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Review

Improving the Representation of Climate Change Adaptation Behaviour in New Zealand's Forest Growing Sector

Grace B. Villamor [1,2,*], Andrew Dunningham [1], Philip Stahlmann-Brown [3] and Peter W. Clinton [1]

1 Scion (New Zealand Forest Research Institute, Ltd.) Titokorangi Drive, Private Bag 3020, Rotorua 3046, New Zealand; andrew.dunningham@scionresearch.com (A.D.); peter.clinton@scionresearch.com (P.W.C.)
2 Center for Development Research, University of Bonn, 3 Genscherallee, 53113 Bonn, Germany
3 Manaaki Whenua—Landcare Research, 17 Whitmore Street, Wellington 6011, New Zealand; brownp@landcareresearch.co.nz
* Correspondence: grace.villamor@scionresearch.com; Tel.: +64-7-343-5799

Abstract: To provide the forest industry with a better understanding of alternatives to simulate future adaptation pathways under evolving climatic and socio-economic uncertainty, we review the literature on how adaptation decisions are modelled in the context of plantation forests. This review leads to the conclusion that the representation of adaptation behaviour and decision-making remain very limited in most of the agent-based models in the forestry sector. Moreover, theoretical frameworks used to understand the adaptation behaviour of forest owners are also lacking. In this paper, we propose the application of protection motivation theory (PMT) as a framework to understand the motivation of forest owners to reduce the negative impacts of climate change on their forest plantations. Furthermore, the use of PMT allows factors affecting the maladaptive behaviour of forest owners to be examined. A survey of New Zealand foresters showed that less than 10% of smallholder forest owners adopted adaptation strategies. This result highlights the importance of addressing the research question "what motivates forest owners to take risk reduction measures?" Exploring this question is crucial to the future success of the New Zealand forestry sector and we suggest that it can be addressed by using PMT. This paper proposes a conceptual framework for an agent-based model as an alternative to simulating adaptation pathways for forest plantations in New Zealand.

Keywords: agent-based model; maladaptation; plantation forests; protection motivation theory; risk; social psychological behaviour

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1. Introduction

Models of forestry and land use systems as a whole are essential to understanding the magnitude and impacts of climate change [1]. At the same time, the need to integrate models of adaptation is widely recognised to support adaptation to climate change [2]. In this paper, we provide a review of agent-based models for climate change adaptation applied to the forestry sector while focusing on behavioural rules. Our review covers the use of theoretical frameworks to understand the adaptation behaviour of forest managers in plantation forests. There are few models in the forestry sector that emphasise climate change and human behaviour towards the adaptation of human responses [3–5]. Hence, this paper proposes an alternative quantitative framework based on social psychology theory, which explicitly integrates risk and adaptation appraisals of forest owners into agent-based models for future-proofing not only for climate change, but also natural environmental hazards.

The Need for Modelling Alternatives in the Forestry Sector

Adaptation is essential to reduce the impacts of climate change. Adaptation is a social process and highly contextual [6–8], framed by uncertainties and constraints. In the context of climate change, adaptation refers to adjustments in ecological, social, and economic systems in response to actual or expected climatic stimuli and their effects or impacts [9]. It takes place mostly in local contexts and entails assessing the current and emerging risks, the social economic and environmental factors that underpin risk and the capacity for risk management [10]. The design and implementation of adaptation strategies in the planted forestry sector requires an understanding of how forest owners' and societal reactions to climate change interact with biophysical, social and economic processes [11].

The large majority of climate change research in forest ecosystems has focused on understanding impacts on ecological processes [12]. In New Zealand's forestry sector, where 1.7 million ha of plantation forests contribute to an annual export value of $6.3 billion [13], the focus has been on the direct and indirect financial impact of climate hazards on exotic forests. However, the understanding of other climate-related risks and of adaptation options and pathways remains limited. Foresters and forest owners have to meet multiple and often conflicting objectives, such as adapting the functioning of plantation forests under climate change risk while simultaneously managing high yields in order to be profitable for their investors. For example, the 2020 New Zealand Superannuation Fund Climate Change report ranked timber investments first of the five investments with the greatest physical climate-related risk to the fund's real assets [14].

The need to understand decision-making in terms of climate-related risks in climate-sensitive sectors such as forestry is widely recognized [15–18]. This includes the need for models that can simulate future adaptations under evolving climatic and socio-economic uncertainty by explicitly representing adaptation and non-rational behaviours that underpin decision making [11,19]. Models also need to incorporate risk preferences and perceptions as motivations for adaptation or maladaptation [1,20] in the context of commercial (plantation) forestry management [1]. Process-based models, such as agent-based models, have the potential to better explore the future adaptation processes of socio-ecological systems [1,3] and are increasingly used to capture interactions between individual decision-making and the environment [21].

