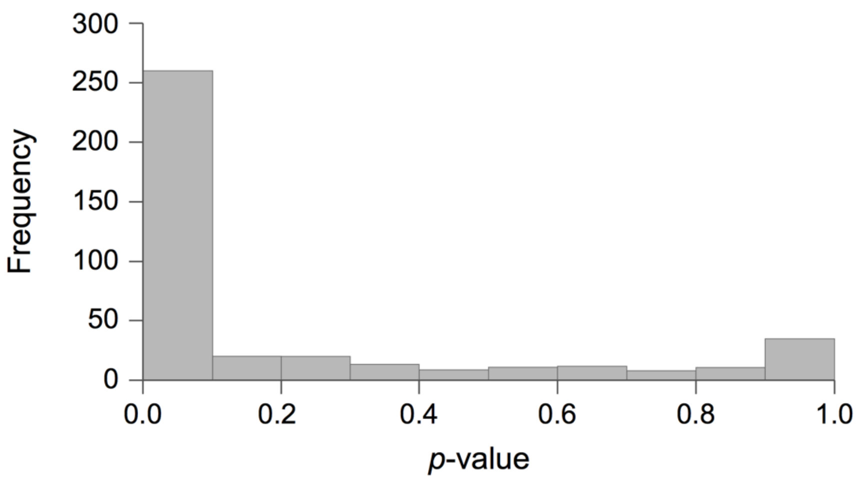

Fig. D2. Histogram of individual sample *p*-values under the iterative spatial Hausman test for FCI-QLD. Histogram represents 400 samples each composed of 4,000 observations tracked over time. While the mean *p*-value (0.2094) suggests a random effects approach, 59% of samples preferred a fixed effects approach ($p < 0.05$).

Appendix E. Results for the random effects models

Table E1. Coefficients (β) of the variables included in the random effects econometric model of net forest cover change. Coefficients represent the percent change in forest cover index (FCI) per 1% change in the explanatory variable.

Variable	Queensland					Brigalow Belt South				
	Coefficient	Std. dev.	95% Conf. Interval			Coefficient	Std. dev.	95% Conf. Interval		
			Lower bound	Upper bound				Lower bound	Upper bound	
(Intercept)	46.76	0.120	46.75	46.76	*	54.10	0.629	54.06	54.14	*
Biophysical characteristics										
Elevation	−0.135	0.089	−0.140	−0.129	*	−0.538	0.083	−0.544	−0.533	*
Slope	0.900	0.008	0.900	0.901	*	1.056	0.008	1.055	1.056	*
Soil pH	−5.835	3.774	−6.069	−5.602	*	−7.875	3.661	−8.102	−7.648	*
Soil clay content	−0.606	0.001	−0.606	−0.606	*	−0.894	0.001	−0.894	−0.894	*
Soil bulk density	0.058	0.264	0.042	0.074	*	0.962	0.445	0.935	0.990	*
Rainfall (5-year moving mean) †	−0.039	0.057	−0.042	−0.035	*	−0.984	0.099	−0.990	−0.978	*
Rainfall variability (average std. dev.)	6.376	0.252	6.361	6.392	*	7.961	0.465	7.932	7.990	*
Maximum temperature (5-year moving mean) †	−20.98	0.819	−21.03	−20.93	*	−23.89	1.108	−23.96	−23.83	*
Drought frequency	0.057	0.053	0.054	0.060	*	1.321	0.629	1.282	1.360	*
Socioeconomic characteristics										
Food price index†	−0.814	0.354	−0.836	−0.792	*	−0.759	0.033	−0.761	−0.757	*
Potential agricultural profit	−0.247	0.159	−0.256	−0.237	*	−0.015	0.122	−0.023	−0.008	*
Distance to protected areas†	−0.001	0.021	−0.002	0.000		0.009	0.024	0.008	0.011	*
Remoteness index	0.194	0.009	0.193	0.194	*	0.633	0.010	0.632	0.633	*
Property characteristics										
Parcel size	0.106	0.029	0.104	0.108	*	0.163	0.033	0.161	0.165	*
Tenure – Leasehold	0.560	0.120	0.552	0.567	*	1.518	0.122	1.511	1.526	*
Tenure – Other	1.920	0.354	1.898	1.941	*					
Political characteristics										
Broad-scale clearing ban†	0.131	0.021	0.129	0.132	*	0.136	0.024	0.135	0.138	*
Policy uncertainty†	−0.155	0.009	−0.155	−0.154	*	−0.177	0.010	−0.178	−0.176	*
Bioregion indicator										
Brigalow Belt South	0.162	0.159	0.153	0.172	*					
Spatial autocorrelation (*r*)	0.249		0.248	0.249	*	0.218		0.218	0.219	*
Random error variance (s_u)	4.505		4.500	4.511	*	4.460		4.454	4.465	*

* Confidence interval excludes zero
† Included in fixed effects model

Table E2. Coefficients (β) of the variables included in the random effects econometric model of remnant forest loss. Coefficients represent the percent change in remnant forest cover index (RCI) per 1% change in the explanatory variable.

Variable	Queensland					Brigalow Belt South				
	Coefficient	Std. dev.	95% Conf. Interval			Coefficient	Std. dev.	95% Conf. Interval		
			Lower bound	Upper bound				Lower bound	Upper bound	
(Intercept)	−0.1074	0.1640	−0.4788	0.1955		−0.4985	0.3950	−1.4129	0.0511	
Biophysical characteristics										
Elevation	−0.0076	0.0037	−0.0151	0.0002		0.0218	0.0255	−0.0066	0.0910	
Slope	0.0438	0.0027	0.0386	0.0487	*	0.0493	0.0026	0.0443	0.0539	*
Soil pH	−0.2080	0.0245	−0.2577	−0.1633	*	−0.3996	0.0234	−0.4428	−0.3542	*
Soil clay content	−0.0374	0.0061	−0.0489	−0.0257	*	−0.0457	0.0065	−0.0575	−0.0326	*
Soil bulk density	0.0003	0.0176	−0.0335	0.0356		0.0347	0.0279	−0.0222	0.0877	
Rainfall (5-year moving mean)†	−0.0073	0.0011	−0.0093	−0.0051	*	−0.0055	0.0019	−0.0092	−0.0019	*
Rainfall variability (average std. dev.)	0.3296	0.0213	0.2899	0.3729	*	0.3416	0.0362	0.2776	0.4089	*
Maximum temperature (5-year moving mean)†	−0.2630	0.0230	−0.3072	−0.2212	*	−0.1554	0.0198	−0.1957	−0.1184	*
Drought frequency	−0.0015	0.0047	−0.0110	0.0079		0.0082	0.0267	−0.0548	0.0570	
Socioeconomic characteristics										
Food price index†	−0.0217	0.0019	−0.0260	−0.0181	*	−0.0235	0.0016	−0.0268	−0.0203	*
Potential agricultural profit	0.0118	0.0048	0.0029	0.0220	*	0.0318	0.0062	0.0194	0.0433	*
Distance to protected areas†	−0.0001	0.0001	−0.0003	0.0001		−0.0001	0.0001	−0.0004	0.0002	
Remoteness index	0.0101	0.0060	0.0000	0.0225		0.0545	0.0132	0.0203	0.0739	*
Property characteristics										
Parcel size	0.0138	0.0020	0.0100	0.0179	*	0.0114	0.0018	0.0077	0.0148	*
Tenure – Leasehold	0.0440	0.0087	0.0279	0.0606	*	0.0973	0.0079	0.0822	0.1114	*
Tenure – Other	0.1486	0.0293	0.0936	0.2068	*					
Political characteristics										
Broad-scale clearing ban†	0.0038	0.0005	0.0029	0.0047	*	0.0031	0.0004	0.0024	0.0039	*
Policy uncertainty†	−0.0024	0.0002	−0.0028	−0.0019	*	−0.0025	0.0002	−0.0029	−0.0021	*
Bioregion indicator										
Brigalow Belt South	0.0442	0.0140	0.0149	0.0689	*					
Spatial autocorrelation (r)	0.6435		0.6062	0.6801	*	0.5121		0.4723	0.5562	*
Random error variance (s_u)	0.0010		0.0008	0.0011	*	0.0010		0.0008	0.0011	*

* Confidence interval excludes zero
† Included in fixed effects model

Appendix F. Full results for the Bayesian impact analyses

Table F1. Results of the Bayesian causal impact analysis of the broad-scale clearing ban for each model. Impacts on the area of avoided deforestation are estimated by intervention year (2004 or 2007) for all fixed effects variables, all fixed effects variables excluding policy uncertainty, and all fixed effects variables excluding the years 2012–2014.

Model	Study area	Impact (km^2)					
		2004			2007		
		All variables	*Excl. policy uncertainty*	*Excl. 2012–2014*	*All variables*	*Excl. policy uncertainty*	*Excl. 2012–2014*
Net forest change	Queensland	39208 ± 11525 **	41707 ± 12773 **	13003 ± 6887 **	69918 ± 19246 **	72139 ± 20600 **	38451 ± 10091 **
	Brigalow Belt South	3344 ± 3360	2772 ± 3489	1355 ± 2017	8262 ± 2992 *	8637 ± 2042 **	5968 ± 1562 *
Remnant forest loss	Queensland	18784 ± 7454 **	19646 ± 7902 **	14174 ± 5082 **	18969 ± 10340 *	6483 ± 4504	13252 ± 7066 **
	Brigalow Belt South	1380 ± 1450	1528 ± 1459	973 ± 1079	94 ± 1502	−323 ± 1376	102 ± 889

* $p < 0.05$
** $p < 0.01$

Appendix G. Details of the covariate matching methodology and evaluation

Matching of treated and untreated samples compared two primary methods under multiple parameter conditions: nearest neighbour (NN) and nearest *k* neighbours (NKN) matching. NN matching identifies the one control observation that best matches each treatment observation, while NKN matching identifies multiple control observations to match with each treatment observation. In this study we selected the nearest four neighbours for NKN matching. A third type of matching using covariate weights—genetic matching (Diamond & Sekhon 2013)—was also applied but consistently produced similar results to NN matching; due to these similarities and the significant computation time required, it was excluded from further analyses. Calipers were applied to define the limits for the maximum search distance for matches, above which treatment observations would be excluded from analysis due to inadequate control matches (Wang et al. 2013). For each matching method, calipers were set to search within 0.25, 0.30, 0.50, and 0.75 standard deviations, as well as without caliper limits. All matching was performed with replacement, and ties between control observations were broken randomly.

No single test can provide the best measure of match balance (the degree of similarity of matched treatment and control observations) due to the high dimensionality of the data (Sekhon 2011). Thus the adequacy of matching methods was compared according to multiple empirical and visual match balance estimations. In addition to absolute and standardized (scale-less) differences in matched and unmatched means, we tested if treatment and control means were equal before (two sample t-test) and after matching (paired t-test), as well as if there was equal distributional balance between treatment and control observations before and afterward (bootstrapped Kolmogorov-Smirnov test). Two distributional measures were also compared, the empirical quantile-quantile (eQQ) and cumulative distribution function (eCDF). Finally, a visual estimation of match balance was compared between methods according to a QQ plot of matched treatment and control values across all covariates, with greatest match balance achieved at a slope of one. No matching method provided the best balance across all covariates, but NN matching with a 0.25 caliper consistently produced the best balance across the most covariates, while retaining a relatively large number of observations (Tables H1, H2, I1), consistent with previous studies investigating optimal caliper options (Wang et al. 2013).

Appendix H. Outcomes of covariate matching

Table H1. Results from all nearest neighbour (NN) and nearest *k* neighbours (NKN) matching methods for each covariate, based upon the standardized difference between remnant (treated) and non-remnant (untreated) tree means. (Continued on next page.)

