Ambio 2021, 50:1364–1377
https://doi.org/10.1007/s13280-020-01491-w

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RESEARCH ARTICLE

Psychosocial drivers of land management behaviour: How threats, norms, and context influence deforestation intentions

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Received: 12 June 2020 / Revised: 6 November 2020 / Accepted: 16 December 2020 / Published online: 26 January 2021

Abstract Understanding how private landholders make deforestation decisions is of paramount importance for conservation. Behavioural frameworks from the social sciences have a lot to offer researchers and practitioners, yet these insights remain underutilised in describing what drives landholders' deforestation intentions under important political, social, and management contexts. Using survey data of private landholders in Queensland, Australia, we compare the ability of two popular behavioural models to predict future deforestation intentions, and propose a more integrated behavioural model of deforestation intentions. We found that the integrated model outperformed other models, revealing the importance of threat perceptions, attitudes, and social norms for predicting landholders' deforestation intentions. Social capital, policy uncertainty, and years of experience are important contextual moderators of these psychological factors. We conclude with recommendations for promoting behaviour change in this deforestation hotspot and highlight how others can adopt similar approaches to illuminate more proximate drivers of environmental behaviours in other contexts.

Keywords Behaviour change · Environmental behaviour · Land clearing · Natural resource management · Protection Motivation Theory · Theory of Planned Behaviour

Supplementary information The online version of this article (https://doi.org/10.1007/s13280-020-01491-w) contains supplementary material, which is available to authorized users.

INTRODUCTION

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 is the most commonly cited proximate driver of deforestation (Barbier and Burgess 2001; Hosonuma et al. 2012). It is estimated to account for 80% of global deforestation activities (Kissinger et al. 2012), and nearly half of the global agricultural area has less than 20% tree cover (Zomer et al. 2009). Thus there are crucial opportunities for conservation scientists and practitioners to work with private landholders to promote adoption of sustainable land management practices.

While promoting positive behaviour change can be exceptionally difficult, there are a number of tools that can be used. The most common approaches include direct regulation, market-based incentives, and voluntary conservation programs (Cocklin et al. 2007). The success of these diverse approaches is contingent upon a thorough understanding of the drivers of landholders' behaviour. For example, direct regulations can be polarising and reduce the public's motivation to protect the environment (Jordan and Matt 2014), and a reliance on the economic 'rationality' of landholders can misguide incentive mechanisms (Howley et al. 2015). There is a growing recognition that traditional models of decision-making are limited in their ability to account for the important social and psychological dimensions underpinning environmental behaviours (Nilsson et al. 2019). Understanding these intrinsic drivers of behaviour can assist researchers and practitioners in identifying who may be more likely to engage in these potentially destructive environmental behaviours in the near future (Burton 2004).

This study investigates what factors predict private landholders' intentions to clear trees on their farm, using Queensland, Australia as an exemplar case study of international significance. A national and global biodiversity hotspot (Williams et al. 2011), ongoing deforestation in Queensland has led to severe habitat fragmentation, endangered species decline, sediment run-off into the Great Barrier Reef, and increased carbon emissions (Reside et al. 2017). Like many other deforestation hotspots, land management decision-making in Queensland is situated against the backdrop of years of controversial environmental regulation; consequently, deforestation is likely driven by a diverse suite of political and psychosocial factors. Traditionally, researchers have used econometric models to understand deforestation behaviours. These models typically aim to predict land use/land cover change using variables like climate and topographic conditions, market prices, income, distance to roads, and environmental policies (Deacon 1994; Barbier and Burgess 2001) (Fig. 1a). While this approach has illuminated some of the most important distal drivers of environmental behaviours around the world, it does not account for the psychological factors that shape decision-making. To identify psychological targets for change, our study has the following objectives: (1) provide the first test and comparison of the Theory of Planned Behaviour and Protection Motivation Theory in predicting deforestation intentions; (2) identify the role of contextual factors—years of experience, social capital, and policy uncertainty—as moderators of deforestation intentions; and (3) propose and evaluate an integrated behavioural model of deforestation intentions in highly contentious and regulated contexts (see Theoretical Framework).

Theoretical framework

The fields of psychology and sociology have much to offer environmental scientists and practitioners interested in understanding what drives environmental behaviours, and scholars have called for greater integration of environmental social science methods across disciplines (Bennett et al. 2017). Many behavioural theories have been proposed by social scientists that examine how proximate psychosocial factors influence behaviour under multiple—sometimes niche—contexts. In more general contexts, the majority of behavioural models argue that constructs like values, beliefs, attitudes, habits, and social norms (i.e. perceptions about the behaviour and expectations of others) most accurately predict how people behave (Klöckner 2013). In some cases, these models have been used to explain 64–95% of people's pro-environmental behaviours, such as recycling and energy use (Kaiser et al. 2005).

One of the most frequently applied behavioural models is the Theory of Planned Behaviour (Ajzen 1985), which posits that behavioural intentions are directly influenced by attitudes about the behaviour, social norms, and perceived behavioural control (a measure of one's sense of ease and control over performing the behaviour) (Fig. 1b). This behavioural framework has received widespread, cross-disciplinary acclaim and frequently outperforms other behaviour models (Kaiser et al. 2005); it has been applied in several environmental contexts to explain farmers' intentions to manage riparian zones (Fielding et al. 2005), reduce pesticide use (Beedell and Rehman 2000), and conserve remnant forest (Mastrangelo et al. 2014). However, no study has applied this theory in the context of farmers' deforestation intentions, and thus represents a promising avenue for validation and comparison to other environmental behaviours and contexts.

Because environmental regulations restrict what people can do on private land, farmers may perceive these command-and-control regulations as a threat to their livelihoods, which could significantly influence their behaviour. Despite the popularity and potential broad applicability of the Theory of Planned Behaviour, this model does not account for how people make decisions in the context of strict environmental regulations. The Protection Motivation Theory (Rogers 1975) is a behavioural model that evaluates how people respond to threats. It describes the fear appraisal process, where individuals evaluate the severity of a threat, their vulnerability to the threat, and the potential efficacy of different coping strategies, which then influences their behavioural intentions (Fig. 1c). While typically applied in the field of health, these coping characteristics have also been important in explaining some pro-environmental behaviours (Kothe et al. 2019). This prominent model of risk perception could represent an untapped resource for explaining environmental behaviours in highly-regulated or high-conflict contexts.