Micro-level interactions between heterogenous agents are at the heart of this modelling approach. Unlike many equation-based models, heterogeneity plays a key role in agent-based models, in which each agent individually assesses its own situation and makes decisions on the basis of a set of rules [22]. Such models simulate the individual actions of diverse agents to predict the resulting system behaviour and outcomes over time [23]. Agent-based models determine how humans (agents) respond to a variety of stimuli and scenarios of environmental and social conditions, including adapting to climate change and responses to adaptation strategies [24]. Adaptation can be modelled because agents have cognition that allows them to receive and exchange information, perceive and evaluate risks, identify and weigh options, make decisions and take actions, and to modify and update their profile according to the outcome of these actions [25]. Agent-based models can also represent underlying socio-economic processes [26], including local contexts. This is an advantage of agent-based models, since cultural and local institutions strongly determine the kinds of adaptive strategies people utilise. The main strength of using agent-based models is the explicit representation of human decision-making.

2. Modelling Climate Change Adaptation and Theoretical Representations

Decision making is the internal process that specifies how agents (in this case, forest owners) behave. Human decisions and subsequent actions change the structure and function of forest systems. As such, integrating human decision-making and behaviour into formal forest growth or management models under uncertainties (e.g., climate change) requires crucial modelling assumptions about the actors and goals, behavioural options, decision rules, and modelling decisions regarding human social interactions [27]. Behavioural theories are useful as: (1) they facilitate identifying a variety of factors and driving forces that influence human decision-making and behaviour, such as adaptation, and (2) they serve as a framework to model, explain, and predict the behaviour of the agent [28], which can later be applied in policy. A range of modelling approaches based on decision theories and behavioural types, some of which have been applied to forestry case studies, have integrated a range of assumptions about actors and goals. These are summarised in Table 1.

The most widely used model in economic theory for decisions over risk is Expected Utility Theory [1,29–33], which assumes that each agent's decision-making is goal-oriented and self-interested, with unlimited cognitive capabilities and rational actors (or utility maximisers). Expected Utility Theory is widely used in agent-based models as it is straightforward to translate into mathematical equations [31]. Risk is further explored through the application of Modern Portfolio theory [34], in which actors seek to minimise the variance and covariance (i.e., risk) of selected assets subject to a lower bound on the total expected return for all selected assets, which can be accommodated in Expected Utility Theory. However, forest owners may be neither rational nor risk-neutral and land managers may not make decisions strictly based on expected utility [35]. Rather, they can be risk-averse, as they are constrained by capital investments and face uncertainty about the future. Bounded rationality and Prospect Theory were conceptualised to address the cognitive limitation and risk aversion of decision makers, respectively [35]. Prospect theory describes how individuals overweigh low-probability/high-impact events and underweigh high-probability/low-impact events. Potential gains and losses are perceived as relative to reference points instead of utility [21]. In forestry, Prospect Theory has been increasingly applied to explore the effect of the perception of risk and time preferences in forest owners' decision-making [36], but has not been applied in agent-based models.

The ability to learn from past experience is an important component of adaptive capacity. Several studies applied the learning theories to examine the influence of past experiences to climate change adaptation in forestry [37–40]. For example, Vulturius and Swartling [40] examined the role of learning in engagement with climate change adaptation and found that forestry stakeholders struggle to form opinions based on what they perceive. However, based on the recent review by Brown et al. [1], a surprisingly large number of behavioural models do not include any form of learning and of those that do, agents are restricted to learning from their own experiences. Nevertheless, learning and related theories (such as social learning) that emphasise the adaptability of human behaviour are promising because they can capture short-term responses to drastically changing environments relevant to climate change adaptation [27].

Table 1. Behavioural and decision theories for forest management.

Behavioural Type	Decision					
	Theory	**Description**	**Assumption**	**Applicability/Example**	**Strength**	**Weakness**
Forward looking	Rational [1] decision makers (*Homo economicus*)	Expected Utility Theory is a theory of choice under risk and uncertainty where the decision maker chooses the option that promises the highest expected utility [29,41].	Actors have perfect and complete knowledge and unlimited computational processing powers. Decision making is goal oriented with stable preferences The rational decision makers maximise their utility or profit (*Maximiser*).	The socio-economic agent model focuses on the selling (supply) and buying (demand) of timber, which later influences the forest succession process [42].	Easy to link to forest growth models based on costs and benefits. Includes: adaptation costs, risk perception, time-preferences and income constraints [21]. Many applications.	Does not include other psychological factors, such as perceived ability to perform, and subjective norms and attitudes [21]. No forest owners and managers are perfectly rational profit maximisers.
	Behavioural economics	Prospect theory. The theory describes how individuals generally overweigh low-probability/high-impact events and underweigh high-probability/low-impact events [35,43].	Human agents are influenced by psychological biases such as endowment effect (i.e., agents derive utility not from wealth, but from gains and losses defined to some reference level), loss aversion (i.e., a loss hurts more than an equally large gain produces joy).	Using the extension of Smooth Prospect theory (SPT), artificial market agents were simulated against traditional agents (based on EUT) using ABM. The results showed that agents based on SPT demonstrated behaviours that were closer to real market data in risky environments [29].	Accounts for loss aversion, bounded rationality in evaluation, risk perception, adaptation costs, time-preference, and income constraints [21].	Does not include other psychological factors, such as perceived ability to perform, and subjective norms and attitudes [21]. Suitable decision rules highly context-dependent [27].
Backward looking	Cognitive/Psychological (*Homo psychologicus*)	Learning theory focuses on the past, where an agent or actor learns that a certain action leads to a reward that feels good or satisfying, and is therefore more likely to repeat this behaviour [27].	Learning from experience and results of past actions. Learning occurs when the outcome of an agent's decision to change or persist with its strategy matches its expectation of success. Decisions are also guided by rewards or punishments.	Agent considers experience of successful year including the historical information (e.g., fire event or pest outbreak) with various levels of risk acceptance [44].	It can describe the adaptivity of agent behaviour to a changing environment (e.g., climate change) with limited information.	High degree of randomness in behavioural changes and local dynamics are often stylized [27]. Dos not specify how information is acquired and how beliefs are formed.