Variable	Match method	Caliper	Standardised Difference in Treatment and Control Means After Matching																		
			1999_{FO}	1999_{FL}	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Regional Ecosystem (RE) code	NN	0.00	-0.16**^^	-0.10**^^	-0.15**^^	-0.12**^^	0.019^^	-0.21**^^	-0.074*^	-0.11**^^	-0.12**^^	-0.15**^^	-0.209**^	-0.69**^^	-0.13**^^	0.006^^	-0.255**^	-0.18**^^	-0.086*^^	-0.236**^	-0.212**^
		0.25	-0.15**^^	-0.033*^^	-0.14**^^	0.010	0.003^	-0.003	-0.042*	0.124**^^	0.148**^^	0.087**^	0.055*^	-0.005^^	0.081**^^	0.042*^	-0.032^	-0.009^^	0.046*^^	-0.029	-0.052*^
		0.50	-0.16**^^	-0.12**^^	-0.16**^^	-0.12**^^	-0.059*^^	-0.2**^^	-0.128**^	0.023^^	-0.029^^	0.023^^	-0.104**^	-0.25**^^	0.009^^	0.012^	-0.108**	-0.08**^^	-0.112**^	-0.076**^	-0.219**^
		0.75	-0.17**^^	-0.11**^^	-0.15**^^	-0.11**^^	-0.039^^	-0.21**^^	-0.111**^	-0.058*^^	-0.083*^^	-0.12**^^	-0.2**^	-0.46**^^	-0.032^^	-0.027^^	-0.224**^	-0.14**^^	-0.11**^^	-0.19**^^	-0.218**^
	NKN	0.00	-0.27**^^	-0.29**^^	-0.26**^^	-0.23**^^	-0.2**^^	-0.25**^^	-0.26**^^	-0.24**^^	-0.27**^^	-0.22**^^	-0.28**^^	-0.79**^^	-0.28**^^	-0.20**^^	-0.35**^^	-0.31**^^	-0.27**^^	-0.36**^^	-0.36**^^
		0.25	-0.32**^^	-0.17**^^	-0.28**^^	-0.09**^^	-0.14**^^	-0.079*^^	-0.15**^^	0.033^^	0.031^^	0.062*^^	-0.049^^	-0.104*^^	-0.12**^^	-0.042^^	-0.10**^^	-0.11**^^	-0.052^^	-0.12**^^	-0.21**^^
		0.50	-0.3**^^	-0.32**^^	-0.31**^^	-0.3**^^	-0.32**^^	-0.36**^^	-0.41**^^	-0.04^^	-0.22**^^	0.001^^	-0.17**^^	-0.23**^^	-0.061^^	-0.064^^	-0.17**^^	-0.11**^^	-0.22**^^	-0.15**^^	-0.36**^^
		0.75	-0.3**^^	-0.31**^^	-0.3**^^	-0.29**^^	-0.29**^^	-0.31**^^	-0.35**^^	-0.21**^^	-0.30**^^	-0.17**^^	-0.23**^^	-0.53**^^	-0.10**^^	-0.11**^^	-0.32**^^	-0.27**^^	-0.29**^^	-0.35**^^	-0.37**^^
Remoteness	NN	0.00	0.174**^	0.5**^^	0.312**^	0.45**^	0.56**^	0.487**^	0.487**^	0.586**^^	0.43**^^	0.512**^^	0.509**^^	0.329**^^	0.551**^	0.653**^	0.488**^	0.528**^^	0.551**^^	0.594**^^	0.516**^^
		0.25	0.12**	0.233**^	0.128**	0.261**	0.251**	0.216**	0.159**	0.259**^	0.258**^	0.21**^	0.19**^	0.178**^^	0.228**^	0.229**^	0.272**^	0.235**^^	0.258**^	0.22**^	0.172**
		0.50	0.211**^	0.307**^^	0.235**^	0.379**^	0.388**^	0.355**^	0.301**^	0.372**^^	0.3**^^	0.273**^^	0.27**^^	0.038^^	0.306**^	0.322**^	0.34**^	0.332**^	0.302**^^	0.313**^^	0.297**^
		0.75	0.247**^^	0.336**^^	0.239**^	0.396**^	0.39**^	0.354**^	0.307**	0.366**^^	0.36**^^	0.349**^^	0.306**^^	0.121**^^	0.376**^	0.366**^	0.362**^	0.339**^^	0.367**^	0.339**^	0.356**^^
	NKN	0.00	0.275**^^	0.602**^^	0.382**^^	0.633**^^	0.621**^^	0.528**^^	0.552**^^	0.749**^^	0.662**^^	0.703**^^	0.595**^^	0.629**^^	0.77**^^	0.89**^^	0.603**^^	0.709**^^	0.699**^^	0.722**^^	0.622**^^
		0.25	0.122**^^	0.207**^^	0.119**^	0.271**^^	0.242**^	0.234**^	0.2**^	0.233**^^	0.268**^^	0.228**^^	0.157**^^	0.273**^^	0.222**^^	0.258**^^	0.283**^^	0.23**^^	0.251**^^	0.23**^^	0.168**^
		0.50	0.236**^^	0.393**^^	0.258**^^	0.406**^^	0.403**^^	0.361**^^	0.357**^^	0.372**^^	0.331**^^	0.31**^^	0.251**^^	0.15**^^	0.315**^^	0.373**^^	0.387**^^	0.309**^^	0.338**^^	0.344**^^	0.332**^^
		0.75	0.303**^^	0.436**^^	0.289**^^	0.431**^^	0.4**^^	0.349**^^	0.37**^^	0.406**^^	0.417**^^	0.437**^^	0.342**^^	0.335**^^	0.419**^^	0.437**^^	0.426**^^	0.393**^^	0.406**^^	0.426**^^	0.415**^^
Slope	NN	0.00	0.528**	0.564**	0.555**	0.582**	0.682**	0.767**	0.532**	0.787**	0.645**	0.85**	0.896**	0.775**^	0.787**	0.922**	0.716**	0.736**	0.702**	0.783**	0.459**
		0.25	0.172**	0.255**	0.221**	0.253**	0.288**	0.302**	0.252**	0.33**	0.334**	0.332**	0.369**	0.3**	0.381**	0.35**	0.315**	0.308**	0.3**	0.348**	0.215**
		0.50	0.277**	0.365**	0.314**	0.362**	0.398**	0.443**	0.356**	0.519**	0.464**	0.54**	0.465**	0.464**^	0.539**	0.548**	0.422**	0.503**	0.477**	0.533**	0.306**
		0.75	0.311**	0.406**	0.346**	0.445**	0.473**	0.535**	0.415**	0.64**	0.513**	0.647**	0.575**	0.616**^	0.651**	0.71**	0.535**	0.615**	0.579**	0.645**	0.38**
	NKN	0.00	0.772**^	0.871**^	0.811**^	0.922**^^	0.997**^	1.034**^^	1.043**^^	1.13**^^	1.041**^	1.173**^^	1.222**^^	1.139**^^	1.174**^	1.328**^^	1.091**^	1.182**^^	1.004**^	1.095**^^	0.741**
		0.25	0.346**^	0.391**	0.336**	0.42**^	0.456**^	0.476**^	0.472**^	0.553**^	0.525**^	0.513**^	0.516**^	0.521**^	0.521**^	0.533**^	0.572**^	0.552**^	0.492**^	0.556**^	0.365**
		0.50	0.431**^	0.569**^	0.472**^	0.575**^	0.611**^	0.612**^	0.638**^	0.805**^^	0.759**^^	0.754**^	0.731**^	0.765**^^	0.778**^	0.782**^	0.731**^^	0.764**^	0.712**^^	0.757**^	0.513**
		0.75	0.444**^	0.62**^	0.534**^	0.66**^	0.685**^^	0.688**^	0.722**^	0.935**^^	0.837**^^	0.862**^^	0.823**^^	0.922**^^	0.903**^^	0.973**^^	0.843**^	0.918**^^	0.793**^^	0.867**^^	0.583**
Parcel size	NN	0.00	0.443**	0.701**^	0.548**	0.406**^	0.39**^	0.614**	0.357**	0.81**^	0.669**^	0.593**^	0.743**^	0.967**^^	0.773**^	0.928**^	0.672**^	0.619**^	0.637**^	0.638**^	0.685**^
		0.25	0.045**	0.034*^	0.052**	0.073**	0.088**^	0.066**	0.051**	0.165**^	0.225**^	0.139**^	0.159**^	0.118**^^	0.182**^	0.119**^	0.214**	0.14**	0.101**	0.128**	0.118**^
		0.50	0.098**	0.177**^	0.119**	0.176**^	0.194**^	0.166**	0.152**	0.221**^	0.328**^	0.175**^	0.192**^	0.419**^^	0.279**^	0.237**^	0.303**^	0.261**^	0.212**^	0.223**^	0.247**^
		0.75	0.136**	0.284**^	0.182**	0.219**^	0.235**^	0.203**	0.173**	0.3**^	0.342**^	0.236**^	0.315**^	0.581**^^	0.478**^	0.353**^	0.412**^	0.312**^	0.301**^	0.261**^	0.361**^
	NKN	0.00	0.545**^^	0.988**^^	0.67**^^	0.419**^^	0.564**^^	0.685**^^	0.672**^^	1.104**^^	0.913**^^	0.867**^^	0.998**^^	1.089**^^	1.099**^^	1.316**^^	0.961**^^	0.923**^^	0.853**^^	0.821**^^	0.906**^^
		0.25	0.029*^^	0.05*^^	0.06**^^	0.055**^^	0.056**^^	0.065**^^	0.041*^^	0.19**^^	0.188**^^	0.156**^^	0.16**^^	-0.003^^	0.16**^^	0.11**^^	0.25**^^	0.162**^^	0.137**^^	0.127**^^	0.107**^^
		0.50	0.115**^^	0.26**^^	0.143**^^	0.168**^^	0.206**^^	0.19**^^	0.19**^^	0.268**^^	0.338**^^	0.245**^^	0.224**^^	0.345**^^	0.324**^^	0.304**^^	0.365**^^	0.29**^^	0.296**^^	0.231**^^	0.288**^^
		0.75	0.149**^^	0.38**^^	0.203**^^	0.188**^^	0.229**^^	0.216**^^	0.2**^^	0.401**^^	0.427**^^	0.348**^^	0.399**^^	0.538**^^	0.513**^^	0.445**^^	0.471**^^	0.384**^^	0.349**^^	0.321**^^	0.476**^^
Tenure	NN	0.00	--	0.016	--	--	--	--	--	-0.004	0.000	0.012	0.065**	-0.004	-0.004	0.013	0.004	0.024	0.000	0.008	0.016*
		0.25	--	0.000	--	--	--	--	--	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		0.50	--	0.000	--	--	--	--	--	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		0.75	--	0.000	--	--	--	--	--	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	NKN	0.00	--	0.002	--	--	--	--	--	-0.006	0.001	0.027	0.116**	-0.001	-0.008	0.038*	0.003	0.045*	-0.003	0.001	0.014
		0.25	--	0.000	--	--	--	--	--	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		0.50	--	0.000	--	--	--	--	--	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

		0.75	--	0.000	--	--	--	--	--	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Drought frequency	NN	0.00	-0.255**	0.075*	0.011^	0.032^	0.276**^	0.11**^	0.425**^	0.336**	0.256**	0.093*	0.202**	0.268**	0.243**	0.413**	0.319**	0.23**	0.243**	0.303**	0.178**
		0.25	0.005	-0.08**	-0.004	-0.018*	-0.006	0.001	-0.01	-0.084**	-0.079**	-0.118**	-0.101**	-0.104**	-0.089**	-0.061**	-0.054**	-0.112**	-0.116**	-0.119**	-0.054**
		0.50	-0.086**	-0.117**	-0.149**^	-0.03^	0.041^	-0.02^	0.005^	-0.061*	-0.014	-0.051*	-0.059*	-0.01	-0.034	-0.012	0.000	-0.078**	-0.056*	-0.045*	-0.006
		0.75	-0.074**	-0.083*	-0.147**^	-0.013^	0.065*^	0.016^	0.02^	0.005	-0.014	-0.048*	-0.019	0.077*	0.073*	0.084**	0.096**	-0.007	0.008	-0.008	0.058*
	NKN	0.00	-0.27**^^	0.073^^	0^^	0.112*^^	0.225**^^	0.099*^^	0.414**^^	0.425**^^	0.302**^^	0.113*^^	0.273**^^	0.347**^^	0.338**^^	0.366**^^	0.234**^^	0.224**^^	0.286**^^	0.327**^^	0.097*^^
		0.25	0.009	-0.08**^^	0.004	-0.03**	-0.016*	-0.003	-0.015	-0.13**^^	-0.11**^^	-0.16**^^	-0.15**^^	-0.16**^^	-0.13**^^	-0.108**^	-0.10**^^	-0.126**^	-0.13**^^	-0.15**^^	-0.11**^^
		0.50	-0.16**^^	-0.11**^^	-0.16**^^	-0.009^^	0.085**^^	0.008^^	0.059*^^	-0.09**^^	-0.006^^	-0.11**^^	-0.062*^^	-0.005^^	-0.049*^^	-0.031^^	-0.045^^	-0.10**^^	-0.061*^^	-0.08**^^	-0.065*^^
		0.75	-0.08**^^	-0.085*^^	-0.12**^^	0.022^^	0.09**^^	0.029^^	0.068*^^	0.02^^	0.026^^	-0.039^^	0.035^^	0.093*^^	0.139**^^	0.122**^^	0.065*^^	-0.004^^	0.055^^	0.003^^	-0.044^^
Rainfall variability	NN	0.00	1.108**^	0.985**^	1.141**^	1.147**^	1.241**^^	1.348**^^	1.303**^^	1.171**^^	1.336**^^	1.078**^	1.061**^	1.213**^^	1.156**^	1.509**^^	1.163**^	1.309**^^	1.167**^^	1.314**^^	0.735**^
		0.25	0.148**	0.232**	0.212**	0.289**	0.294**	0.271**	0.295**	0.382**	0.428**	0.278**	0.324**	0.383**^^	0.341**	0.301**	0.368**	0.347**	0.408**	0.402**^	0.197**
		0.50	0.472**	0.592**^	0.526**^	0.712**^	0.696**^^	0.739**^	0.65**^	0.683**	0.847**^	0.576**^	0.644**	0.72**^^	0.722**^	0.734**	0.744**	0.767**^	0.704**	0.768**^	0.33**
		0.75	0.569**	0.7**^	0.654**^	0.901**^^	0.839**^	0.839**^	0.839**^	0.855**^	0.979**^	0.678**^	0.749**	0.825**^^	0.88**^	0.971**^	0.93**^	1.05**^	0.849**^	0.981**^	0.445**
	NKN	0.00	1.34**^^	1.27**^^	1.483**^^	1.511**^^	1.703**^^	1.552**^^	1.668**^^	1.668**^^	1.708**^^	1.501**^^	1.42**^^	1.59**^^	1.696**^^	1.924**^^	1.565**^^	1.745**^^	1.526**^^	1.705**^^	1.001**^^
		0.25	0.162**	0.27**^^	0.19**^	0.311**^^	0.338**^^	0.296**^	0.323**^	0.44**^^	0.48**^	0.473**^^	0.357**^	0.464**^^	0.43**^^	0.361**^^	0.421**^^	0.415**^^	0.455**^^	0.463**^^	0.222**^
		0.50	0.47**^^	0.687**^^	0.562**^^	0.867**^^	0.91**^^	0.841**^^	0.823**^^	0.902**^^	1.037**^^	0.895**^^	0.833**^^	0.971**^^	0.946**^^	0.938**^^	0.891**^^	0.924**^^	0.899**^^	0.956**^^	0.455**^^
		0.75	0.575**^	0.775**^^	0.712**^^	1.052**^^	1.075**^^	0.922**^^	0.963**^^	1.15**^^	1.215**^^	0.978**^^	0.925**^^	1.108**^^	1.147**^^	1.192**^^	1.096**^^	1.165**^^	1.124**^^	1.16**^^	0.62**^^

*   paired t-test, $p<0.05$
** paired t-test, $p<0.001$
^   Kolmogorov-Smirnov test (bootstrapped), $p<0.05$
^^ Kolmogorov-Smirnov test (bootstrapped), $p<0.001$

Table H2. Comparison of final nearest neighbour (0.25 caliper) matched and unmatched covariate means for remnant (treated) and non-remnant (untreated) observations, according to four measures of matching adequacy. Adequate matching reduces differences to near-zero. (Continued on next pages.)