Importantly, the decision-making processes that influence behaviour can be highly dynamic and context-specific. Psychological drivers of change may vary according to how people interpret biophysical, economic, and political signals in their decision making. For example, individual goals or motivations may change with age (Farmar-Bowers and Lane 2009), people with greater access to social capital (i.e. social supports and networks) may be more influenced by their peers (McDonald et al. 2014; Sulemana and James 2014), and uncertainties regarding impending policy changes can lead to rapid or unexpected behaviours (Simmons et al. 2018b). These issues make it exceptionally difficult to understand how people in different contexts make environmental decisions. Despite their potential importance for driving environmental behaviours around the world, few studies have explored how these

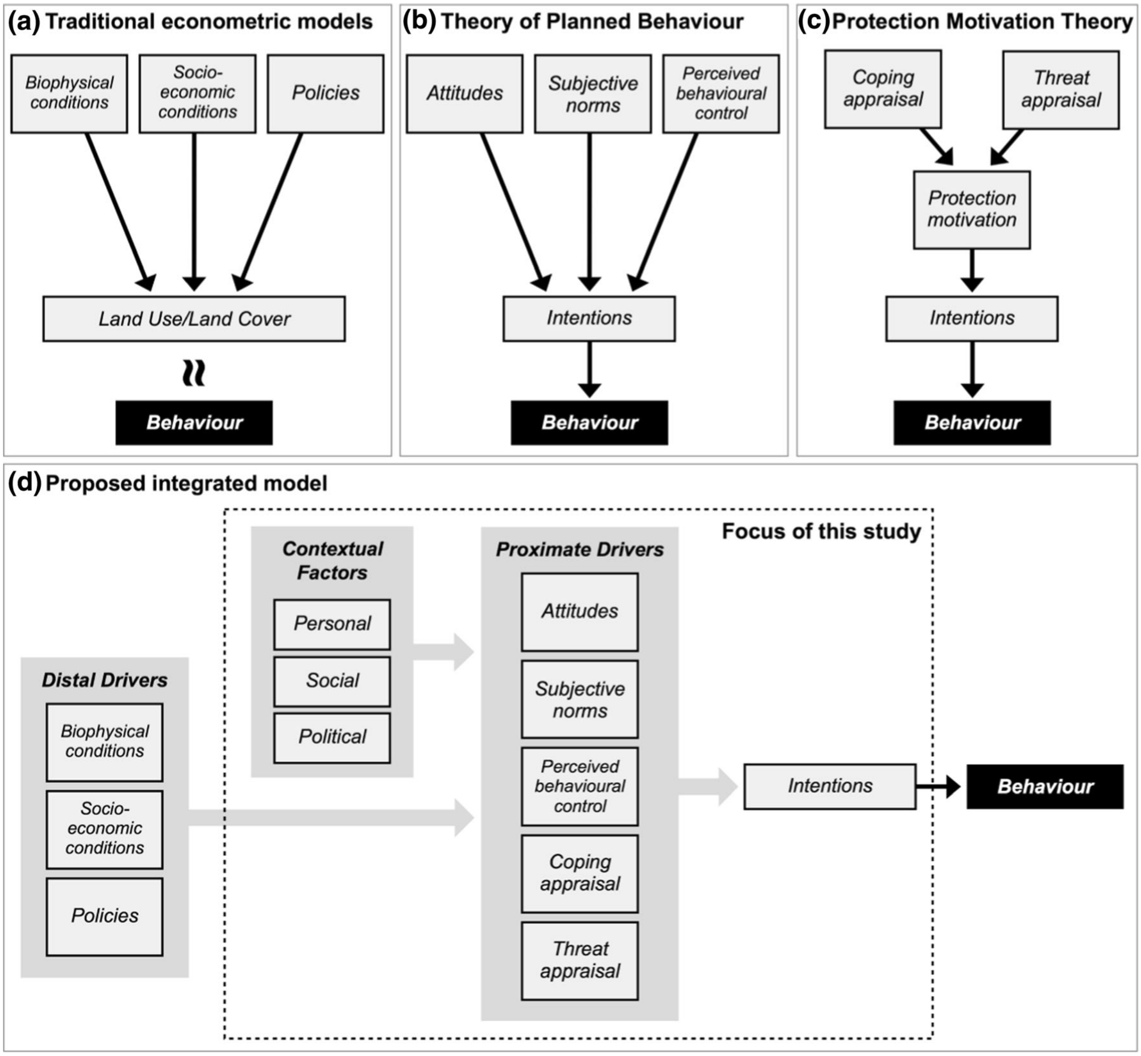

Fig. 1 **a** Traditional econometric models typically apply distal behavioural drivers, such as biophysical conditions, socio-economic conditions, and national or international policies, to predict land use/land cover changes, which are used to reflect individual behaviours. Popular psychological models, such as **b** the Theory of Planned Behaviour and **c** Protection Motivation Theory, focus instead on the role of different proximate drivers of behavioural intentions, which ultimately influence realised individual behaviours. **d** In the context of highly-regulated environmental behaviours on private land, we propose a more integrated model that recognises the importance of proximate drivers from both psychological models as the mechanisms in which distal drivers are interpreted and modified by personal, social, and political contextual factors. In this study, we focus on the proximate drivers of behavioural intentions and the influence of moderating contextual factors (dashed box)

contextual factors moderate the influence of attitudes, normative and control beliefs, and threat perceptions on environmental behaviours.