Table 1. *Cont.*

Behavioural Type	Decision					
	Theory	**Description**	**Assumption**	**Applicability/Example**	**Strength**	**Weakness**
Sideward looking	Social influence *(Homo sociologicus)*	Social learning theory (i.e., adaptive management approach) The attitudes and decisions of one agent connected to another agent influence agents' attitudes or decisions. Agent learns from its interactions with nonspecific agents. This results in a change in understanding that goes beyond the individual, situating them within wider groups in society [45].	Assumes that successful intervention as a learned process depends on the appropriate communication channels. Social influence is exerted when the agent cannot reach his/her own decision and thus imitates the behaviour of the majority [46].	Scenario-based landscape planning (participatory planning process on climate change adaptation). The FLAME model has the agent's decision constrained by the opinions of other agents with whom they have communicated [47].	Specifies how the information is acquired and beliefs are formed by individuals. Explains the formation of consensus, the emergence of clustered opinion distributions and polarization.	High degree of randomness in behavioural changes and local dynamics are often stylized [27].
		Social network theory focuses on the role of social relationships in transmitting information, channelling personal or media influence, and enabling attitudinal or behavioural change.	Assumes that social structure influences the behaviour, opinions, or beliefs of individual actors or agents, which in turn drives changes in social structure. Actors with similar characteristics tend to form new links between each other while breaking links with agents that have diverging characteristics.	Information received from others (e.g., social network), updates agents' knowledge and updates their options according to their objectives. An analytical hierarchy process was applied to operationalise the agents' behaviour in the context of the roundwood and wood fuel markets [48].		

Table 1. *Cont.*

Behavioural Type	Decision					
	Theory	**Description**	**Assumption**	**Applicability/Example**	**Strength**	**Weakness**
Combination	Social/Cognitive/Psychological	Theory of planned behaviour focuses on intention as the main determinant or predictor of behaviour [49].	Assumes that the stronger the intention to engage in a behaviour, the more likely its performance. Three factors affect the intention: (1) attitude toward the behaviour, which refers to the degree to which a person has a favourable or unfavourable assessment of the behaviour in question; (2) subjective norms, which refers to an individual's perception about how significant others would judge the behaviour under consideration; and (3) perceived behavioural control, which refers to the perceived ease or difficulty of performing behaviour (reflecting past experience).	Applied to understanding forest owners' timber stand improvement intention [50]. May be explored for planned adaptation in forest management Applied to explore the determinants of behaviours (recycling) through the development of the agent-based model; cognitive model of agent-based model was develop based on the result of the structural equation model [51].	Includes individual attitudes and subjective norms [21].	Does not include risk attitudes and time preferences [21]. The original theory does not provide a mathematical formalization [31].

Table 1. *Cont.*

Behavioural Type	Decision					
	Theory	**Description**	**Assumption**	**Applicability/Example**	**Strength**	**Weakness**
		Protection motivation theory (PMT) focuses on the conditions under which fear appeals may influence attitudes and behaviour [52,53].	Assumes that fear and anxiety act as driving forces that motivate trial-and-error behaviour and decision-making towards adaptive practices. It assumes that various environmental (e.g., fear appeals) and intrapersonal sources of information can initiate two independent appraisal processes: (1) threat appraisal and (2) coping appraisal.	Climate change adaptation decisions in forestry. It explains and understands factors influencing climate change adaptation (and maladaptation) behaviour as well as crisis events due to environmental stresses [54]. Provides understanding as to the motivation for health and safety in forestry operations.	Combines risk perception and perceived costs and benefits of economic theories with individual coping perceptions [21,55]. Explains the subjective adaptive capacity of individuals (i.e., perceived self-efficacy).	Does not include a full distribution of risks and does not include risk attitudes and time preferences [21].