Year	Covariate	Mean treatment	Mean control	Mean difference	Standardized difference	Mean raw eQQ	Mean eCDF
1999_{FL}	*RE code*						
	Unmatched	11065	11067	−2	−0.6716	1.4813	0.0039
	Matched	11064	11064	0	−0.0333	0.4898	0.004
	Remoteness						
	Unmatched	11.02	9.7989	1.2211	31.574	1.2212	0.0837
	Matched	10.826	10.817	0.009	0.2329	0.0167	0.0015
	Slope						
	Unmatched	2.4048	1.5106	0.8942	30.118	0.894	0.0881
	Matched	1.8816	1.8768	0.0048	0.2546	0.0077	0.0013
	Parcel size						
	Unmatched	85.378	51.738	33.64	30.396	33.636	0.0405
	Matched	80.164	80.127	0.037	0.0338	0.3344	0.0021
	Tenure						
	Unmatched	0.6232	0.6132	0.0099	2.0518	0.0099	0.005
	Matched	0.6394	0.6394	0	0	0	0
	Drought frequency						
	Unmatched	27.016	27.658	−0.642	−9.6526	0.6602	0.0239
	Matched	27.264	27.269	−0.005	−0.0799	0.0102	0.0004
	Rainfall variability						
	Unmatched	201.08	195.66	5.42	22.673	5.4782	0.033
	Matched	199	198.94	0.06	0.2322	0.105	0.0006
1999_{FO}	*RE code*						
	Unmatched	11055	11057	−2	−0.7018	1.9154	0.0036
	Matched	11054	11055	−1	−0.1544	0.5468	0.0038
	Remoteness						
	Unmatched	9.6045	8.2703	1.3342	35.809	1.3342	0.091
	Matched	9.3822	9.3778	0.0044	0.1195	0.0121	0.0009
	Slope						
	Unmatched	2.2445	1.3775	0.867	28.613	0.8669	0.0836
	Matched	1.8046	1.8011	0.0035	0.1718	0.0066	0.0011
	Parcel size						
	Unmatched	53.004	25.866	27.138	38.518	27.136	0.0495
	Matched	49.138	49.108	0.03	0.0445	0.127	0.0016
	Drought frequency						
	Unmatched	28.539	29.142	−0.603	−8.9684	0.6156	0.0207
	Matched	28.882	28.882	0	0.0047	0.0047	0.0002
	Rainfall variability						
	Unmatched	195.07	188.74	6.33	25.489	6.4799	0.0387
	Matched	193.03	192.99	0.04	0.1478	0.0843	0.0005
2000	*RE code*						
	Unmatched	11058	11058	0	−0.0695	0.2196	0.0012
	Matched	11058	11058	0	−0.141	0.4663	0.0034

	Remoteness						
	Unmatched	9.5561	8.3712	1.1849	31.676	1.1849	0.0784
	Matched	9.3514	9.3467	0.0047	0.1282	0.0115	0.0008
	Slope						
	Unmatched	2.2756	1.3852	0.8904	30.097	0.8903	0.0899
	Matched	1.8349	1.8304	0.0045	0.2213	0.0072	0.0012
	Parcel size						
	Unmatched	52.578	27.082	25.496	36.442	25.493	0.0441
	Matched	49.372	49.335	0.037	0.0524	0.1281	0.0023
	Drought frequency						
	Unmatched	28.588	29.06	−0.472	−6.9275	0.5072	0.0166
	Matched	28.915	28.915	0	−0.0042	0.0045	0.0002
	Rainfall variability						
	Unmatched	195.63	188.89	6.74	27.511	6.8704	0.0447
	Matched	193.62	193.57	0.05	0.2117	0.0917	0.0006
2001	*RE code*						
	Unmatched	11067	11067	0	−0.0797	0.1219	0.0002
	Matched	11067	11067	0	0.0102	0.2078	0.0023
	Remoteness						
	Unmatched	9.7123	8.4784	1.2339	31.953	1.2343	0.0789
	Matched	9.4248	9.415	0.0098	0.2611	0.0147	0.0011
	Slope						
	Unmatched	2.3761	1.6111	0.765	25.852	0.7647	0.0749
	Matched	1.9476	1.9423	0.0053	0.2528	0.0093	0.0014
	Parcel size						
	Unmatched	55.67	30.142	25.528	32.573	25.529	0.0277
	Matched	51.305	51.249	0.056	0.0731	0.1822	0.0031
	Drought frequency						
	Unmatched	28.3	29.15	−0.85	−12.334	0.8497	0.0288
	Matched	28.701	28.702	−0.001	−0.0178	0.0032	0.0001
	Rainfall variability						
	Unmatched	198.35	189.98	8.37	34.982	8.4963	0.0586
	Matched	196.3	196.23	0.07	0.2888	0.1208	0.0008
2002	*RE code*						
	Unmatched	11067	11068	−1	−0.552	0.9171	0.0009
	Matched	11066	11066	0	0.0034	0.262	0.0029
	Remoteness						
	Unmatched	9.7149	8.4751	1.2398	31.958	1.2401	0.0791
	Matched	9.4059	9.3964	0.0095	0.2509	0.0142	0.0011
	Slope						
	Unmatched	2.454	1.6358	0.8182	26.241	0.818	0.0765
	Matched	1.983	1.9767	0.0063	0.2884	0.0097	0.0016
	Parcel size						
	Unmatched	55.812	30.653	25.159	32.568	25.157	0.0282
	Matched	51.056	50.989	0.067	0.0878	0.1666	0.0024
	Drought frequency						
	Unmatched	28.198	29.035	−0.837	−12.186	0.8396	0.0292

	Matched	28.624	28.624	0	−0.0055	0.0039	0.0002
	Rainfall variability						
	Unmatched	198.39	189.7	8.69	35.956	8.8196	0.0574
	Matched	196.18	196.11	0.07	0.2942	0.1069	0.0007
2003	*RE code*						
	Unmatched	11067	11067	0	−0.0516	0.2672	0.0012
	Matched	11067	11067	0	−0.0028	0.1844	0.0019
	Remoteness						
	Unmatched	9.4032	8.3308	1.0724	27.972	1.0726	0.0672
	Matched	9.1044	9.0964	0.008	0.2156	0.0141	0.0011
	Slope						
	Unmatched	2.4244	1.6041	0.8203	25.955	0.8201	0.0759
	Matched	1.9538	1.9472	0.0066	0.3022	0.0101	0.0017
	Parcel size						
	Unmatched	49.122	29.58	19.542	28.313	19.541	0.023
	Matched	44.445	44.401	0.044	0.0659	0.1581	0.0022
	Drought frequency						
	Unmatched	28.577	29.272	−0.695	−10.111	0.7043	0.0225
	Matched	28.999	28.999	0	0.001	0.0035	0.0001
	Rainfall variability						
	Unmatched	197.02	188.87	8.15	33.784	8.2938	0.0553
	Matched	194.81	194.75	0.06	0.2713	0.108	0.0007
2004	*RE code*						
	Unmatched	11069	11069	0	0.0472	0.3474	0.0011
	Matched	11068	11068	0	−0.0419	0.125	0.0012
	Remoteness						
	Unmatched	9.5932	8.4525	1.1407	29.542	1.1413	0.0708
	Matched	9.2769	9.271	0.0059	0.159	0.0121	0.0009
	Slope						
	Unmatched	2.4054	1.6381	0.7673	26.117	0.7671	0.0751
	Matched	1.954	1.9488	0.0052	0.2522	0.009	0.0015
	Parcel size						
	Unmatched	53.318	30.29	23.028	30.963	23.03	0.0246
	Matched	48.685	48.648	0.037	0.0515	0.1703	0.0026
	Drought frequency						
	Unmatched	28.486	29.164	−0.678	−9.7533	0.6924	0.0218
	Matched	28.919	28.92	−0.001	−0.0097	0.0029	0.0001
	Rainfall variability						
	Unmatched	198.42	189.75	8.67	35.024	8.7514	0.0556
	Matched	196.11	196.04	0.07	0.2955	0.1045	0.0007
2005	*RE code*						
	Unmatched	11075	11074	1	0.2857	0.4727	0.0005
	Matched	11074	11074	0	0.1245	0.1693	0.0022
	Remoteness						
	Unmatched	11.358	10.228	1.13	28.535	1.134	0.0756
	Matched	11.187	11.176	0.011	0.2593	0.0182	0.002
	Slope						

	Unmatched	2.6573	1.8084	0.8489	26.606	0.8486	0.0766
	Matched	2.0794	2.0726	0.0068	0.3305	0.0109	0.0017
	Parcel size						
	Unmatched	96.985	70.709	26.276	20.77	26.269	0.0218
	Matched	91.381	91.175	0.206	0.1647	0.4219	0.0028
	Tenure						
	Unmatched	0.5551	0.5555	−0.0004	−0.0801	0.0004	0.0002
	Matched	0.5632	0.5632	0	0	0	0
	Drought frequency						
	Unmatched	26.477	27.345	−0.868	−13.275	0.8713	0.0303
	Matched	26.668	26.674	−0.006	−0.0843	0.0094	0.0004
	Rainfall variability						
	Unmatched	204.48	197.05	7.43	32.244	7.4711	0.0475
	Matched	202.24	202.16	0.08	0.3823	0.1213	0.0008
2006	*RE code*						
	Unmatched	11073	11073	0	0.0477	0.1549	0.0003
	Matched	11074	11074	0	0.1478	0.2253	0.0028
	Remoteness						
	Unmatched	11.129	10.028	1.101	27.558	1.1033	0.0735
	Matched	10.962	10.951	0.011	0.258	0.0179	0.002
	Slope						
	Unmatched	2.5195	1.7896	0.7299	26.004	0.7298	0.0723
	Matched	2.0544	2.0479	0.0065	0.3337	0.0099	0.0015
	Parcel size						
	Unmatched	86.176	64.526	21.65	18.553	21.647	0.0203
	Matched	81.996	81.735	0.261	0.2248	0.4248	0.0032
	Tenure						
	Unmatched	0.587	0.5877	−0.0007	−0.14	0.0007	0.0003
	Matched	0.5915	0.5915	0	0	0	0
	Drought frequency						
	Unmatched	26.81	27.591	−0.781	−11.663	0.7824	0.027
	Matched	26.996	27.001	−0.005	−0.0786	0.009	0.0003
	Rainfall variability						
	Unmatched	203.69	196.57	7.12	30.662	7.2044	0.0445
	Matched	201.77	201.68	0.09	0.4278	0.1214	0.0008
2007	*RE code*						
	Unmatched	11071	11071	0	−0.0801	0.105	0.0002
	Matched	11071	11071	0	0.0872	0.1049	0.0017
	Remoteness						
	Unmatched	11.078	9.9445	1.1335	28.379	1.1345	0.0758
	Matched	10.905	10.897	0.008	0.2096	0.0161	0.0018
	Slope						
	Unmatched	2.4018	1.7043	0.6975	25.51	0.6974	0.0712
	Matched	1.9511	1.9449	0.0062	0.3315	0.0091	0.0015
	Parcel size						
	Unmatched	91.435	61.027	30.408	23.699	30.403	0.0221
	Matched	85.622	85.448	0.174	0.1393	0.4253	0.0029
	Tenure						

	Unmatched	0.5985	0.5992	−0.0007	−0.14	0.0007	0.0003
	Matched	0.6055	0.6055	0	0	0	0
	Drought frequency						
	Unmatched	26.904	27.745	−0.841	−12.686	0.8415	0.0279
	Matched	27.092	27.1	−0.008	−0.1181	0.01	0.0004
	Rainfall variability						
	Unmatched	202.96	196.07	6.89	29.525	7.0213	0.0452
	Matched	200.97	200.91	0.06	0.2779	0.1186	0.0008
2008	*RE code*						
	Unmatched	11072	11072	0	−0.034	0.1721	0.0004
	Matched	11072	11072	0	0.0549	0.137	0.0016
	Remoteness						
	Unmatched	11.008	9.9983	1.0097	25.253	1.0127	0.0667
	Matched	10.821	10.814	0.007	0.1899	0.0167	0.0019
	Slope						
	Unmatched	2.4691	1.7306	0.7385	25.955	0.7383	0.0729
	Matched	1.998	1.991	0.007	0.3695	0.0096	0.0015
	Parcel size						
	Unmatched	92.11	64.046	28.064	21.846	28.06	0.0195
	Matched	85.17	84.973	0.197	0.1598	0.4219	0.0028
	Tenure						
	Unmatched	0.597	0.5962	0.0008	0.1663	0.0008	0.0004
	Matched	0.6053	0.6053	0	0	0	0
	Drought frequency						
	Unmatched	27.057	27.829	−0.772	−11.601	0.7743	0.0277
	Matched	27.257	27.264	−0.007	−0.1011	0.011	0.0005
	Rainfall variability						
	Unmatched	203.15	195.59	7.56	32.178	7.6085	0.0493
	Matched	201.16	201.08	0.08	0.3252	0.1116	0.0007
2009	*RE code*						
	Unmatched	11069	11073	−4	−4.1342	3.7079	0.027
	Matched	11069	11069	0	−0.0052	0.2758	0.0035
	Remoteness						
	Unmatched	10.871	9.898	0.973	25.078	0.9786	0.0675
	Matched	10.721	10.714	0.007	0.1778	0.0197	0.002
	Slope						
	Unmatched	2.3745	1.7064	0.6681	24.348	0.668	0.0679
	Matched	1.9183	1.9125	0.0058	0.3002	0.0135	0.0024
	Parcel size						
	Unmatched	77.015	58.524	18.491	18.762	18.491	0.0168
	Matched	72.692	72.578	0.114	0.1182	0.4593	0.0081
	Tenure						
	Unmatched	0.57	0.6151	−0.0451	−9.1076	0.0451	0.0225
	Matched	0.5835	0.5835	0	0	0	0
	Drought frequency						
	Unmatched	27.238	27.758	−0.52	−7.4353	0.6297	0.019
	Matched	27.4	27.407	−0.007	−0.1039	0.0099	0.0004