MATERIALS AND METHODS

Study area context

During 1990–2010, Australia exhibited the second highest annual rate of deforestation in the world (FAO 2015) despite the rise of more progressive deforestation regulations in the beginning of the twenty-first century. More than 50% of this deforestation occurred in the state of Queensland (Evans 2016), threatening 97 of 121 vulnerable or endangered terrestrial fauna species listed in the state, as well as several endemic flora species (Ponce Reyes et al. 2016; Reside et al. 2017). The state remains a contemporary global deforestation hotspot, having lost 60% of its forests over the last 40 years due to the rapid replacement of remnant (primary) vegetation for pasture expansion on private agricultural lands (Evans 2016). To counteract escalating deforestation rates, the Queensland Government enacted the controversial *Vegetation Management Act* in

1999, which placed clearing regulations on all remnant woody vegetation on private lands, including an eventual state-wide ban on broad-scale clearing in 2007 (McGrath 2007). The Act has since been the focus of a heated, 20-year long debate, with farmers protesting what they believe are unfair, illegitimate, and economically destructive restrictions on how they manage their land (Productivity Commission 2004). It has also undergone considerable changes over time as political regimes shift (Simmons et al. 2018a), leading many farmers to argue that the new amendments are unclear and impede their ability to make long-term management decisions (Productivity Commission 2004).

Previous studies have identified biophysical, socioeconomic, and political drivers of forest cover change in the state based on past clearing behaviours (Simmons et al. 2018b), and evidence suggests that the Act has had limited effectiveness at reducing clearing (Simmons et al. 2018c). Although such environmental regulations can have positive direct and indirect effects on deforestation rates (Meyfroidt and Lambin 2011), greater emphasis is now shifting toward understanding the social dimensions of tree clearing in Queensland (Simmons et al. 2020a), as it is becoming clear that regulatory interventions alone are not sufficient to change landholders' clearing behaviour. Using Queensland as a case study allows us to take a rare look into the factors driving the deforestation intentions of these landholders, which has not been previously attempted in a global biodiversity hotspot. Yet many of the contextual factors surrounding the culture of deforestation in Queensland are reflected in other countries, such as Brazil and Colombia, where strict regulations and political conflict may increase deforestation intentions through similar mechanisms investigated in this study (Azevedo et al. 2017; Negret et al. 2017).

Participants

Data is drawn from a larger survey of 265 farmers/graziers, landowners, and/or members of farming families in Queensland, Australia, which has previously been used to identify different typologies of landholders (Simmons et al. 2020a) and the factors associated with their participation in private land conservation programs (Simmons et al. 2020b). A social research company recruited participants within and surrounding Queensland's contemporary deforestation hotspots to complete a survey online or over the telephone during May 2018. Participants who indicated that they managed a current grazing/production property, and they currently (or in the last 5 years) have trees on their property that are not used for production purposes, were included in this study ($N = 176$). This sample predominantly consisted of males (77%), who were 59 years old on average and had been managing their property for 30 years. While this sample has a relatively high average age of participants, many of these older farmers are still expected to be actively managing their land. Overall, the sample represented a variety of ages (25–93 years old), education, and income levels for statistical comparison (see Tables S1, S2 for demographic information), and included participants from a variety of postcodes across the state to maximise the spatial representation of our sample. The study received ethical clearance (Approval #2017001054).

Survey content

Tree clearing intentions

Participants' future clearing intentions was measured on a six point scale (1 = 'strongly disagree' to 6 = 'strongly agree') based on the following prompt: "I intend to engage in tree clearing on my property during the next 6 months." Because this categorical variable is measured on an ordinal scale, we first investigated if there was evidence to assume a linear progression between each response option. A test of this proportional odds assumption indicated that the assumption did not hold, and thus the results of an ordinal logistic regression would likely be biased (Brant 1990). Therefore, clearing intention was classified as a binary outcome for regression analyses: weak intentions (scores 1–3) and strong intentions (scores 4–6). For descriptive analyses of clearing intentions, we use the original six point scale.

Components from the Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) has yet to be applied to heavily-regulated environmental behaviours, so we devised two TPB models for comparison: one focused on the behaviour (i.e. tree clearing), as is typically used, and the other focused on following clearing regulations. A single variable measured attitudes toward tree clearing (*pro-clearing attitudes*) based on four survey items (Cronbach's $\alpha = 0.82$), and another variable measured attitudes toward regulations (*anti-regulation attitudes*) based on four items (Cronbach's $\alpha = 0.65$). One item measured their perceived *tree clearing norms*, and one item measured perceived *regulatory compliance norms*. Perceived behavioural control was incorporated using two variables: *controllability* (how much control participants have over tree clearing decisions on their property), and *self-efficacy* (how difficult it is to follow regulations) (see Table 1 for detailed descriptions of each variable).

Table 1 Description of the survey items used for analysis. Unless otherwise stated, items on a 1 to 6 scale represent (1 = 'strongly disagree' to 6 = 'strongly agree'). Aggregated variables (attitudes and vulnerability) represent an average score for each survey item. See Table S1 for a description of the demographic variables included in the survey

Variables	Survey items	Scale
Clearing intentions	"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[a]	(1, 6)
	Tree clearing should be stopped[a]	
	People are clearing too many trees[a]	
	People who clear trees from their property do not care about the environment[a]	
Anti-regulation	In my opinion, vegetation management regulations…	(1, 6)
	Are a burden to me	
	Are fair to farmers[a]	
	Are necessary[a]	
	Should be more strict[a]	
Social norms		
Tree clearing	Most of the farmers in my community clear trees	(1, 6)
Compliance	Most of the farmers in my community follow the vegetation management regulations	(1, 6)
Perceived behavioural control		
Controllability	How much personal control do you feel you have over tree clearing decisions on your property? ('very little control' to 'complete control')	(1, 6)
Self-efficacy	Following the vegetation management regulations set forth by the Queensland Government is… ('extremely difficult' to 'extremely easy')	(1, 6)
Threat appraisal		
Severity (relative threat of regulation)	To what degree do the following pose a threat to the property you manage? (no threat to severe threat)	(− 5, 5)[b]
	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)
Vulnerability	I am confident that I can still enjoy a comfortable lifestyle while following vegetation management regulations	(1, 6)
	Vegetation management regulations are a threat to my business or livelihood[a]	
Coping appraisal		
Clearing efficacy	Clearing trees from my property will not harm the environment[a]	(1, 6)
Regulatory efficacy	Vegetation management regulations will not protect the environment[a]	(1, 6)
Self-efficacy	Following the vegetation management regulations set forth by the Queensland Government is… ('extremely difficult' to 'extremely easy')	(1, 6)
Contextual factors		
Social capital	Are you an active member of a local community group, organisation, or club (e.g. a sport, craft, or social club)?	(1, 4)[c]
Policy uncertainty	To what extent do talks of new clearing regulations in Parliament influence how you make tree clearing decisions on your property? ('no influence at all' to 'strong influence')	(1, 6)
Years managing property	Approximately how many years have you managed your current farm or other grazing or production properties?	