[1] Rationality was defined as the maximization of available utility and all agents were assumed to be rational.

The Theory of Planned Behaviour is one of the most widely applied non-rational theories that explains human behaviours [28]. The theory describes how behavioural beliefs and attitudes, normative beliefs, and subjective norms, together with control beliefs, lead to an intention to perform a behaviour and influence the actual execution of that behaviour [31,49]. In forestry, the Theory of Planned Behaviour has been increasingly applied to explain forest management decisions and the intentions of forest owners, such as timber improvement and adaptation measures, and attitudes [50,56–59]. However, it has not yet been used as behavioural framework for agent-based models of adaptation to climate change in the forestry sector.

The Protection Motivation Theory (PMT) is another psychological theory that explains forest owners' behaviour [54,60]. PMT was originally developed based on the expectancy value theory to explain the effects of fear appeals on health attitudes and behaviours [52,53]. Later, Milne et al. [61] further developed PMT to include decision-making in response to threats. Since then, PMT has been adapted to other contexts, such as environmental risks and natural disasters, including hurricanes [55], flood risks [62,63], and wildfires [64], and used to explain agricultural adaptation behaviour and decisions [65]. It has become a useful framework to evaluate stakeholders' perceived severity of climate change consequences, the perceived probability of climate change risks, the perceived effectiveness of adaptive behaviours to cope with climate change, and the perceived ability to perform adaptive behaviours successfully [65–67]. Applications of PMT to model the farmers' adaptation in agent-based models are growing in the agriculture sector [68–70].

In general, these are some examples of behavioural theories that can be applied to understand adaptation behaviours in the context of the forestry sector. Similar to the conclusion of several behavioural theory reviews, there is not a single theory that considers all relevant decision variables; instead, the choice of theory depends on the research questions, contexts, and purpose of the model, including its assumptions [1,21,27,28].

3. Integrating Climate Change Adaptation Decisions and Behaviour: Agent-Based Model Applications

In the forestry sector, there are only two examples of the application of agent-based models in which explicit adaptation decisions have been incorporated [1]. Rammel and Seidl [4] and Blanco et al. [3] both focused on adaptation to maintain yields, economic benefits, and potential ecosystem characteristics. An overview of the differences in agents' decision behaviour and structural functionalities is presented in Table 2. The two examples employed utility functions within their agents' decisions, along with heuristic decision rules. Utility functions are not always in the form of monetary income; instead, these could be in abstract forms of yield (such as the Cobb–Douglas utility function) or ecological indicators [71]. In Rammer and Seidl [4], for example, the model accounts for the dynamic response of forest owners to changes in environment. There are two adaptation decisions in the form of silvicultural decisions (specifically, passive and active). Passive adaptation decisions of agents are modelled by dynamically adjusting harvesting levels to changing growing conditions (e.g., +3 °C warming over 150 years), whereas active adaptation is modelled through a reduction in the rotation period. In their simulation, adaptation attributes such as the timing (i.e., reactive vs. proactive) of forest management were explored, and the authors concluded that the timing and pattern of adaptation had strong effects on ecosystem trajectories.

The forest owners in the model developed by Blanco et al. [3] are autonomous, risk-spreading, and proactive, with the goal of promoting resilience. Forest owners are typified by their objectives (e.g., producers, recreationists, etc.). Each agent type is associated with specific forest types and associated management practices. The agents' decisions are based on the level of service provision, societal demand, and overall supply levels and marginal utility functions. Coping ability determines each agent's autonomous adaptation and it is calculated by assigning a yearly score to each management strategy, depending on the scenario. The simulation results showed that the coping ability of forest owners varies due to contextual factors, such as felling events, the magnitude of unmet demand for forest services, and competition for other land uses.

Table 2. Examples of incorporating adaptation decisions in agent-based models for the forestry sector.