	Rainfall variability						
	Unmatched	202.88	194.45	8.43	35.398	8.4473	0.059
	Matched	200.8	200.71	0.09	0.383	0.1566	0.0011
2010	*RE code*						
	Unmatched	11075	11075	0	0.1085	0.1075	0.0001
	Matched	11074	11074	0	0.0813	0.0656	0.0015
	Remoteness						
	Unmatched	11.124	10.153	0.971	24.807	0.9757	0.0649
	Matched	10.941	10.932	0.009	0.2279	0.0169	0.0018
	Slope						
	Unmatched	2.4628	1.7485	0.7143	26.052	0.7142	0.0723
	Matched	1.9858	1.9787	0.0071	0.3822	0.0104	0.0017
	Parcel size						
	Unmatched	81.148	64.063	17.085	17.541	17.084	0.0183
	Matched	76.062	75.891	0.171	0.1817	0.3944	0.0029
	Tenure						
	Unmatched	0.6009	0.6006	0.0003	0.0597	0.0003	0.0001
	Matched	0.6103	0.6103	0	0	0	0
	Drought frequency						
	Unmatched	26.786	27.472	−0.686	−10.202	0.6859	0.0239
	Matched	26.943	26.949	−0.006	−0.0889	0.0098	0.0004
	Rainfall variability						
	Unmatched	203.83	196.42	7.41	32.674	7.4704	0.0524
	Matched	201.8	201.73	0.07	0.341	0.1232	0.0009
2011	*RE code*						
	Unmatched	11073	11073	0	−0.0743	0.0316	0.0001
	Matched	11072	11072	0	0.0416	0.0569	0.0013
	Remoteness						
	Unmatched	10.89	9.8583	1.0317	25.98	1.0334	0.0686
	Matched	10.663	10.654	0.009	0.2294	0.0166	0.0017
	Slope						
	Unmatched	2.5535	1.7255	0.828	26.142	0.8277	0.0764
	Matched	1.9529	1.9462	0.0067	0.3501	0.0103	0.0016
	Parcel size						
	Unmatched	84.543	58.533	26.01	21.473	26.008	0.0212
	Matched	77.405	77.266	0.139	0.119	0.3591	0.0032
	Tenure						
	Unmatched	0.6421	0.6419	0.0003	0.0548	0.0003	0.0001
	Matched	0.651	0.651	0	0	0	0
	Drought frequency						
	Unmatched	27.147	27.895	−0.748	−10.962	0.7477	0.026
	Matched	27.379	27.384	−0.005	−0.0611	0.0078	0.0003
	Rainfall variability						
	Unmatched	203.83	195.73	8.1	33.261	8.1614	0.0509
	Matched	201.43	201.36	0.07	0.3014	0.1217	0.0008
2012	*RE code*						

	Unmatched	11074	11074	0	0.0616	0.249	0.0002
	Matched	11074	11074	0	−0.0323	0.1571	0.0015
	Remoteness						
	Unmatched	11.061	9.9603	1.1007	27.573	1.1019	0.073
	Matched	10.902	10.891	0.011	0.2721	0.0179	0.0018
	Slope						
	Unmatched	2.602	1.8367	0.7653	26.007	0.7651	0.0732
	Matched	2.1299	2.1234	0.0065	0.3154	0.0102	0.0016
	Parcel size						
	Unmatched	86.852	63.651	23.201	19.976	23.195	0.0216
	Matched	82.432	82.187	0.245	0.2138	0.4154	0.0025
	Tenure						
	Unmatched	0.6251	0.625	0.0001	0.0308	0.0002	0.0001
	Matched	0.6358	0.6358	0	0	0	0
	Drought frequency						
	Unmatched	26.954	27.723	−0.769	−11.548	0.7711	0.027
	Matched	27.135	27.138	−0.003	−0.0538	0.0081	0.0003
	Rainfall variability						
	Unmatched	203.78	196.17	7.61	32.592	7.7242	0.0474
	Matched	201.91	201.83	0.08	0.3681	0.117	0.0007
2013	*RE code*						
	Unmatched	11073	11073	0	−0.0596	0.0625	0.0003
	Matched	11073	11073	0	−0.0086	0.1395	0.0019
	Remoteness						
	Unmatched	11.172	10.044	1.128	28.675	1.1301	0.0757
	Matched	10.982	10.973	0.009	0.235	0.0173	0.002
	Slope						
	Unmatched	2.6066	1.7639	0.8427	27.472	0.8424	0.0798
	Matched	2.0588	2.0526	0.0062	0.3077	0.0109	0.0018
	Parcel size						
	Unmatched	87.183	62.209	24.974	20.929	24.972	0.023
	Matched	81.25	81.086	0.164	0.1402	0.3474	0.0026
	Tenure						
	Unmatched	0.5996	0.5992	0.0004	0.0877	0.0004	0.0002
	Matched	0.6022	0.6022	0	0	0	0
	Drought frequency						
	Unmatched	26.77	27.577	−0.807	−12.081	0.8099	0.0281
	Matched	27.008	27.015	−0.007	−0.1116	0.0102	0.0004
	Rainfall variability						
	Unmatched	203.91	196.02	7.89	33.349	7.9014	0.0492
	Matched	201.7	201.63	0.07	0.3472	0.1215	0.0008
2014	*RE code*						
	Unmatched	11071	11071	0	0.0428	0.147	0.0004
	Matched	11071	11071	0	0.0462	0.1188	0.0016
	Remoteness						
	Unmatched	11.09	9.9968	1.0932	27.594	1.0941	0.0733
	Matched	10.935	10.925	0.01	0.2575	0.0164	0.0019
	Slope						

	Unmatched	2.4401	1.7208	0.7193	25.745	0.7192	0.0719
	Matched	1.9755	1.9698	0.0057	0.3004	0.0101	0.0017
	Parcel size						
	Unmatched	85.573	62.776	22.797	20.161	22.789	0.0203
	Matched	81.673	81.559	0.114	0.1011	0.3238	0.0028
	Tenure						
	Unmatched	0.5959	0.5953	0.0006	0.1293	0.0006	0.0003
	Matched	0.6025	0.6025	0	0	0	0
	Drought frequency						
	Unmatched	26.894	27.668	−0.774	−11.547	0.7751	0.0263
	Matched	27.074	27.081	−0.007	−0.116	0.0094	0.0004
	Rainfall variability						
	Unmatched	203.05	196.33	6.72	28.75	6.8548	0.0427
	Matched	201.21	201.12	0.09	0.4084	0.1205	0.0007
2015	*RE code*						
	Unmatched	11073	11074	−1	−0.1631	0.1917	0.0003
	Matched	11073	11074	−1	−0.0289	0.0994	0.0013
	Remoteness						
	Unmatched	11.219	10.087	1.132	28.832	1.1345	0.0759
	Matched	11.06	11.051	0.009	0.2201	0.0158	0.0017
	Slope						
	Unmatched	2.5735	1.8024	0.7711	25.539	0.771	0.0729
	Matched	2.0675	2.0606	0.0069	0.348	0.0098	0.0015
	Parcel size						
	Unmatched	89.775	64.454	25.321	21.683	25.314	0.0228
	Matched	86.139	85.988	0.151	0.1283	0.3821	0.0021
	Tenure						
	Unmatched	0.602	0.6012	0.0008	0.1571	0.0008	0.0004
	Matched	0.606	0.606	0	0	0	0
	Drought frequency						
	Unmatched	26.719	27.518	−0.799	−12.013	0.8012	0.0272
	Matched	26.911	26.919	−0.008	−0.1191	0.0114	0.0005
	Rainfall variability						
	Unmatched	203.84	196.55	7.29	31.717	7.3688	0.045
	Matched	201.96	201.87	0.09	0.4022	0.1202	0.0007
2016	*RE code*						
	Unmatched	11068	11068	0	−0.0001	0.4094	0.0012
	Matched	11068	11068	0	−0.052	0.2783	0.0027
	Remoteness						
	Unmatched	10.821	10.062	0.759	19.06	0.7602	0.0501
	Matched	10.719	10.713	0.006	0.1718	0.0132	0.0013
	Slope						
	Unmatched	2.5398	1.5218	1.018	33.452	1.0179	0.101
	Matched	2.0337	2.0293	0.0044	0.2148	0.0068	0.0011
	Parcel size						
	Unmatched	88.434	60.988	27.446	23.285	27.438	0.028
	Matched	84.514	84.376	0.138	0.1184	0.3627	0.0022
	Tenure						

Unmatched	0.5544	0.5515	0.0029	0.5766	0.0029	0.0014
Matched	0.5674	0.5674	0	0	0	0
Drought frequency						
Unmatched	27.152	27.457	−0.305	−4.4962	0.3636	0.012
Matched	27.309	27.312	−0.003	−0.0539	0.0083	0.0003
Rainfall variability						
Unmatched	201.92	196.7	5.22	21.465	5.2894	0.0312
Matched	200.13	200.08	0.05	0.197	0.0914	0.0005

Appendix I. Full results for the causal inference analysis

Table I1. Summary of the causal inference results using nearest neighbour matching (0.25 caliper) for all years. n = number of observations in sample; n_1= number of treated observations in sample; n_m = number of matched observations; n_d = number of observations dropped by caliper.

	1999_{FL}	1999_{FO}	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
ATT	0.0329*	0.0446*	0.0191	-0.0002	-0.0022	0.0026	-0.0081	-0.0047	-0.0011	-0.0004	-0.0009	-0.0034	-0.0013	-0.0015	-0.0043	-0.0058	-0.0073	-0.0065	-0.0121
SE	0.0012	0.0013	0.0009	0.0005	0.0008	0.0007	0.0008	0.0006	0.0006	0.0005	0.0004	0.0005	0.0003	0.0003	0.0004	0.0005	0.0005	0.0006	0.0007
95% CI	0.0023	0.0025	0.0018	0.0010	0.0015	0.0014	0.0015	0.0011	0.0012	0.0009	0.0007	0.0009	0.0005	0.0006	0.0008	0.0010	0.0010	0.0012	0.0014
T-statistic	28.568	35.252	20.486	-0.4045	-2.9171	3.6888	-10.495	-8.1583	-1.8888	-0.8467	-2.3737	-7.4131	-5.0057	-4.9541	-10.627	-11.517	-13.557	-10.811	-16.923
p-value	< 0.001	< 0.001	< 0.001	0.686	0.004	< 0.001	< 0.001	< 0.001	0.059	0.397	0.018	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
n	560244	550015	550018	550000	550015	550022	550037	552714	552586	551428	551784	549952	550796	551356	551967	552925	552540	553214	559422
n_1	52571	52375	50944	50151	50313	50307	50179	50269	50366	50239	50132	55032	50041	50064	50082	50144	50160	50270	50309
n_m	47260	48366	47134	45870	45784	46056	45792	45557	46086	46158	45939	49145	45121	44751	46069	45460	46205	46009	46225
n_d	5311	4009	3810	4281	4529	4251	4387	4712	4280	4081	4193	5887	4920	5313	4013	4684	3955	4261	4084

* Estimate represents the social preference effect (SP)

Table I2. Results of the 'social preference' scenario impact estimates (ATT_{SP}) between annual ATT_{PC} estimates and the counterfactual estimate of 1999_{FO} ($SP_{FO} = 0.0446$) for 2000–2004 and 1999_{FL} ($SP_{FL} = 0.0329$) for 2005–2016. Chi-square (χ^2) df = 1. All p-values were significant at $\alpha < 0.05$ following the Holm-Bonferroni Method.