[a]Scores reversed for analysis

[b]Scale of the generated single score differs from items' scale; see main text for calculation

[c]Scale represents 1 = 'never a member,' 2 = 'no longer a member,' 3 = 'a member but not actively involved,' 4 = 'very actively involved'

Components from the Protection Motivation Theory

Protection Motivation Theory (PMT) describes the influence of threat appraisal and coping appraisal on behavioural intentions. Threat appraisal is represented as two variables: the perceived severity of the threat and vulnerability to the threat. To measure *threat severity*, one question asked participants to rank the severity of several potential threats to their property (e.g. droughts, declining terms of trade, and clearing regulations) (Table 1). The average difference in threat level of clearing regulations compared to all other threats was calculated to represent a continuous score of the relative threat of clearing regulations (− 5 = 'lowest threat' to 5 = 'greatest threat'). *Threat vulnerability* was quantified based on the average of two items measuring how much clearing regulations threaten their livelihoods and their ability to maintain a comfortable lifestyle.

Coping appraisal comprises people's perceptions of how effective different coping mechanisms might be for mitigating threats (response efficacy) and their capacity to perform the behaviour (self-efficacy). We include two measures of response efficacy: one addressing their perceptions of the impact of tree clearing on the environment (*clearing efficacy*), and one addressing the impact of regulations on the environment (*regulatory efficacy*) (Table 1). In this model, we also include the measure of *self-efficacy* from the TPB model to account for their perceived ability to comply with regulations.

Broader contextual factors

Contextual factors can be important modifiers of these psychosocial drivers of behaviour described in the aforementioned models. We selected three contextual factors a priori to use as moderating variables in our analyses based upon their relevance for the Queensland context arising from both empirical and anecdotal evidence, as well as their potential relevance for other deforestation contexts around the world. Our first contextual variable measures how long participants have been managing their current property (*years managing property*) (Table 1). Previous studies have shown that farmers' motivations can change over time (Farmar-Bowers and Lane 2009); especially in the Queensland context, where more experienced farmers have been affected by the dynamic policy timeline over the last 25 years, it is important that the influence of experience is accounted for in understanding their environmental behaviours. Given the recognised importance of social influence for guiding decision-making (McDonald et al. 2014; Streletskaya et al. 2020), it is likely that farmers' attitudes and perceptions will be influenced by others in their social networks—particularly if they are exposed to more social interactions. However, farmers have frequently argued that their actions will not be influenced by people in their community (e.g. Productivity Commission 2004). To determine if this contextual factor is important, we included a measure of participants' *social capital* (i.e. their involvement in local groups, organisations, or clubs). Finally, there is evidence that farmers' clearing behaviours in Queensland are influenced by fears of impending regulatory changes on their property (Simmons et al. 2018b), provoking spikes in 'pre-emptive' clearing to avert potential lost opportunities in the future. While this perverse pre-emptive response is highly relevant to the Queensland context, similar behaviours have been observed elsewhere in response to species trade bans (Rivalan et al. 2007) and new listings under the U.S. Endangered Species Act (Lueck and Michael 2003). To account for this potential influence on the drivers of clearing intentions, we include a measure of the influence of *policy uncertainty* on participants' land management decision-making (Table 1).

Modelling clearing intentions

Logistic regressions were performed in R version 3.5.3 to test the ability of different behavioural models to predict strong clearing intentions. The two TPB models and the PMT model were tested and compared. For an additional comparison of the influence of contextual factors on model performance, we extended each model to include the contextual variables as moderators of clearing intentions. Each contextual model underwent parameter reduction to produce the most optimal model according to the Akaike Information Criterion (AIC), and results were compared to the original model configurations. A final integrated model was tested after including all variables and interactions from the TPB and PMT models; the integrated model underwent sequential parameter reduction to produce the final best-fitting model of clearing intentions. Age and gender were included in all models following an initial test of the influence of all demographic variables on clearing intentions. No issues of multi-collinearity were identified in any models according to calculated variable inflation factors (Table S3).

RESULTS

The average strength of participants' future clearing intentions was low but highly variable, 2.85 ± 1.89 (*mean* ± *SD*). Land managers with strong clearing intentions constituted 36% of participants and were primarily concentrated in south-central Queensland—a historical clearing hotspot in the state (Fig. 2). Land managers with weak clearing intentions (64%) were more prevalent near