<table>
<tr><th rowspan="2">Aspect</th><th colspan="2">Model</th></tr>
<tr><th>Rammer and Seidl [4]</th><th>Blanco et al. [3]</th></tr>
<tr><td>Agent:</td><td>Forest managers/forest owners</td><td>Forest owners</td></tr>
<tr><td>Interaction type:</td><td>Agent-emergent ecosystem dynamics.
Based on the ecosystem information provided by the biophysical mode (i.e., iLand); silvicultural assessment is made for each stand at each time step (or year)</td><td>Agent—environment
LPJ-GUESS ecosystem model—to simulate forest dynamics</td></tr>
<tr><td>Agent behaviour/ decisions:</td><td>Two-tiered architecture:
1. Operational management decision *: annually/stand level
1.1 Planting (style: regular, random, grouped)
1.2 Thinning (types of thinning i.e., intensities)
1.3 Harvesting (type)
1.4 Salvaging (based on legal constraints)
2. Strategic management decision: (e.g., harvest stand in a given year) decadal
- Change rotation age
- Change target species
- Change thinning intensity
- Change silvicultural system
* Decisions are based on key indicators: stand age, stocking level, species composition, and diameter distributions</td><td>Based on management roles/objectives and associated management preferences:
1. Producer (economically oriented)
2. Multi-objective (economic, environmental and social objectives)
3. Recreationalist (recreational objectives)
4. Conservationist
5. Passive (no clear objectives)
Management preferences are based on:
- Forest types (species composition)
- Thinning programme
Competition—limited supply of land (using benefit function, which assigned value to production based on the societal demand level of each service)
Forest rotation period</td></tr>
<tr><td>Adaptation/ decisions:</td><td>Silvicultural decisions:
1. Adjustment of operational management to changing stand conditions (passive adaptation) (e.g., timing and distribution)
2. Alteration of key parameter of prevailing management strategy (active adaptation) (design of suited of policies)</td><td>Adaptation measure assumed to be known according to each management role (e.g., species composition, number of thinnings, rotation lengths)
Coping ability is assessed using coping index, which reflects whether a management strategy is at least as competitive under an uncertain future global change scenario as under a reference scenario.</td></tr>
<tr><td>Sub-models:</td><td>Simple decision heuristics</td><td>Gaussian probability distribution to represent individual differences in dedication to land use</td></tr>
<tr><td>Scenario settings:</td><td>Passive vs. active adaptation</td><td>Combined representative concertation pathways and shared socio-economic pathways</td></tr>
<tr><td>Programming:</td><td>Combined Javascript and C++</td><td>Java Eclipse (http://crafty-abm.sourceforge.net/) (accessed on 28 September 2020).</td></tr>
</table>

Both models' agent behaviour representations are based on the expected utility frameworks. The advantage of using Expected Utility Theory is that it is well integrated in forest ecosystem models that simulate forest dynamics under climate change scenarios. However, as argued above, pure optimization assumptions do not always reflect real-world adaptive behaviours. Instead, this is considered a shortfall or an adaptation deficit [33], suggesting that the representation of agent behaviour remains weak.

Indeed, there is a window of opportunity to further develop and improve the representation of adaptation to climate change in the forestry sector based on more realistic behavioural theories of decision-making (Table 1). Moreover, there are suggested ways to improve the modelling and simulation of climate change adaptation relevant for the forestry sector, such as [11]:

- Embedding human and social behaviours and constraints within models, either through integrating agent-based models with process-based models or through structured approaches to constrain model input changes that reflect time-varying scenario-specific settings.
- Reflecting on the importance of extreme events in driving adaptation [72].
- Accounting for the full cost of adaptation, in terms of the type and the amount that can occur, thus reflecting the financial constraints on adaptation [33]. Existing forests are constrained by a high level of investment in existing crops and infrastructure, and by the long time frame before economic return, reducing the flexibility to adapt.
- Working with stakeholders and decision makers to better understand the triggers and goals of adaptation policies and measures.
- Behavioural models should consider the perception of the risks of the landowner/manager, since most adaptations are made in response to the perceived risk of extreme events or the experience of the changing variability in climatic parameters [73,74].

Taking these suggestions into consideration (such as strong social behaviours, accounting for the full costs of adaptation and the incorporation of risk perception, including the limitations in Table 1), the following section further describes a conceptual framework from the viewpoint of a combination of cognitive and social psychology to represent forest owners' adaptation behaviour.

4. Protection Motivation Theory (PMT): A Social–Psychological Framework

Most adaptations are made in response to the perceived risk of extreme events or the experience of the changing variability in climatic parameters [16,63]. PMT is a useful framework to address the above case because it explicitly addresses risk and adaptation.

PMT is comprised of two 'appraisals'. The threat-or-risk appraisal focuses on the source of the threat and factors that increase or decrease the probability or likelihood of maladaptive responses (e.g., avoidance, denial, wishful thinking). The risk of the threat (or exposure) is estimated by the likelihood of the threat occurring and its severity, should it occur. It assumes that the probability of engaging in risk reduction behaviours is a positive function of the amount of risk perceived.

The coping-or-adaptation appraisal focuses on the coping responses available to the individual to deal with the threat and factors that increase or decrease the probability or likelihood of adaptive responses. The extent to which individuals can cope with threats is evaluated by assessing their capability of acting (self-efficacy) and the anticipated effectiveness of the action at reducing the threat (response efficacy). Self-efficacy is defined as one's perception of how competent he or she is at organising and executing the actions needed to manage a risky situation (whether a person feels able to implement a certain measure). One example is the formulation of practical guidelines on how to deploy adaptation measures. According to Blennow et al. [75], self-efficacy, or adaptive capacity, is an individual phenomenon that either promotes or hinders adaptive action. Response efficacy refers to one's belief that recommended behaviours will be effective at reducing or eliminating risk. For example, risk communication emphasises the effectiveness of flood mitigation measures. Response costs refers to the perceived costs associated with protection actions, such as financial costs, time, effort, and emotional costs.