Year	ATT_{SP} estimate	95% CI	χ^2	Odds ratio	p-value
2000	−0.0254	[−0.0297, −0.0211]	8.90	0.844	0.0028
2001	−0.0448	[−0.0482, −0.0413]	144.4	0.349	< 0.0001
2002	−0.0468	[−0.0508, −0.0428]	360.0	0.311	< 0.0001
2003	−0.0420	[−0.0458, −0.0381]	150.7	0.441	< 0.0001
2004	−0.0526	[−0.0566, −0.0486]	635.5	0.213	< 0.0001
2005	−0.0376	[−0.0410, −0.0342]	361.3	0.217	< 0.0001
2006	−0.0340	[−0.0374, −0.0306]	185.2	0.342	< 0.0001
2007	−0.0333	[−0.0364, −0.0301]	113.4	0.363	< 0.0001
2008	−0.0338	[−0.0367, −0.0308]	106.8	0.299	< 0.0001
2009	−0.0363	[−0.0394, −0.0331]	294.8	0.217	< 0.0001
2010	−0.0342	[−0.0370, −0.0314]	119.0	0.163	< 0.0001
2011	−0.0344	[−0.0372, −0.0315]	134.2	0.194	< 0.0001
2012	−0.0372	[−0.0402, −0.0341]	362.2	0.114	< 0.0001
2013	−0.0387	[−0.0420, −0.0355]	445.9	0.139	< 0.0001
2014	−0.0401	[−0.0434, −0.0368]	543.3	0.127	< 0.0001
2015	−0.0394	[−0.0428, −0.0360]	468.0	0.184	< 0.0001
2016	−0.0450	[−0.0486, −0.0413]	772.1	0.138	< 0.0001

Appendix J. Ethics approval letter

THE UNIVERSITY OF QUEENSLAND

Sub-Committee Human Research Ethics Approval

Project Title:	Social dimensions of land clearing: landholder typologies, attitudes, and behaviours in the Brigalow Belt South- 22/03/2018 AMENDMENT
Chief Investigator:	Mx Blake Simmons
Supervisor:	Prof Kerrie Wilson
Co-Investigator(s):	Dr Angela Dean, Mr Joshua Brown
School(s):	School of Biological Sciences, The University of Queensland
Approval Number:	2017001054
Granting Agency/Degree:	ARC grant
Duration:	31st July 2019

Comments/Conditions:

Amendment 22/03/2018
- Addition of Investigator: Joshua Brown
- CV - Joshua Brown
- Participant Information Sheet & Consent_Interview, 22/03/2018
- Participant Information Sheet & Consent_Online, 23/03/2018
- Protocol, 22/03/2018
- Questionnaire, 22/03/2018

Note: if this approval is for amendments to an already approved protocol for which a UQ Clinical Trials Protection/Insurance Form was originally submitted, then the researchers must directly notify the UQ Insurance Office of any changes to that Form and Participant Information Sheets& Consent Forms as a result of the amendments, before action.

Name of responsible Sub-Committee:
University of Queensland Science, Low & Negligible Risk Ethics Sub-Committee
This project complies with the provisions contained in the*National Statement on Ethical Conduct in Human Research* and complies with the regulations governing experimentation on humans.

Name of Ethics Sub-Committee representative:
Dr Karen McNamara
Chairperson
University of Queensland Science, Low & Negligible Risk Ethics Sub-Committee

Signature

26/03/2018
Date

Appendix K. Full list of survey items included in the analysis

Table K1. Description of all survey items analysed including the scale and Cronbach's alpha (α) of single scores generated for multi-item scales. (Continued on next pages.)

Variables	Items	Scale	α
Values			
Economic	I view my farm as first and foremost a business enterprise	[1, 6]	0.747
	When planning future farming activities I only focus on how profitable they will be		
	A maximum annual return from my property is my most important aim		
Lifestyle	The lifestyle that comes with being on the farm is very important to me	[1, 6]	0.748
	Farming communities are a great place to live		
	We do not make a fortune from farming but the lifestyle is great		
Conservation	The most important thing is leaving my property in better shape than I found it	[1, 6]	0.743
	Land stewardship by farmers is more important than anything else about farming		
	Managing environmental problems on my farm is a very high priority		
Place Attachment	I am happiest when I'm on my farm	[1, 6]	0.644
	I feel my farm is a part of me		
Attitudes *			
Pro-Clearing	I am concerned about the rate of tree clearing in Queensland †	[1, 6]	0.819
	Tree clearing should be stopped †		
	People are clearing too many trees †		
	People who clear trees from their property do not care about the environment †		
Anti-VMA	In my opinion, vegetation management regulations…	[1, 6]	0.648
	Are a burden to me		
	Are fair to farmers †		
	Are necessary †		
	Should be more strict †		
Good Farmer Identity Definition	A 'good farmer'…		
Profit-maximizing	Always finds a way to maximise their profits	[1, 6]	
Altruistic	Puts the needs of the community before his/her own needs	[1, 6]	
Law-abiding	Obeys laws that restrict what can and can't be done on his/her farm	[1, 6]	
Productivity-maximizing	Always finds a way to maximise the productivity of their land	[1, 6]	
Lifestyle-focused	Enjoys the farming lifestyle even if profits are low	[1, 6]	
Good Farmer Self-Identity			
'Good farmer' perception	I think of myself as a 'good farmer'	[1, 6]	
'Better farmer' perception	I am a 'better farmer' than most people in my community	[1, 6]	
Relative threat of the VMA *	To what degree do the following pose a threat to the property you manage?	[−5, 5] ‡	
	Drought and extreme weather	[1, 6]	
	Pest species (e.g. feral cats, pigs, foxes, rabbits)	[1, 6]	
	Mining activities	[1, 6]	
	Your personal health and well-being	[1, 6]	
	Escalating costs of running the business	[1, 6]	
	Changing prices for agricultural products	[1, 6]	
	Vegetation management regulations	[1, 6]	
	Chemical and pesticide use regulations	[1, 6]	
Trust in the government	The Queensland Government has my best interests in mind	[1, 6]	0.712
	I can trust the Queensland Government to always do what is right		
Security			
Comfortable lifestyle	I am confident that I can still enjoy a comfortable lifestyle while following vegetation management regulations	[1, 6]	
No threat to livelihood	Vegetation management regulations are a threat to my business or livelihood †	[1, 6]	
Loss Aversion			
Possessions	I get easily attached to material things (e.g. my car, my furniture)	[1, 5]	
Profits	If profits become very high, I wouldn't want to return to previous profit levels	[1, 5]	
Autonomy	I could not cope with losing the freedom to make decisions on my property	[1, 5]	
Land	Losing some land for grazing or cropping is bad, but I would manage†	[1, 5]	
Emotions to Regulations	When you think about vegetation management regulations in Queensland, do you feel…		

Negative *	Angry Depressed Anxious Exhausted	[1, 6]	0.859
Positive	Relieved Hopeful	[1, 6]	0.796
Perceived Behavioural Control	How much personal control do you feel you have over tree clearing decisions on your property? Following the vegetation management regulations set forth by the Queensland Government is… [difficult to easy]	[1, 6]	0.669
Social Norms *			
Tree clearing	Most of the farmers in my community clear trees	[1, 6]	
Disobeying regulations	Most of the farmers in my community follow the vegetation management regulations †	[1, 6]	
Awareness of Norms	I know how most farmers in my area manage their land Most farmers in my area know how I manage my land *	[1, 6]	0.797
Financial Strain	Within the last four weeks, how often have you… Had serious financial worries? Not been able to do the things you like to do because of shortages of money? Not been able to do the things you need to do because of shortages of money?	[1, 5]	0.908
Life Satisfaction	Thinking about your own life and personal circumstances, how satisfied are you with your life as a whole?	[0, 10]	
Social Capital	Are you an active member of the following?		
Ag involvement	An agricultural organisation (e.g. AgForce, Queensland Farmers' Federation)	[1, 4]	
General involvement	A local community group, organisation, or club (e.g. sport, craft, social club)	[1, 4]	
Trees Present	Are there any trees (including tree regrowth) currently on your property that are not grown or harvested for production purposes?	Yes/No	
Clearing Purposes **	In the last 5 years, how often have you cleared trees from your property for the following purposes?		
Relevant	Restorative purposes (e.g. thinning) Necessary maintenance (e.g. regrowth or weed removal) Infrastructure (e.g. fences, barns or sheds) Fodder development or expansion	[0, 4]	0.758
Not Relevant	High-value agriculture development or expansion Pasture development or expansion	[0, 4]	0.709
Clearing Amount **	In the last 5 years, how often have you cleared the following amount of trees from your property?	[0, 102.5] ‡	
	Single trees	[0, 4]	
	Less than 1 hectare (ha)	[0, 4]	
	1 - 5 ha	[0, 4]	
	5 - 10 ha	[0, 4]	
	More than 10 ha	[0, 4]	
Clearing Influences	To what extent do the following influence how you make tree clearing decisions on your property?		
Ag prices	Agricultural or livestock prices	[1, 6]	
Droughts	Recent droughts	[1, 6]	
Regulations	Vegetation management restrictions	[1, 6]	
Profitability	Potential profitability of the land	[1, 6]	
Aesthetics	Aesthetic or attractive value of trees	[1, 6]	
Policy uncertainty	Talks of new clearing regulations in Parliament	[1, 6]	
Costs	Feasibility or costs associated with clearing	[1, 6]	
Clearing Amount Relative to Others **	Compared to other farmers/graziers in your community, do you think you clear trees more or less than they do?	[1, 5]	
Clearing Intentions (next 6 months) **	"I intend to engage in tree clearing on my property during the next 6 months."	[1, 6]	
Voluntary Program Participation	Have you participated in any of these programs? Landcare grants for private land conservation (e.g. Sustainable agriculture, Restoration) Land management agreements (e.g. Land for Wildlife) Conservation covenant (e.g. The Nature Refuges Program) Other projects or programs	[1, 5]	
Incentives for Participation (% yes)	Which of the following factors are the main reasons why you have participated in one or more of these programs?		
Importance	The intrinsic value or importance of nature	Yes/No	
Environmental	The environmental benefits for my property or my community	Yes/No	

Risk-aversion	To minimise environmental threats or risks to my property or family	Yes/No
Community influence	My neighbours or other farmers in my community have benefited from them	Yes/No
Financial	The financial benefits for my property or my community	Yes/No
Barriers to Participation (% yes)	Which of the following factors are the main reasons why you have not participated in one or more of these programs?	
Exposure	Lack of exposure or knowledge of the programs	Yes/No
Loss-aversion	Loss of autonomy or control over my property	Yes/No
Financial	Loss of income or market value of my land	Yes/No
Community influence	My neighbours or other farmers in my community regret participating in them	Yes/No
Importance	I do not think nature needs to be protected on my property	Yes/No
Demographics		
Survey eligibility	Which of the following best describes you?	[0, 1]
Manager	I manage a farm or other grazing or production property	
Non-manager	I have a family member who manages a farm or other grazing or production property	
	I interact with farmers or graziers for my work	
Years managing	Approximately how many years have you managed your current farm or other grazing or production properties?	[1, 99]
Primary decision-maker	Are you primarily responsible for making management decisions on this property?	[0, 1]
Education	What is the highest level of education you have completed?	[0, 1]
	Did not complete high school	
	High school	
	Diploma or TAFE/Technical Certificate	
	Bachelor Degree	
	Post-Graduate Degree	
Income	The average person in Queensland has a total personal income of $40,000 to $50,000 per year. Is your personal income above, below or roughly equal to this average?	[1, 3]
	Below this average	
	Equal to this average	
	Above this average	
Postcode (residence)	What is the postcode at your main place of residence?	
Postcode (property)	What is the postcode (or postcodes) that your property is in?	

* Variables used for psychosocial clusters
** Variables used for clearing clusters
† Scores reversed for analysis
‡ Scale of the generated single score differs from items' scale; see main text for calculation

Appendix L. Results of model selection for all typologies

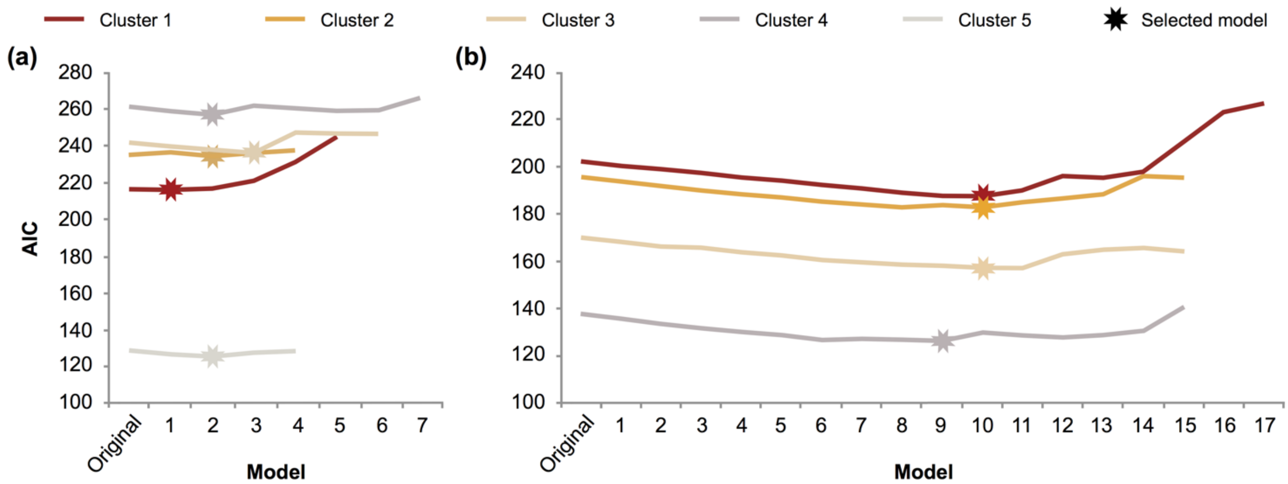

Fig. L1. Selection of the most parsimonious model predicting cluster membership. Models for (a) psychosocial typologies and (b) clearing typologies selected according to the Akaike information criterion (AIC).

Appendix M. Summary of participants' responses to all variables

Table M1. Comparison of the demographic and psychosocial characteristics of the entire land managers' sample and the four clearing typologies identified. Continuous variables are represented as *mean (SD)* and categorical variables are represented as *% (number of participants)*. Significant differences between clusters are in **bold**. (Continued on next page.)