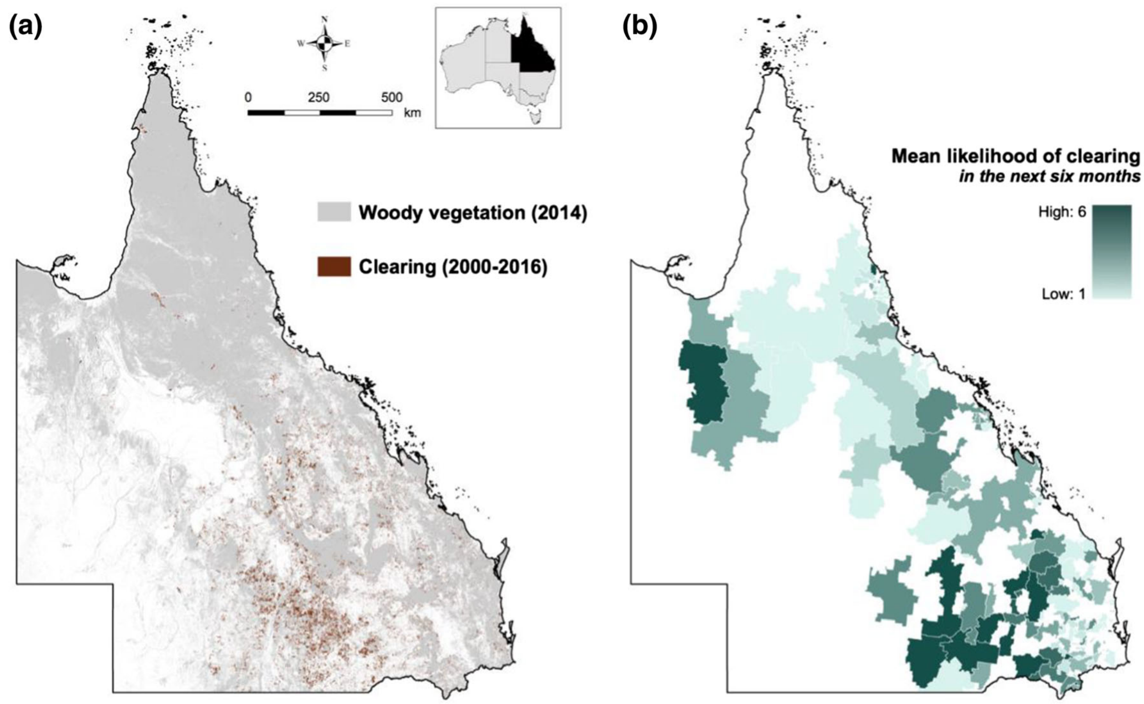

Fig. 2 **a** Extent of tree clearing across Queensland, Australia since enactment of the Vegetation Management Act in 1999. **b** Land managers' clearing intentions, averaged by the postcode of primary residence. Woody vegetation and clearing data retrieved from Queensland Spatial Catalogue (2016a, b)

the coast and northern Queensland, where extensive clearing is less common in recent history.

Comparison of behavioural models

The TPB model using variables about tree clearing performed better than the TPB model using variables about regulations (Table 2). In the TPB (regulations) model, no independent variables were associated with intentions, except for age. When adding contextual factors, compliance norms were associated with stronger intentions, and multiple interactions were identified: the influence of policy uncertainty strengthened clearing intentions for land managers with higher self-efficacy, and more years of experience strengthened intentions for those with higher anti-regulation attitudes. In the TPB (clearing) model, clearing norms were associated with stronger clearing intentions, and policy uncertainty weakened intentions in those with strong pro-clearing attitudes. Greater social capital was also associated with stronger clearing intentions. The PMT model performed better than the TPB models and identified a significant association between threat severity and clearing intentions. Model fit also improved when adding contextual factors: land managers that believe regulations will protect the environment had weaker intentions, and greater influences of policy uncertainty weakened intentions in those who view the regulations as a more severe threat.

Integrated model of clearing intentions

The final integrated model greatly enhanced the best-fitting behaviour models and identified important variables from all of the previous models (AIC = 177.50, McFadden pseudo R^2 = 0.430) (Table 3). Overall, women are 36–94% less likely to have strong clearing intentions, and younger land managers are slightly more likely to have stronger intentions. Those who have been managing their property for a shorter period of time are only 2–28% more likely to have stronger clearing intentions. More pronounced effects were observed for the psychological drivers of intentions. Threat severity, compliance norms, and policy uncertainty exerted the greatest average increase on clearing intentions (by 7–54 orders of magnitude), but their confidence intervals also extend several orders of magnitude. In contrast, pro-clearing and anti-regulation attitudes strongly reduced the likelihood of intending to clear trees, with more modest confidence intervals.

The effects of most psychological factors are strongly moderated by contextual factors, which may explain the wide confidence intervals for those individual variables. Social capital had the strongest moderating effects of all

Table 2 Predictors of clearing intentions for the classic behavioural models before and after inclusion of moderating contextual factors. OR = Odds ratio; CI = confidence interval