According to McEligot et al. [55], the initial steps of appraising threats resemble a traditional risk assessment, based upon perceived hazard probability and consequences; by contrast, the coping appraisal resembles a cost-benefit analysis, utilising the decision maker's perception of their self-efficacy (i.e., ability to affect the response), response efficacy (i.e., the responses' ability to mitigate the risk), and response cost. Protective measures (or adaptation responses) are those actions that are suitable for reducing threats and are adopted if larger risk perceptions are accompanied by (positive) coping appraisals. By contrast, non-protective (or maladaptive) responses are adopted if high risk perceptions are accompanied by low coping appraisals.

Personal experience of the effects of climate change and social influence (such as norms and networks) can also be integrated with PMT [76] to enhance the understanding of adaptation to climate change. Thus, this integrated theoretical framework can help to explain the risk behaviour and the motivation of forest owners and the cognitive perceptual process that forest owners experience when faced with the decisions related to the protection of forest plantations from climate-related risks. However, its application to climate change adaptation in forestry within the context of agent-based models remains unexplored.

5. PMT Application to Adaptation of New Zealand's Commercial Forestry

Plantation forestry is an important primary industry in New Zealand. A plantation forest is defined as an intensively managed planted forest that, at maturity, is composed of one or two species, has one age class, and has regular tree spacing [77]. About 1.7 million ha of land (7% of New Zealand's land area) is plantation forest, of which 90% is planted with radiata pine (*Pinus radiata)* and 5% is planted with Douglas fir (*Pseudotsuga menziesii*) [78].

New Zealand forests are not exempted from the impacts of climate change. Negative impacts on forest plantations are projected from climate models. Along with climate change mitigation strategies (e.g., planting forests for carbon sequestration), adaptation measures and options are necessary. Table 3 outlines potential adaptation options or protection measures for forest operations involving radiata pine [79,80]. These options are adaptive strategies of risk minimisation for short-, medium-, and long-term vulnerability to climate change.

Table 3. Climate drivers, risks, and their adaptation options for forest operations of radiata pine. Source: Dunningham et al. [79] and Meason and Mason [80].

Risks	Climate Driver	Impacts	Adaptation	
			Reactive/Strategic	Proactive/Transformational
Change in growth productivity and wood quality	Increasing temperature Decreasing rainfallStrong winds	Productivity can be reduced from the indirect impacts from the increased risk of fire, pest, disease, and weed establishment and enhanced growth	• Identify new sites and relocation • Develop more flexible forest management plans • New silvicultural regimes	• Genetic and breeding programmes • Develop new products • Create options for higher-value products/markets
Pest and diseases outbreak	Increasing temperature Increasing rainfall	The climate changes can make forests more suitable for pests to establish viable populations	• Change to silvicultural and harvest regimes (i.e., rotation)	• Genetic modification to enhance resistance • Relocation/ disestablishment of forests • Deployment of alternative species
Fire	Increasing temperature Decreasing rainfall	The productivity of understorey and the increase in dryness can increase fuel loads	• Improved detection and monitoring of fires • More firebreaks	• Landscape-level fire planning • Altering distributions of plantations and plantation age classes
Erosion	Increasing rainfall and wind	Loss of established forests Loss of soil for pot-harvested stands	• Harvest timing • Timing of planting • Use of cover crops	• Replanting options that replace root binding • Slope stabilisation • Develop options for cover crops

Table 3. *Cont.*

Risks	Climate Driver	Impacts	Adaptation	
			Reactive/Strategic	Proactive/Transformational
Drought	Decreasing rainfall Increasing temperature	Impact can be significant for newly planted stands	• Genotype resistance • Breeding programs • Planting timing	• Land use change • Deployment of alternative species
Wind throw and toppling	Increasing wind/storm incidence	Loss of productivity from stem-break damaged (non-utilisable) trees Some production loss from toppled trees, depending on the ability to quickly extract and process fallen trees.	• Age class structuring • Timing of planting • Methods of planting • Thinning regimes	• Deployment of alternative species • Site selection

There are many barriers to the implementation and adoption of adaptation strategies by forest owners, including owners' limited understanding of specific contextualised risks and impacts and a lack of frameworks to communicate and articulate these impacts [81,82]. For large-scale exotic forest owners, the lack of actionable and specific risk-based research and tools has been identified as a barrier to incorporating practical adaptation strategies into their decision-making processes [83]. These explanations may underlie the low adoption of adaptation strategies by smallholder forest owners. To test this possibility, we employed the 2017 Survey of Rural Decision Makers [84], which asks whether respondents planted new land in forestry, changed pasture species or pasture management, provided more shelter for stock, changed livestock class or livestock management, changed crops or crop management, replanted different timber species, changed rotation length by harvesting sooner, changed rotation length by harvesting later, undertook new forestry management practices such as thinning or fertiliser application, converted to an uneven-aged forest, and/or changed seed sources. More the 90% of the respondents answered no to these questions (Table 4). The same survey revealed that most respondents anticipated changes in temperature, rainfall, and drought, leading us to ask what motivates forest owners to adapt.