Variables	Sample	Inactive clearers	Irregular clearers	Perceived active clearers	Active clearers	*p*-value
Values						
Economic	4.24 (1.10)	4.08 (1.19)	3.90 (0.98)	4.57 (1.01)	4.46 (1.02)	**0.023**
Lifestyle	5.18 (0.92)	5.11 (0.96)	5.28 (0.72)	5.30 (0.91)	5.08 (1.03)	0.653
Conservation	5.31 (0.73)	5.26 (0.75)	5.30 (0.74)	5.39 (0.56)	5.32 (0.89)	0.860
Place Attachment	5.29 (0.85)	5.19 (0.82)	5.31 (0.80)	5.47 (0.73)	5.23 (1.08)	0.328
Attitudes						
Pro-Clearing	4.64 (1.28)	4.40 (1.39)	4.24 (1.31)	5.14 (1.02)	4.79 (1.15)	**0.004**
Anti-VMA	4.61 (1.08)	4.27 (1.21)	4.46 (1.09)	4.88 (0.92)	4.97 (0.81)	**0.011**
Good Farmer Identity Definition						
Profit-maximizing	4.72 (1.15)	4.60 (1.09)	4.49 (1.31)	4.96 (1.07)	4.86 (1.16)	0.182
Altruistic	3.97 (1.21)	3.97 (1.13)	3.60 (1.17)	4.11 (1.43)	4.14 (1.06)	0.147
Law-abiding	4.74 (1.29)	4.71 (1.48)	4.60 (1.03)	4.63 (1.29)	5.08 (1.14)	0.177
Productivity-maximizing	5.07 (1.05)	5.18 (0.93)	4.71 (1.15)	5.22 (1.09)	5.05 (1.03)	0.110
Lifestyle-focused	4.66 (1.35)	4.50 (1.34)	4.89 (1.28)	4.74 (1.42)	4.59 (1.36)	0.475
Good Farmer Self-Identity						
Perception as 'good farmer'	5.20 (0.93)	5.02 (1.08)	5.31 (0.93)	5.35 (0.74)	5.22 (0.85)	0.395
Perception as 'better farmer'	4.14 (1.32)	4.00 (1.19)	4.40 (1.38)	4.11 (1.39)	4.19 (1.39)	0.471
Relative threat of the VMA	0.54 (1.34)	0.15 (1.53)	0.57 (1.34)	0.87 (1.22)	0.74 (0.97)	**0.044**
Trust in the government	1.41 (0.79)	1.56 (0.92)	1.34 (0.59)	1.35 (0.82)	1.31 (0.66)	0.438
Security						
Comfortable lifestyle	2.87 (1.60)	3.13 (1.77)	3.09 (1.46)	2.72 (1.64)	2.43 (1.28)	0.178
No threat to livelihood	3.18 (1.83)	3.58 (1.87)	3.26 (1.75)	2.70 (1.68)	3.03 (1.89)	0.110
Loss Aversion						
Possessions	2.45 (1.25)	2.50 (1.26)	2.51 (1.38)	2.47 (1.22)	2.28 (1.16)	0.848
Profits	3.40 (1.29)	3.52 (1.20)	3.29 (1.34)	3.53 (1.31)	3.17 (1.36)	0.527
Autonomy	4.40 (1.03)	4.43 (0.98)	4.43 (0.95)	4.33 (1.13)	4.39 (1.10)	0.993
Land	4.19 (1.42)	4.27 (1.50)	4.17 (1.25)	4.42 (1.37)	3.81 (1.47)	0.261
Emotions to Regulations						
Negative	3.76 (1.49)	3.28 (1.66)	3.83 (1.29)	4.09 (1.42)	4.08 (1.29)	**0.029**
Positive	1.96 (1.20)	2.10 (1.35)	1.89 (1.02)	1.91 (1.19)	1.88 (1.10)	0.899
Perceived Behavioural Control	2.41 (1.27)	2.68 (1.36)	2.51 (1.31)	2.13 (1.17)	2.19 (1.11)	0.128
Social Norms						
Tree clearing	3.18 (1.72)	2.77 (1.82)	3.66 (1.51)	2.58 (1.56)	4.15 (1.41)	**< 0.001**
Disobeying regulations	2.38 (1.31)	2.43 (1.28)	2.57 (1.26)	2.30 (1.35)	2.22 (1.37)	0.465
Awareness of Norms	4.70 (1.15)	4.44 (1.31)	4.49 (1.17)	5.06 (0.93)	4.90 (0.94)	**0.039**
Financial Strain	2.58 (1.17)	2.56 (1.27)	2.96 (0.94)	2.41 (1.06)	2.44 (1.29)	0.126
Life Satisfaction	7.64 (1.89)	7.70 (1.83)	6.71 (2.04)	8.04 (1.40)	7.94 (2.15)	**0.009**
Social Capital						
Ag involvement	2.25 (1.15)	2.00 (1.07)	2.17 (1.15)	2.56 (1.16)	2.36 (1.22)	0.091
General involvement	2.76 (1.26)	2.48 (1.24)	2.77 (1.24)	2.80 (1.31)	3.14 (1.20)	0.096
Trees Present						0.098 [f]
Managers with trees	89% (161)	82% (51)	97% (34)	89% (41)	95% (35)	
Managers without trees	11% (19)	18% (11)	3% (1)	11% (5)	5% (2)	
Clearing Purposes [*]						
Relevant	1.47 (0.90)	0.59 (0.51)	1.73 (0.45)	1.52 (0.54)	2.61 (0.53)	
Not Relevant	1.09 (1.05)	0.07 (0.25)	1.26 (0.55)	1.16 (0.64)	2.54 (0.80)	

Clearing Amount *	12.23 (21.58)	0.62 (2.12)	5.18 (8.44)	9.54 (16.86)	41.68 (26.55)	
Clearing Influences						
Ag prices	2.42 (1.82)	1.85 (1.67)	2.17 (1.69)	2.35 (1.70)	3.70 (1.75)	**< 0.001**
Droughts	2.24 (1.72)	1.73 (1.54)	2.23 (1.61)	1.89 (1.35)	3.54 (1.91)	**< 0.001**
Regulations	3.10 (2.05)	2.37 (1.89)	2.74 (1.92)	3.46 (2.15)	4.22 (1.77)	**< 0.001**
Profitability	3.32 (1.91)	2.50 (1.85)	3.06 (1.78)	3.57 (1.82)	4.65 (1.46)	**< 0.001**
Aesthetics	2.69 (1.82)	2.31 (1.90)	2.20 (1.62)	2.70 (1.66)	3.78 (1.65)	**< 0.001**
Policy uncertainty	2.56 (1.90)	2.05 (1.81)	2.14 (1.72)	2.78 (1.91)	3.54 (1.83)	**< 0.001**
Costs	2.98 (1.97)	2.07 (1.78)	2.80 (1.84)	3.35 (1.95)	4.19 (1.71)	**< 0.001**
Clearing Amount Relative to Others *	2.34 (0.89)	2.05 (0.86)	1.57 (0.50)	2.98 (0.26)	2.76 (0.95)	
Clearing Intentions (next 6 months) *	2.87 (1.90)	1.42 (0.88)	2.77 (1.83)	3.37 (1.73)	4.78 (1.42)	
Voluntary Program Participation	2.26 (0.76)	2.03 (0.73)	2.43 (0.76)	2.30 (0.69)	2.45 (0.80)	**0.009**
Incentives for Participation (% yes)						
Importance	75% (53)	73% (11)	81% (13)	62% (13)	84% (16)	0.383
Environmental	93% (66)	93% (14)	94% (15)	100% (21)	84% (16)	0.287
Risk-aversion	79% (56)	80% (12)	75% (12)	81% (17)	79% (15)	0.976
Community influence	49% (35)	73% (11)	38% (6)	43% (9)	47% (9)	0.198
Financial	56% (40)	53% (8)	31% (5)	71% (15)	63% (12)	0.095
Barriers to Participation (% yes)						
Exposure	53% (80)	49% (24)	55% (17)	59% (24)	50% (15)	0.809
Loss-aversion	41% (62)	37% (18)	32% (10)	56% (23)	37% (11)	0.144
Financial	32% (48)	35% (17)	26% (8)	37% (15)	27% (8)	0.685
Community influence	14% (21)	8% (4)	6% (2)	17% (7)	27% (8)	0.067
Importance	24% (36)	29% (14)	13% (4)	20% (8)	33% (10)	0.210
Demographics						
Manager						
Manages a farm	100% (180)	--	--	--	--	--
Does not manage a farm	0% (0)	--	--	--	--	--
Years managing their property	30.34 (17.46)	32.77 (16.94)	29.4 (15.11)	30.13 (17.74)	27.41 (20.02)	0.395
Decision-maker						0.372 p
Primary decision-maker	72% (129)	71% (44)	63% (22)	80% (37)	70% (26)	
Joint decisions, no decisions	28% (51)	29% (18)	37% (13)	20% (9)	30% (11)	
Age	59.36 (13.53)	63.17 (14.12)	57.91 (10.84)	60.53 (12.76)	53.14 (13.92)	**0.005**
Gender						0.111 p
Male	77% (135)	73% (44)	66% (23)	80% (36)	89% (32)	
Female	23% (41)	27% (16)	34% (12)	20% (9)	11% (4)	
Education						0.609 p
High school	53% (93)	58% (35)	46% (16)	49% (22)	56% (20)	
Tertiary	47% (83)	42% (25)	54% (19)	51% (23)	44% (16)	
Income						0.540 p
Less than $50,000	30% (52)	33% (20)	29% (10)	22% (10)	33% (12)	
Equal to $50,000	30% (52)	23% (14)	37% (13)	38% (17)	22% (8)	
More than $50,000	41% (72)	43% (26)	34% (12)	4% (18)	44% (16)	
Remoteness						
Property postcode	5.22 (3.61)	4.86 (3.85)	5.42 (2.96)	4.54 (3.06)	6.56 (4.33)	**0.035**
Residence postcode	5.26 (3.74)	4.71 (3.84)	5.41 (3.15)	4.85 (3.50)	6.56 (4.50)	0.055
Years at current residence	35.69 (23.2)	35.15 (23.17)	36.91 (20.78)	37.98 (25.04)	32.50 (23.65)	0.788

* Variables used to generate clusters
p Result according to Pearson's chi-squared test
f Result according to Fisher's exact test

Table M2. Comparison of the demographic and psychosocial characteristics of the entire sample and the five psychosocial typologies identified for all participants. Continuous variables are represented as *mean (SD)* and categorical variables are represented as *% (number of participants)*. Significant differences between clusters are in **bold**. (Continued on next page.)

Variables	Sample	Refusers	Reluctant acceptors	Neutrals	Acceptors	Supporters	*p*-value
Values †							
Economic	4.36 (1.07)	4.40 (1.04)	4.54 (1.06)	4.43 (1.11)	4.33 (1.12)	3.90 (1.01)	**0.014**
Lifestyle	5.15 (0.91)	5.22 (0.76)	5.32 (0.88)	5.11 (0.93)	4.97 (1.07)	4.97 (0.94)	0.434
Conservation	5.33 (0.74)	5.12 (0.76)	5.62 (0.43)	5.44 (0.53)	5.16 (1.00)	5.16 (0.89)	**0.010**
Place Attachment †	5.33 (0.82)	5.28 (0.73)	5.55 (0.67)	5.30 (0.74)	5.22 (1.12)	5.13 (0.90)	0.140
Attitudes *							
Pro-Clearing	4.63 (1.30)	5.39 (0.56)	5.61 (0.48)	4.35 (1.02)	4.12 (0.96)	2.66 (1.20)	
Anti-VMA	4.61 (1.15)	5.43 (0.40)	5.32 (0.65)	4.56 (0.83)	4.15 (0.76)	2.73 (0.88)	
Good Farmer Identity Definition							
Profit-maximizing	4.84 (1.16)	4.81 (1.05)	4.84 (1.32)	5.03 (1.03)	4.76 (1.21)	4.77 (1.11)	0.348
Altruistic	3.90 (1.22)	3.59 (1.28)	4.00 (1.30)	4.31 (1.18)	4.00 (0.98)	3.50 (1.17)	0.135
Law-abiding	4.73 (1.41)	4.11 (1.45)	5.06 (1.54)	4.66 (1.49)	4.76 (1.10)	5.00 (1.13)	**< 0.001**
Productivity-maximizing	5.12 (1.08)	5.19 (1.02)	5.14 (1.31)	5.28 (0.96)	5.00 (0.89)	4.96 (1.04)	0.234
Lifestyle-focused	4.64 (1.34)	4.38 (1.53)	4.76 (1.37)	4.59 (1.32)	4.82 (1.06)	4.62 (1.42)	0.738
Good Farmer Self-Identity †							
Perception as 'good farmer'	5.23 (0.89)	5.30 (0.79)	5.41 (0.82)	5.20 (0.91)	5.24 (0.72)	4.80 (1.20)	**0.025**
Perception as 'better farmer'	4.12 (1.27)	4.43 (1.36)	4.18 (1.45)	3.80 (0.87)	4.00 (1.12)	4.10 (1.33)	0.986
Relative threat of the VMA *	0.42 (1.57)	1.21 (0.85)	1.49 (0.77)	−0.49 (1.44)	0.50 (1.07)	−1.81 (1.34)	
Trust in the government	1.50 (0.96)	1.07 (0.21)	1.08 (0.32)	1.61 (0.99)	1.81 (1.18)	2.38 (1.31)	**< 0.001**
Security							
Comfortable lifestyle	2.84 (1.63)	2.08 (1.18)	1.96 (1.15)	3.09 (1.63)	3.41 (1.37)	4.58 (1.58)	**< 0.001**
No threat to livelihood	3.20 (1.89)	2.95 (1.81)	1.84 (1.39)	3.88 (1.66)	3.24 (1.58)	5.35 (1.02)	**< 0.001**
Loss Aversion †							
Possessions	2.43 (1.27)	2.23 (1.01)	2.44 (1.47)	2.8 (1.35)	2.24 (1.33)	2.50 (1.05)	0.694
Profits	3.34 (1.33)	3.30 (1.39)	3.46 (1.39)	3.56 (1.33)	3.16 (1.28)	3.10 (1.25)	0.529
Autonomy	4.40 (1.01)	4.47 (0.86)	4.72 (0.86)	4.24 (1.27)	4.00 (1.19)	4.40 (0.75)	**0.009**
Land	4.19 (1.40)	4.83 (1.21)	4.26 (1.55)	4.28 (1.37)	3.72 (1.28)	3.55 (1.15)	**0.006**
Emotions to Regulations							
Negative *	3.74 (1.54)	4.21 (1.23)	4.69 (1.17)	3.87 (1.39)	3.39 (1.23)	1.55 (0.59)	
Positive	2.16 (1.34)	1.57 (0.92)	1.47 (0.81)	2.39 (1.28)	2.72 (1.34)	3.37 (1.55)	**< 0.001**
Perceived Behavioural Control	2.38 (1.25)	2.07 (0.91)	1.81 (1.05)	2.28 (1.18)	2.76 (1.05)	3.54 (1.48)	**< 0.001**
Social Norms *							
Tree clearing	3.04 (1.72)	3.12 (1.26)	3.12 (1.76)	1.78 (1.04)	4.37 (1.64)	2.62 (1.81)	
Disobeying regulations	2.25 (1.25)	3.14 (0.65)	1.22 (0.42)	1.47 (0.57)	3.22 (1.48)	2.73 (1.16)	
Awareness of Norms	4.68 (1.15)	4.52 (0.95)	5.21 (1.06)	4.86 (0.94)	4.21 (1.22)	4.27 (1.31)	**< 0.001**
Financial Strain	2.58 (1.22)	2.77 (1.30)	2.61 (1.23)	2.74 (1.13)	2.28 (1.17)	2.47 (1.23)	0.797
Life Satisfaction	7.49 (1.99)	7.19 (2.07)	7.67 (2.16)	7.25 (2.29)	7.82 (1.45)	7.46 (1.79)	0.586
Social Capital							
Ag involvement	2.32 (1.16)	2.53 (1.07)	2.33 (1.15)	2.40 (1.29)	2.16 (1.11)	2.10 (1.25)	0.134
General involvement	2.65 (1.26)	2.70 (1.29)	2.79 (1.26)	2.88 (1.24)	2.44 (1.29)	2.30 (1.22)	0.206
Trees Present †							**0.034** ᵖ
Managers with trees	76% (156)	89% (39)	82% (41)	62% (24)	70% (30)	79% (22)	
Managers without trees	24% (48)	11% (5)	18% (9)	38% (15)	30% (13)	21% (6)	
Clearing Purposes †							
Relevant	1.44 (0.91)	1.34 (0.79)	1.77 (0.86)	1.42 (0.94)	1.50 (1.11)	0.94 (0.66)	**0.006**
Not Relevant	1.10 (1.06)	0.97 (0.84)	1.30 (1.1)	1.17 (1.24)	1.41 (1.17)	0.50 (0.75)	**0.009**