Model	Variable	Original model		Model with moderators	
		OR	95% CI	OR	95% CI
Theory of Planned Behaviour (*regulations*)	Age	0.96	(0.94, 0.99)*	0.96	(0.92, 0.99)*
	Gender (female)	0.45	(0.20, 1.03)	0.38	(0.15, 0.96)*
	Attitudes − anti-regulation	1.36	(0.94, 1.97)[a]	0.55	(0.24, 1.30)[a]
	Norms − regulatory compliance	1.22	(0.94, 1.58)	3.18	(1.11, 9.13)*[a]
	PBC − self-efficacy	0.98	(0.70, 1.37)	0.58	(0.29, 1.17)
	Social capital			5.08	(1.20, 21.59)*[a]
	× Norms − compliance			0.76	(0.58, 1.01)
	Policy uncertainty			1.96	(0.62, 6.22)[a]
	× Norms − compliance			0.87	(0.72, 1.06)
	× PBC − self-efficacy			1.30	(1.02, 1.65)*
	Years managing property			0.88	(0.78, 1.00)
	× Attitudes − anti-regulation			1.03	(1.00, 1.05)*
	AIC	221.4		195.8	
	McFadden pseudo R^2	0.093		0.264	
Theory of Planned Behaviour (*clearing*)	Age	0.96	(0.94, 0.99)*	0.96	(0.92, 0.99)*
	Gender (female)	0.44	(0.19, 1.01)	0.39	(0.15, 1.00)*
	Attitudes − pro-clearing	1.09	(0.82, 1.46)	1.94	(1.00, 3.73)*[a]
	Norms − tree clearing	1.29	(1.06, 1.57)*	1.31	(1.04, 1.64)*
	PBC − controllability	0.86	(0.69, 1.08)	0.78	(0.50, 1.23)
	Social capital			1.47	(1.07, 2.01)*
	Policy uncertainty			5.00	(1.45, 17.24)*[a]
	× Attitudes − pro-clearing			0.76	(0.61, 0.94)*
	× PBC − controllability			1.12	(0.96, 1.30)
	Years managing property			1.00	(0.98, 1.03)
	AIC	219.5		190.4	
	McFadden pseudo R^2	0.101		0.270	
Protection Motivation Theory	Age	0.96	(0.93, 0.98)*	0.96	(0.92, 1.00)*
	Gender (female)	0.32	(0.13, 0.78)*	0.30	(0.12, 0.76)*
	Threat − severity	1.39	(1.01, 1.92)*	6.80	(1.65, 27.95)*[a]
	Threat − vulnerability	1.12	(0.83, 1.50)	0.89	(0.62, 1.27)
	Coping − self-efficacy	1.12	(0.77, 1.61)	1.23	(0.80, 1.91)[a]
	Coping − clearing efficacy	0.97	(0.79, 1.18)	0.96	(0.76, 1.20)
	Coping − regulatory efficacy	0.82	(0.66, 1.00)	0.52	(0.29, 0.94)*
	Social capital			1.05	(0.47, 2.33)[a]
	× Threat − severity			0.78	(0.56, 1.09)
	× Coping − regulatory efficacy			1.15	(0.95, 1.38)
	Policy uncertainty			2.19	(1.56, 3.07)*[a]
	× Threat − severity			0.72	(0.58, 0.90)*
	Years managing property			1.00	(0.97, 1.03)
	AIC	218.0		192.4	
	McFadden pseudo R^2	0.125		0.287	

*$p < 0.05$

[a]Confidence interval spans more than one order of magnitude

Table 3 Predictors of clearing intentions for the best-fitting integrated behavioural model after parameter reduction. OR = Odds ratio; CI = confidence interval

Variable	OR	95% CI
Age	0.95	(0.91, 1.00)*
Gender (female)	0.20	(0.06, 0.64)*
Norms – tree clearing	1.31	(0.99, 1.72)
Attitudes – pro-clearing	0.11	(0.03, 0.51)*
× Social capital	1.86	(1.17, 2.96)*[a]
Attitudes – anti-regulation	0.22	(0.06, 0.85)*
× Years managing property	1.06	(1.02, 1.11)*
Norms – regulatory compliance	7.60	(2.02, 28.59)*[a]
× Social capital	0.64	(0.45, 0.91)*
× Policy uncertainty	0.79	(0.63, 1.00)*
Threat – severity	53.73	(4.22, 683.84)*[a]
× Social capital	0.65	(0.40, 1.04)
× Policy uncertainty	0.64	(0.49, 0.85)*
× Years managing property	0.97	(0.94, 1.00)
Threat – vulnerability	3.84	(0.80, 18.31)[a]
× Social capital	0.71	(0.50, 1.01)
× Years managing property	0.98	(0.95, 1.01)
Coping – regulatory efficacy	0.92	(0.57, 1.47)
× Policy uncertainty	0.91	(0.80, 1.04)
Social capital	4.51	(0.41, 49.38)[a]
Policy uncertainty	11.25	(2.72, 46.46)*[a]
Years managing property	0.84	(0.72, 0.98)*
AIC	177.5	
McFadden pseudo R^2	0.430	

*$p < 0.05$

[a]Confidence interval spans more than one order of magnitude

contextual factors. The expected association between compliance norms and clearing intentions—i.e. that stronger compliance norms are associated with lower clearing intentions—was only observed in land managers with higher social capital; in those with lower social capital, the reverse association was observed (Fig. 3a). A similar effect of social capital is observed for the effect of pro-clearing attitudes (Fig. 3b). Land managers with strong pro-clearing attitudes are much more likely to intend to clear trees when social capital is high; for those with low social capital, pro-clearing attitudes were negatively associated with clearing intentions.

Policy uncertainty exerted a small effect on compliance norms. Stronger compliance norms were associated with lower clearing intentions, but only in land managers who reported being influenced by policy uncertainty; in those not influenced by policy uncertainty, stronger compliance norms were associated with increased clearing intentions (Fig. 3c). The effect of policy uncertainty was more prominent when examining its influence on the relationship between threat severity and clearing intentions. Perceiving regulations to be a more severe threat to their property was associated with stronger clearing intentions, but only in those less influenced by policy uncertainty; in land managers more influenced by policy uncertainty, threat severity was associated with reduced clearing intentions (Fig. 3d). Finally, the number of years participants have been managing their property had a small but significant moderating effect (Table 3). In land managers with more experience, strong anti-regulation attitudes were associated with greater clearing intentions; conversely, anti-clearing attitudes were associated with lower clearing intentions in landholders with fewer years of experience (Fig. 3e).

DISCUSSION

Our results provide evidence and support for the integration of social science methods across environmental disciplines, and illuminate the potential importance of these under-utilised psychosocial factors to land management contexts around the world. This study is the first to compare the abilities of the Theory of Planned Behaviour and Protection Motivation Theory to predict tree clearing intentions. While the TPB has frequently outperformed other pro-environmental behavioural models (Kaiser et al. 2005), the PMT outperformed both TPB models in predicting clearing intentions. The best-fitting model of clearing intentions integrated elements from both, emphasising the potential limitations of applying singular psychosocial frameworks to complex natural resource management behaviours. Additionally, all behavioural models improved when political, social, and land management contextual factors were incorporated, further highlighting the complexity of land management decision-making.

Land managers' perceived threat of clearing regulations was a much stronger predictor than attitudes, norms, and perceived behavioural control, underscoring the importance of threat appraisal in highly-regulated conservation contexts. This finding is exceptionally important, both for psychological theory and its application to deforestation behaviours. Many land managers ranked regulations as a greater threat than other threats typically considered, such as droughts, personal health, and escalating business costs. Threat perceptions of environmental regulations have not received enough attention in behaviour models (Kothe et al. 2019). In these highly-regulated contexts, this threat appraisal is likely capturing perceptions of lost freedoms, choices, or opportunities. We expect this strong predictor of clearing intentions in Queensland is likely to be present in other global deforestation hotspots, as well.