To address the question of forest owners' motivation to adapt, we developed, and propose here, a conceptual framework for improving forest owners' adaptation to climate change using ABM. Our goal is to contribute to the understanding of how risk arising from future uncertainty and risk reduction strategies can be integrated into decision-making for future-proofing plantation forests in the New Zealand context. Our review of behavioural theories for climate change adaptation in the forestry sector highlighted the strengths of the PMT framework; therefore, we propose to use a PMT framework for the behavioural representation of the agents' (forest owners) adaptation decisions (Figure 1).

Table 4. The 2017 survey of rural decision makers' item-and-response options covering small-to medium forest owners (Source: Brown [84]).

Survey Items	Response	Frequency	Percent
Temperature: expectation to change by 2050	Decrease slightly	8	1.6
	No change	63	13.1
	Increase slightly	316	65.4
	Increase a lot	57	11.8
	Unsure	39	8.1

Table 4. *Cont.*

Survey Items	Response	Frequency	Percent
Rainfall: expectation to change by 2050	Decrease a lot	9	1.8
	Decrease slightly	75	15.5
	No change	125	25.8
	Increase slightly	156	32.3
	Increase a lot	50	10.4
	Unsure	68	14.1
Drought: prevalence to change by 2050	Decrease a lot	6	1.2
	Decrease slightly	33	6.8
	No change	118	24.4
	Increase slightly	190	39.4
	Increase a lot	77	15.9
	Unsure	59	12.2
Adaptation strategy:			
Planted new land in forestry	Yes	14	9.4
	No	134	90.5
Change/replant different timber species	Yes	8	5.4
	No	140	94.6
New forest management practices (e.g., thinning)	Yes	5	3.4
	No	143	96.6
Convert to an uneven-aged forest	Yes	4	2.7
	No	144	98.0
Change rotation length: Harvest sooner	Yes	3	2.0
	No	145	98.0
Change rotation length: Harvest later	Yes	4	2.7
	No	144	97.3
Flooding concern: based on past experience	Yes	168	34.8
	No	303	62.7
	Unsure	12	2.4
Flooding mitigation scheme: participation	Yes	54	11.2
	No	405	83.8
	Unsure	24	4.9

Figure 1 presents the general conceptual framework of the agent-based model, in which two systems (social and biophysical) interact. Both the social and the biophysical systems are influenced by external factors, such as climate and market changes [85]. Their interactions result in emergent properties, such as the overall resilience and adaptation of planted forests under climate and market changes over time.

Within the social system, PMT is adopted to determine the forest owner (agent)'s protection motivation or intention to apply any adaptation measure (as listed in Table 3). The agent's protection motivation or intention to adapt (I_a) is a function of risk appraisal (RA) and adaptation appraisal (CA) (as described in Section 4) for an adaptation measures (m) at time (t), which can be calculated as follows [21,53]:

$$I_a = \alpha * RA_t + \beta * CA_{t,m} \tag{1}$$

where

$$RA_t = \gamma * PS_t + \delta * PP_t \tag{2}$$

$$CA_{t,m} = \varepsilon * SE_{tm} + \theta * RE_{tm} - \zeta * RC_{tm} \tag{3}$$

where PS is perceived severity, PP is perceived probability, SE is self-efficacy, RE is response efficacy, and RC is response cost. The weights of the different variables (α, β, γ, δ, ε, θ, ζ) depend on the contexts of the adaptation decisions and can be estimated with a statistical analysis of the survey data [21].