Clearing Amount †	12.39 (21.3)	11.81 (21.2)	18.14 (23.6)	10.24 (26.0)	12.64 (18.4)	4.61 (12.4)	**0.005**
Clearing Influences †							
Ag prices	2.29 (1.73)	2.52 (1.92)	2.45 (1.92)	2.11 (1.41)	2.68 (1.70)	1.33 (0.97)	0.088
Droughts	2.23 (1.66)	2.21 (1.72)	2.67 (1.88)	1.78 (1.40)	2.14 (1.39)	2.00 (1.64)	0.279
Regulations	2.92 (2.01)	2.86 (2.03)	3.94 (2.34)	3.00 (1.61)	2.68 (1.62)	1.33 (0.77)	**< 0.001**
Profitability	3.24 (1.91)	3.45 (2.03)	4.09 (1.81)	2.67 (1.81)	3.27 (1.61)	1.89 (1.53)	**< 0.001**
Aesthetics	2.46 (1.71)	2.41 (1.82)	2.33 (1.63)	2.33 (1.53)	2.45 (1.50)	2.89 (2.17)	0.927
Policy uncertainty	2.68 (1.95)	2.41 (1.88)	3.94 (2.06)	2.67 (1.97)	2.32 (1.46)	1.22 (0.73)	**< 0.001**
Costs	2.97 (2.01)	3.07 (2.09)	4.28 (1.99)	2.61 (1.91)	2.59 (1.56)	1.33 (0.77)	**< 0.001**
Clearing Amount Relative to Others †	2.34 (0.92)	2.52 (0.87)	2.52 (0.87)	2.39 (0.98)	2.23 (0.97)	1.83 (0.86)	**0.003**
Clearing Intentions (next 6 months) †	2.92 (1.87)	2.90 (1.74)	3.61 (2.03)	2.83 (1.82)	3.00 (1.95)	1.67 (1.08)	**0.004**
Voluntary Program Participation	2.29 (0.79)	2.23 (0.81)	2.16 (0.79)	2.42 (0.71)	2.27 (0.78)	2.50 (0.84)	0.300
Incentives for Participation (% yes) †							
Importance	71% (71)	74% (14)	74% (20)	70% (16)	56% (10)	85% (11)	0.488
Environmental	91% (91)	89% (17)	93% (25)	83% (19)	94% (17)	100% (13)	0.459
Risk-aversion	80% (80)	89% (17)	74% (20)	83% (19)	78% (14)	77% (10)	0.760
Community influence	53% (53)	37% (7)	44% (12)	61% (14)	72% (13)	54% (7)	0.201
Financial	58% (58)	53% (10)	59% (16)	61% (14)	61% (11)	54% (7)	0.976
Barriers to Participation (% yes) †							
Exposure	51% (107)	42% (18)	54% (27)	47% (20)	55% (26)	57% (16)	0.606
Loss-aversion	40% (85)	58% (25)	36% (18)	47% (20)	38% (18)	14% (4)	**0.005**
Financial	33% (70)	40% (17)	32% (16)	37% (16)	36% (17)	14% (4)	0.215
Community influence	14% (30)	16% (7)	14% (7)	23% (10)	11% (5)	4% (1)	0.192
Importance	23% (48)	26% (11)	24% (12)	16% (7)	26% (12)	21% (6)	0.828
Demographics							
Manager							0.966 [p]
Manages a farm	80% (211)	82% (45)	78% (54)	82% (40)	77% (44)	80% (28)	
Does not manage a farm	20% (54)	18% (10)	22% (15)	18% (9)	23% (13)	20% (7)	
Years managing their property	34.33 (21.0)	36.83 (22.4)	29.36 (20.9)	39.97 (24.9)	35 (19.26)	32.52 (15.0)	0.580
Decision-maker							0.179 [p]
Primary decision-maker	72% (146)	68% (30)	68% (34)	62% (24)	84% (36)	79% (22)	
Joint decisions, no decisions	28% (58)	32% (14)	32% (16)	38% (15)	16% (7)	21% (6)	
Age	61.81 (13.7)	63.28 (12.0)	56.62 (15.7)	63.6 (13.0)	65.15 (13.4)	63.4 (10.94)	0.080
Gender							0.748 [p]
Male	72% (191)	67% (37)	71% (49)	78% (38)	75% (43)	69% (24)	
Female	28% (74)	33% (18)	29% (20)	22% (11)	25% (14)	31% (11)	
Education							0.889 [p]
High school	55% (145)	56% (31)	51% (35)	60% (29)	54% (31)	54% (19)	
Tertiary	45% (119)	44% (24)	49% (34)	40% (19)	46% (26)	46% (16)	
Income							0.211 [p]
Less than $50,000	30% (78)	39% (21)	36% (25)	22% (11)	18% (10)	31% (11)	
Equal to $50,000	30% (79)	28% (15)	30% (21)	27% (13)	38% (21)	26% (9)	
More than $50,000	40% (106)	33% (18)	33% (23)	51% (25)	45% (25)	43% (15)	
Remoteness							
Property postcode †	5.12 (3.57)	4.88 (3.09)	6.92 (4.76)	4.80 (3.50)	4.81 (3.74)	3.20 (2.87)	**< 0.001**
Residence postcode	5.23 (3.66)	5.28 (3.20)	6.63 (4.07)	4.62 (3.39)	5.16 (3.74)	3.30 (3.05)	**< 0.001**
Years at current residence	37.68 (24.0)	42.11 (24.3)	30.08 (22.4)	41.19 (24.6)	41.41 (25.8)	37.08 (21.7)	0.413

* Variables used to generate clusters

† Excluded from regression due to smaller sample size

p Result according to Pearson's chi-squared test

Appendix N. Detailed typology descriptions

Clearing typologies

Membership within the *inactive clearers* typology was driven by stronger pro-regulation attitudes, minimal influence of costs on tree clearing decisions, less participation in voluntary programs, and a greater perception that clearing is not the norm in their community. *Inactive clearers* may be less influenced by costs of running the farming business because the land is already extensively cleared or due to the characteristics of their property, such as topographic features and the spatial distribution of trees. Situated within an anti-clearing community, this may enhance the pro-regulation attitudes of *inactive clearers*, as there may be less relevance or burden for these land managers. The lack of program participation is likely due to a lack of need to protect trees from clearing or the minimal real benefits that could be attained under their current circumstances.

Irregular clearers perceive more people in their community to be clearing trees. Coupled with significantly weaker economic values than other land managers, this may contribute to their disproportionately low perception of their own clearing behaviours relative to others. *Irregular clearers*' decisions are also less influenced by the aesthetic value of trees. This may be because clearing occurs more out of necessity than desire, which would explain their relatively frequent, small-scale clearing efforts within the last five years. Interestingly, *irregular clearers* reported a significantly smaller life satisfaction score than other typologies. The potential cause of this, or it's interactions with other variables, warrants further investigation.

Perceived active clearers tend to have their properties within more urban areas, where clearing is not perceived as the norm, and have stronger economic values, which may explain why they perceive their amount of clearing to be much higher than others around them, when they ranked moderately low compared to the majority of land managers in this survey. Their clearing decisions are also less influenced by droughts, which may be a product of semi-urban living, where more economic opportunities and water sources may be available. Given the typology's insignificant relationship with norm awareness, the relatively strong clearing intentions of these *perceived active clearers* may indicate two potential roles for them within their community: (1) they are 'lone-wolf' *active clearers* situated in areas under-represented in this survey, where the minimal amount of clearing reported is, in fact, very high in their community; (2) they represent up-and-coming *active clearers* that may have recently began clearing greater areas of trees, whose clearing history has yet to reflect future clearing behaviours.

Active clearers represent the opposing typology to *inactive clearers*. These land managers may be more active due to their younger age (53 years) and therefore may have a greater vested interest in protesting additional restrictions to the VMA, especially given their greater reliance on droughts for clearing decisions, which was a significant point of argument from rural landholders during the most recent VMA debate. Surprisingly, *active clearers* reported to be more influenced by the aesthetic value of trees than all other clearing typologies. This could suggest that the aesthetic values of nature may be most important for reducing (relatively) larger-scale clearing—i.e. some clearing-area threshold may exist beyond which the aesthetics can most successfully reduce tree clearing.

Inconsistencies in the relationship between perceived clearing norms and clearing typology characteristics can be identified. Where clearing is perceived to be the norm, *active clearers* and *irregular clearers* are found, and where clearing is not the norm, *inactive clearers* and *perceived active clearers* are found. While *active clearers* and *inactive clearers* do not tend to overlap as often in the landscape (consistent with their reported clearing norms), *irregular clearers* and *perceived active clearers* are present throughout low- and high-clearing regions. Thus it is very possible that *irregular* and *perceived active clearers* are frequently situated alongside their more extremist counter-typologies, while the *active* and *inactive clearers* experience minimal interaction with one another.

<u>Psychosocial typologies</u>

Refusers and *reluctant acceptors* primarily differed according to their perception of disobedience norms, and these different perceptions may partly be a product of their unique psychosocial characteristics. Both typologies share strong conservative attitudes and negative perceptions and emotions toward the VMA, yet *reluctant acceptors* perceive most people to still abide by these regulations, seemingly reluctantly. Given *reluctant acceptors*' unique emphasis on defining 'good farmers' as law-abiding citizens, this potential contradiction between attitudes and norms may stem from these participants' unique farmer identity, wherein there is an inherent altruistic or sacrificial obligation to obey regulations, regardless of the perceived threat of those regulations to their own security.

Refusers, on the other hand, perceive their community to behave in alignment with their negative feelings toward regulations. These participants, however, are less aware of other farmers' land management behaviours. It may be likely that *refusers*' strong distrust in the government and diminished sense of security, when coupled with their strong anti-regulation attitudes and emotions, fuels their unique definition of a less law-abiding 'good farmer'; given their relative ignorance to farmers in their surrounding community, this may result in a skewed perception that most farmers must be reconciling these negative perceptions with disobedient behaviours.

Neutrals were also more aware of others' land management behaviours, and a key distinction between the two types of security measures is emphasised in this group. Whereas *refusers* felt less secure that they could live a comfortable lifestyle following the VMA—more of an indication of convenience—the *neutrals* were more secure that the VMA would not pose a threat to their livelihood—more of an indication of sustenance. Because *neutrals* recognise some inconvenience but very little threat to the farmers' livelihoods, this could explain why they hold moderate pro-clearing and anti-regulation attitudes, yet they do not see the VMA as a threat and perceive most farmers to be obeying regulations and avoiding tree clearing. Though the directionality of these psychosocial interactions is unknown, these participants appear to see the burden regulations place on landholders, but they do not perceive tree clearing or disobedience to be as significant of an issue.