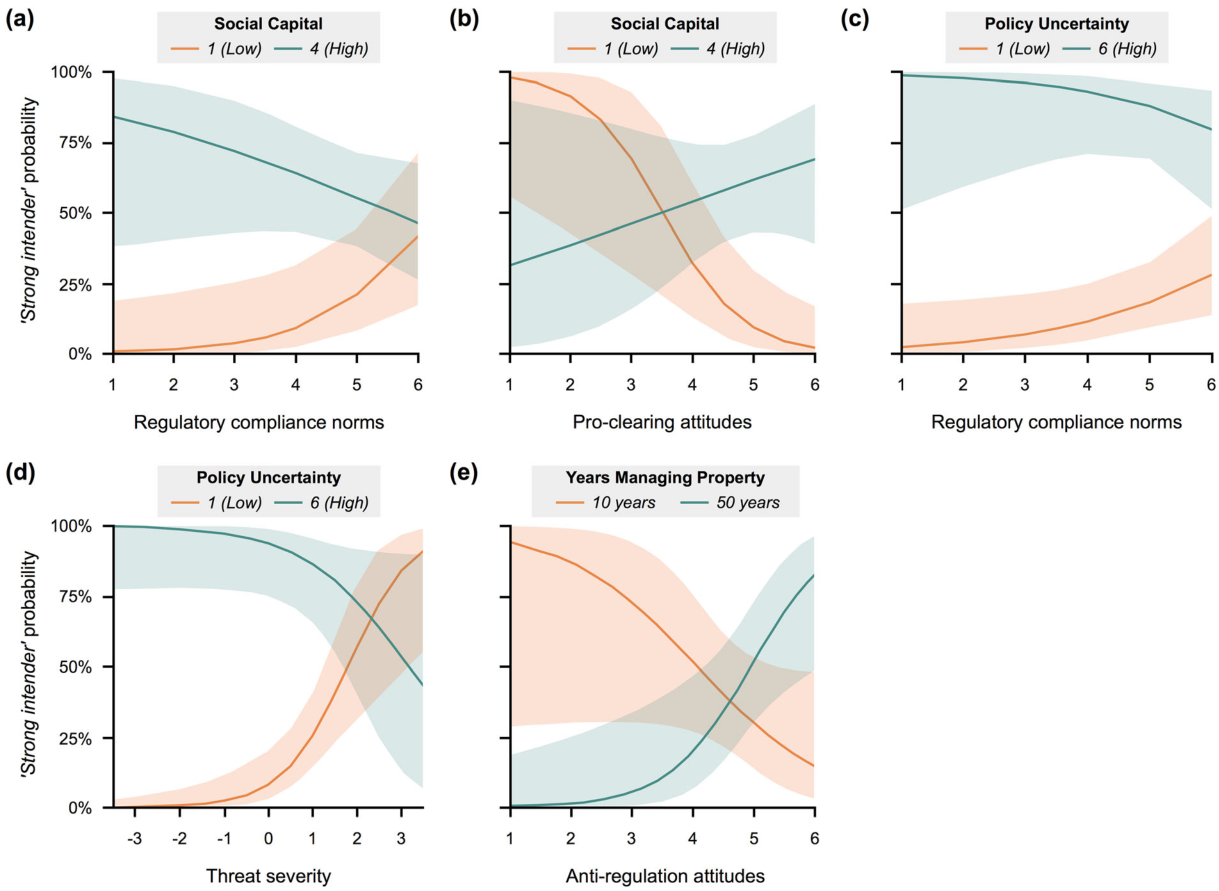

Fig. 3 Predicted probabilities of a land manager having strong intentions to clear trees in the next 6 months based on the interactions between **a** social capital and compliance norms, **b** social capital and pro-clearing attitudes, **c** policy uncertainty and compliance norms, **d** policy uncertainty and threat appraisal (severity) of the clearing regulations, and **e** years managing their property and anti-regulation attitudes. Shaded areas represent the 95% confidence interval around the mean predicted probability. Interaction effects are strongest when confidence intervals are smallest and when confidence intervals of higher (green) and lower (red) values are farthest apart; effects become insignificant at the point when confidence intervals overlap

Importance of context on attitudes, norms, and threats

The factors predicting strong clearing intentions are reflective of communities with a more contentious history with regulatory interventions, and this could partly explain why policy effectiveness has been limited in these areas (Simmons et al. 2018c). Land managers are more likely to have strong clearing intentions if they believe regulations are one of the greatest threats facing their property, but this effect is moderated by the influence of policy uncertainty. That is, farmers whose land management decisions are heavily influenced by talks of regulatory changes in Parliament tend to have much stronger clearing intentions, even if they don't view regulations as a greater threat. Policy uncertainty exerts a similar effect on compliance norms, increasing the strength of clearing intentions regardless of their beliefs about other farmers obeying or disobeying regulations. These results are crucial, both for Queensland and other heavily-regulated deforestation contexts around the world. They lend support to previous evidence of pre-emptive or 'panic' clearing in Queensland (Simmons et al. 2018b), where clearing rates dramatically increased in the lead-up to important policy changes. This 'reactance' response to new regulations is a frequent occurrence in all types of government policy (Proudfoot and Kay 2014), yet it is rarely given explicit consideration in models of deforestation and other land management behaviours.

Social capital also exerted moderating effects on the association between clearing attitudes and compliance norms. Land managers who have strong pro-clearing attitudes and believe most farmers are disobeying regulations have stronger clearing intentions when they are more actively involved in their community. Individuals will often seek social verification (validation from their peers) of their behaviours or intentions (Bandura 2001). While the extent of this verification may vary depending on the issue, many studies have shown that people's pro-environmental behaviours are heavily influenced by the perceived actions of those around them (McDonald et al. 2014; Sulemana and James 2014). These results lend support to the potential influence of social verification in Queensland, where social capital may provide a conduit for sharing social norms or attitudes about tree clearing (Dean et al. 2016). However, we did not collect information on the type of social capital participants are involved in, which would be an important avenue to explore in future studies.

Interestingly, despite strong clearing intenders having slightly more pro-clearing and anti-regulation attitudes than weak intenders, these attitudinal relationships were insignificant in the TPB model. Moreover, after controlling for other psychological and contextual factors in the final integrated model, the relationship of attitudes on clearing intentions reversed: land managers with stronger pro-clearing and anti-regulation attitudes tend to have weaker clearing intentions. On their own, attitudes may be poor predictors of behavioural intentions, as they may be heavily dependent upon other drivers of behaviour included in this study. These results reflect recent scepticism on the frequent prioritisation of targeting attitudes over other psychological drivers for creating behaviour change (Nilsson et al. 2019). While we did find that the effects of anti-regulation attitudes on intentions are moderated to some extent by land managers' years of experience, more research is needed to examine how attitudes interact with other psychosocial factors to influence behaviour in these complex environmental contexts.

It is worth noting that, in contrast to theorised expectations, the measures of perceived behavioural control (i.e. controllability and self-efficacy), were not strongly associated with clearing intentions. In a meta-analysis of the effects of perceived behavioural control in various behavioural contexts, Notani (1998) found that perceived behavioural control is a significant predictor of intentions in studies using students, but not in studies using a sample of non-students, which may be indicative that perceived behavioural control is most influential in people with less confidence or experience in performing a particular behaviour. Other studies have found that perceived behavioural control may be more important in behaviours that are perceived to be beneficial but present some barriers to adoption (Schultz 2014); yet this is not likely to be the case in Queensland, as many farmers do not see the benefit of avoiding tree clearing. In the context of farmers' land management regimes, most predictive perceived behavioural control variables in the literature are related to the adoption of *new* management practices or innovations (e.g. Borges and Oude Lansink 2016; Pickering et al. 2018). In this study, however, these variables represent how much control they have over *existing* tree clearing decisions and their ability to abide by the regulations. Most land managers believed they had little control over clearing decisions and felt it was difficult to follow regulations; this is more reflective of opportunity limitations, rather than limitations in cost, time, procedural knowledge, or skill. This was intentional during survey design, as clearing is a common practice for most land managers, but this inherent difference may explain why our results differ from many traditional behavioural models. Perceptions on the repercussions of disobeying clearing regulations may also have an effect on the link between perceived behavioural control and clearing intentions. Though farmers can face substantial financial penalties for clearing trees designated as protected remnant vegetation, several amendments made to the Act in 2012 and 2013 introduced new exemptions and reduced penalties, varied enforcement processes, and reduced the number of permits required (Simmons et al. 2018a). Thus, farmers with a low sense of self-efficacy and controllability may still intend to clear trees if the risk of penalty is low.

Recommendations and future directions

Our findings highlight the potential benefits of promoting pro-environmental and compliance norms in communities. We recommend greater promotion of landholders who are engaging in best management practices—through diverse channels like the media, natural resource management groups, and local champions—to increase social verification of responsible vegetation management. In addition, the frequency of regulatory changes to the Vegetation Management Act should be minimised to reduce effects of policy uncertainty on land managers' clearing intentions; when changes do occur, it is possible that communicating freedoms that still remain, rather than focusing on the freedoms that have been lost, could attenuate threat perceptions and potential reactance behaviours (Cornforth 2009). Community-based social marketing provides a pragmatic approach to creating positive behaviour change that integrates these principles of psychology and social marketing by designing strategic campaigns that promote pro-environmental knowledge, attitudes, and behaviours within targeted communities (McKenzie-Mohr 2011). Future research should explore the potential effectiveness of these approaches in Australia and other land management contexts around the world.

Although this study has utilised two of the most common theories used to understand intentions, a number of behavioural frameworks could also be investigated in more unique contexts, and some potentially important characteristics were not obtained in the survey, such as habits

(Klöckner 2013) and income reliance on farming (Comerford 2013). Future studies would benefit from testing the influence of these additional drivers of deforestation intentions, which may also help inform behaviour change strategies. Finally, despite our success in predicting behavioural intentions, predicting actual behaviour remains a significant challenge for researchers, practitioners, and policy-makers (Bamberg and Möser 2007). The spatial information collected from participants in this study will allow future investigations to compare expected intentions with realised clearing behaviours following completion of the survey. This will be important for estimating linkages between intentions and action, and why intentions may not lead to the corresponding behaviour in some deforestation contexts. Behavioural models can be an exceptionally important component of researchers' toolkit for understanding how people make environmental decisions on their property, with the ability to complement existing approaches, such as econometric models of land use/land cover change.

CONCLUSION

Identifying drivers of deforestation is critical to strategizing pro-environmental behaviour change interventions. Greater emphasis should be placed on the importance of diverse psychosocial drivers of deforestation intentions, which can be enhanced or suppressed by important political, social, and land management contexts. In cases like Queensland, the most effective strategies may not involve new regulatory interventions, but strategic communication of existing regulations and local compliance norms in communities where historic clearing is most extensive. We urge environmental scientists and practitioners to integrate more social science methods into their investigations of land use/land cover change to illuminate more proximate drivers of important environmental behaviours, like deforestation. Particularly in highly contentious or regulated environmental contexts, constructs like threat perceptions, norms, and social capital may be better predictors of behaviours than traditional econometric models using more distal drivers of behaviour. Ultimately, as societies and cultural norms evolve over time, changes in the psychosocial factors underlying environmental decision-making must be monitored to ensure that interventions are eliciting the desired changes in environmental behaviours.

Acknowledgements This work was supported by the Discovery and Future Fellowship programs of the Australian Research Council, and the Australian Research Council Centre of Excellence for Environmental Decisions (CE11001000104), funded by the Australian Government.

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