Acceptors most strongly perceived VMA disobedience to be the norm in their community, and they were the only typology to perceive tree clearing as the norm. Interestingly, the only significant driver of group membership was a lower awareness of norms—the lowest of all typologies. *Acceptors* had weaker pro-clearing and anti-regulation attitudes than the average participant, and like *refusers*, the diminished awareness of their community's land management practices may skew their perception of the prevalence of clearing and disobedience in their area; in this case, the perception that most people are deforesting and ignoring regulations may contribute to their less conservative attitudes and emotions, potentially seeing government intervention as a justifiable solution to a normalised problem.

Supporters contrast most strongly with *reluctant acceptors*, having the most liberal or 'green' characteristics across attitudes, emotions, and perception of the VMA's threat. Not surprisingly, membership into this typology was uniquely driven by a greater sense of security and control, as well as stronger positive emotions. These participants were also located in more urban areas throughout Queensland. Although the majority of *supporters* did not perceive clearing and disobedience to be strong norms in their community, their perception of clearing norms was lower than the average participant, and their perception of disobedience norms was higher. This split between clearance and disobedience norms is interesting, as these participants view the regulated issue (clearing) as a lesser concern, yet they view the disobedience of the regulations as a greater concern, relative to the majority of participants surveyed. Those within this typology may be more influenced by urban perceptions rural farmers' outrage over the VMA, and thus the strong liberal psychosocial characteristics may stem from a stronger desire for government intervention amidst the perceived protest from other landholders.

Overall, interesting trends emerge in the descriptive characteristics of the psychosocial typologies. People who were most aware of others' land management behaviours tend to agree that farmers are very obedient, and abstaining from tree clearing is typically the norm. On the other hand, people who were reportedly least aware of others' behaviours have a greater tendency to believe that people are more disobedient and more likely to be clearing trees. When participants shared similar conservative typological characteristics but differed according to their law-abiding definition of a 'good farmer,' there is a stark difference in their perception of obedience norms in the community. Identity may thus be an important moderator of perceived social norms, particularly when they equate their own identity with others in their area. Expectedly, people with a greater sense of security viewed clearing to be atypical in their community, and they were the only ones who did not view the VMA as a substantial threat.

Appendix O. Results of the relationship between typologies and clearing hotspots

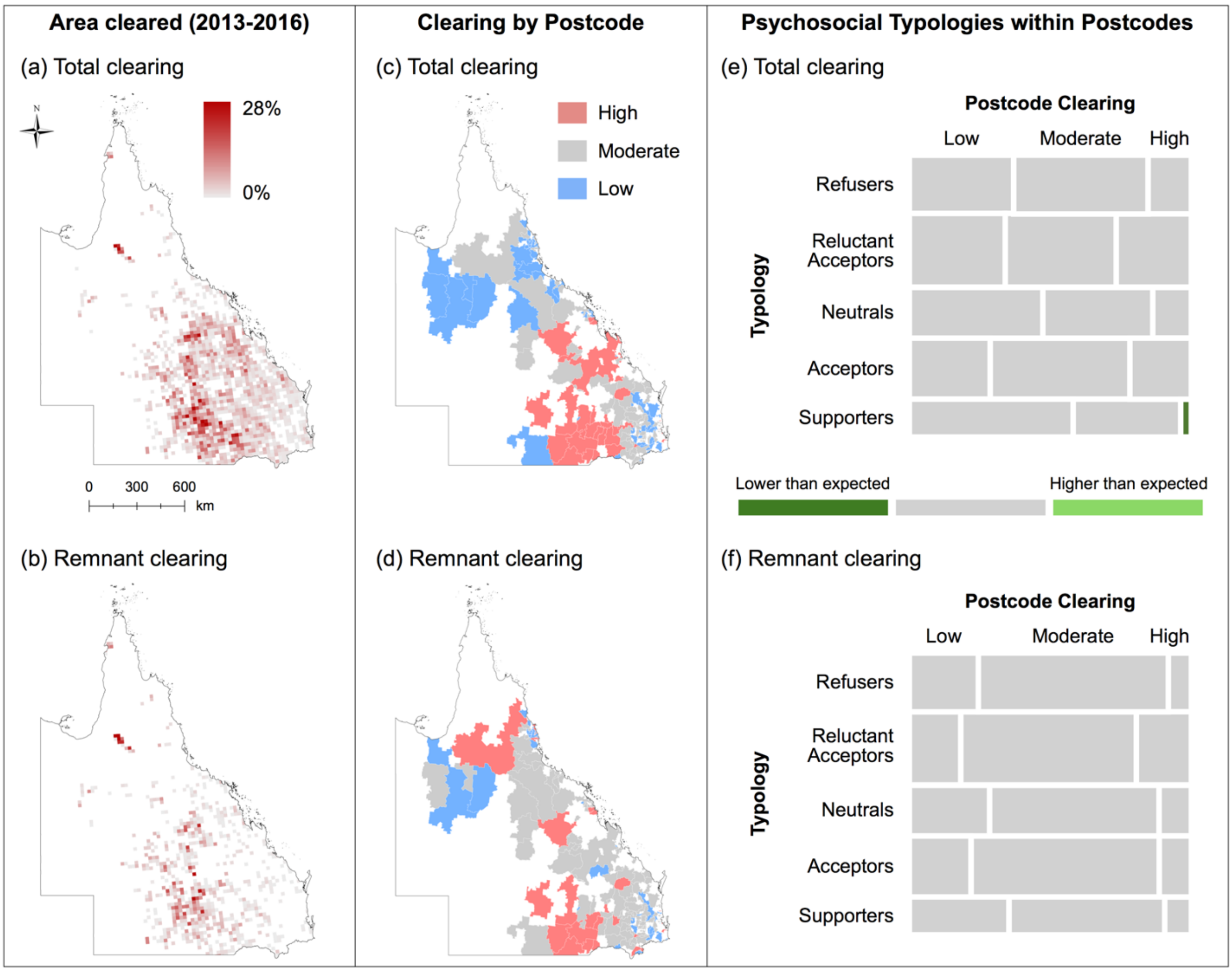

Fig. O1. Relationship between psychosocial typology and postcode clearing hotspots within the last five years. Land clearing rates of (a) all woody vegetation and (b) remnant woody vegetation during 2013–2016 as percent of 400 km^2 pixel area. Postcode clearing rates in (c) and (d) calculated as the percent area cleared within postcode boundaries and represented as *low*, *moderate*, or *high*. (e) Significantly fewer *supporters* resided within high total clearing postcodes. (f) No significant relationship between typologies and remnant clearing hotspots. Cell size of (e) and (f) is proportional to the observed counts within each category.

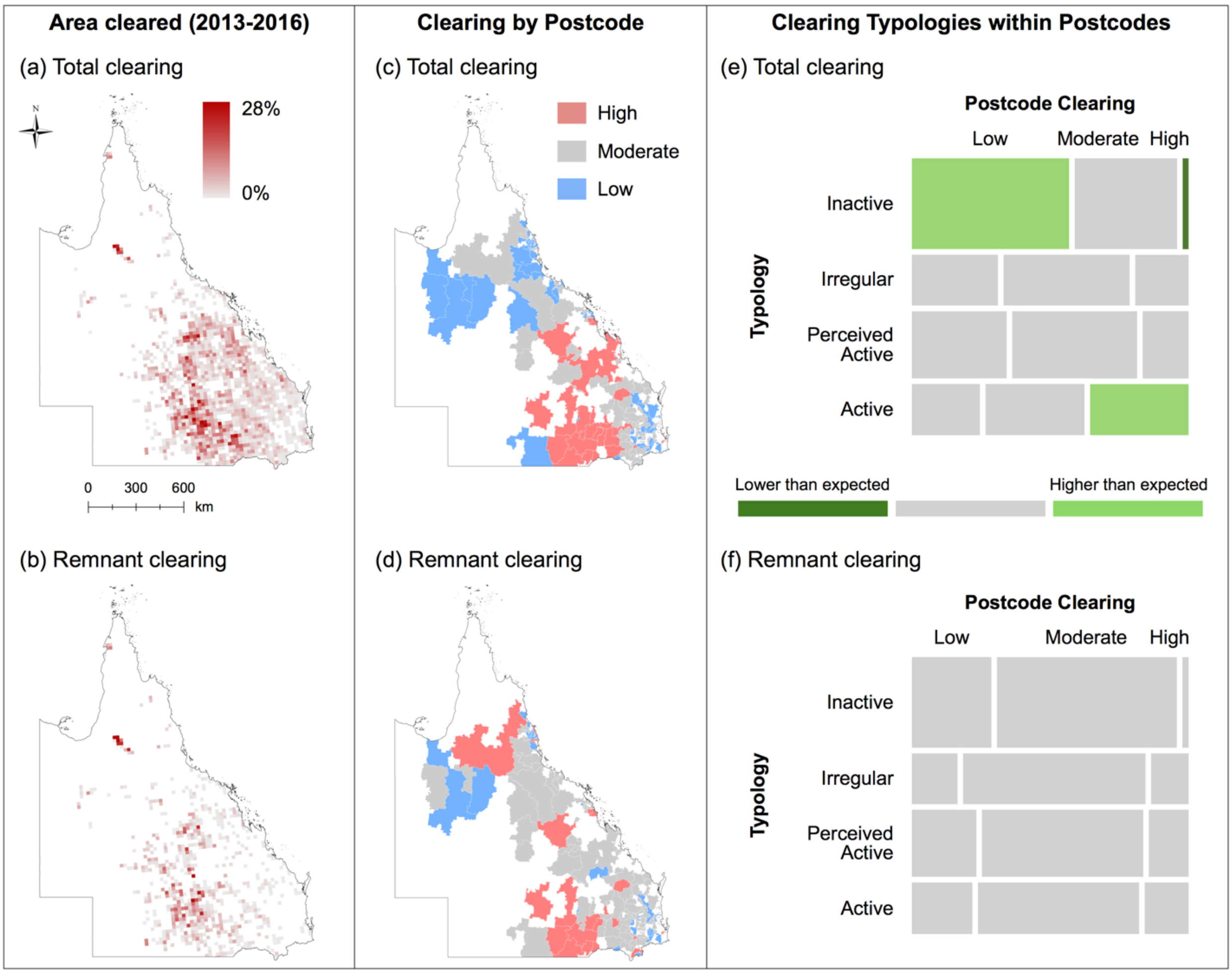

Fig. O2. Relationship between clearing typology and postcode clearing hotspots within the last five years. Land clearing rates of (a) all woody vegetation and (b) remnant woody vegetation during 2013–2016 as percent of 400 km^2 pixel area. Postcode clearing rates in (c) and (d) calculated as the percent area cleared within postcode boundaries and represented as *low*, *moderate*, or *high*. (e) *Inactive clearers* primarily resided in low clearing postcodes, and the number of *active clearers* residing within high clearing postcodes was higher than expected. (f) No significant relationship between typologies and remnant clearing hotspots was observed. Cell size of (e) and (f) is proportional to the observed counts within each category.

Appendix P. Results of the relationship between clearing and psychosocial typologies

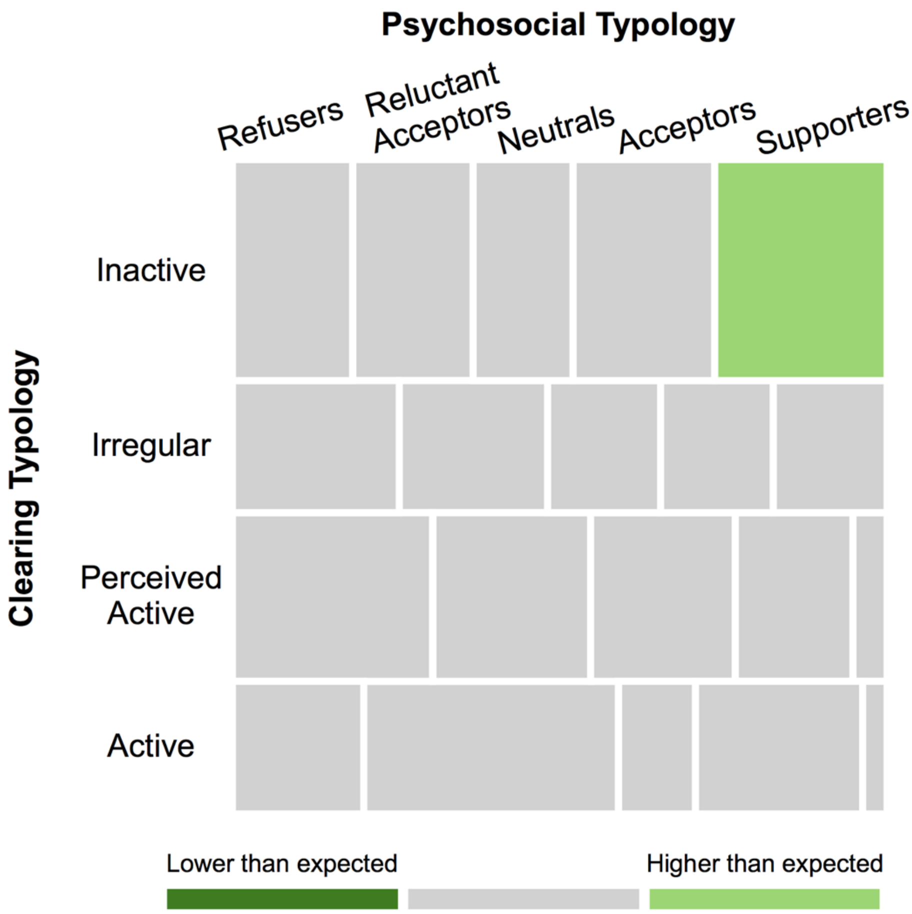

Fig. P1. Relationship between land managers' clearing typology and psychosocial typology. A significantly high number of managers within the *supporters* typology were also classified within the *inactive clearers* typology (Pearson's χ^2, $\alpha = 0.05$).