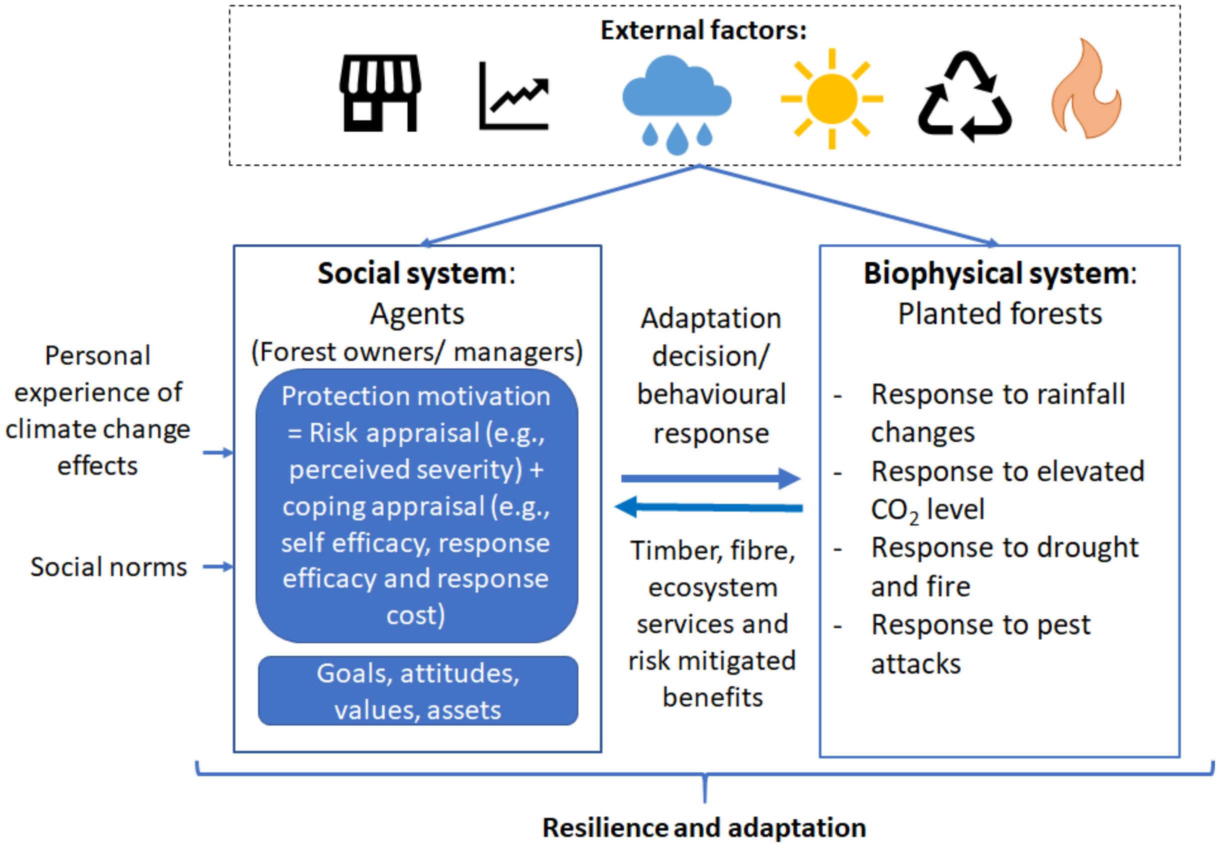

Figure 1. Proposed conceptual framework integrating the PMT framework for improving agents' adaptation behaviour.

Based on the PMT, the agent will only implement a certain adaptation measure when the risk appraisal and coping appraisal are high. There are two ways to estimate this [21]: (1) using probabilities [70], in which the greater the intention to adapt, the larger the probability is that the forest owner will invest in the adaptation measure; and (2) using thresholds [68], according to which the forest owner only invests if their intention to adapt is above a certain threshold. In another model, developed by Grothmann and Patt [63] and Lindell and Perry [76], both threats and coping appraisals are influenced by personal characteristics and experiences, as well as social networks [53], as shown in Figure 1. Based on the specified equations, we can determine the socio-psychological variables or factors affecting their intention to adapt, as well as the potential for maladaptive behaviour.

Our intention is to continue to parameterize and calibrate the proposed empirical agent-based model [86]. This work included a survey of forest owners to obtain input data and the selection of a process-based model to simulate forest yield and growth (e.g., CABALA [87] or 3-PG model [88,89]) under various climate scenarios for plantation forests in New Zealand [85], which will be a sub-model for biophysical systems (Figure 1). We proposed to translate this conceptual model (Figure 1) to an empirical agent-based model using NetLogo platform [90], which is freely available and easy to use, to test the proposed behavioural framework.

The integration of PMT as a behavioural representation of agents in an agent-based model for adaptation modelling has been applied in the agricultural sector, particularly for drought events [68–70]. Like most agent-based model applications, there are often not enough data to carry out such a validation. To address this limitation, we have applied, and will continue to apply mixed approaches, such as seeking stakeholders' agreement with regards to model outputs, conducting expert validation, and modelling output corroboration [91–93]. It is also important to perform a sensitivity analysis as part of the validation process [42].

6. Future Research

Modelling approaches, such as agent-based models, are useful for understanding the impacts of climate change on forestry, but the use of these types of model remains limited in climate change adaptation applications. However, to develop and successfully implement adaptive climate change policies, knowledge of how individual forest owners learn about and perceive climate change impacts, risks, and options for adaptation is required. Unfortunately, most agent-based models are based on Expected Utility Theory, which assumes full rationality and fails to account for risk. While other theories have been posited in the wider literature on behavioural change, we advocate using a PMT framework for understanding adaptation in the context of climate change adaptation in plantation forestry. This framework also offers an advantage in that it identifies perceptions of risk and the preferences of different types of forest owner; it can also explain their subjective adaptive capacity (i.e., perceived self-efficacy). In addition, the framework can be used to investigate maladaptive behaviour and explore whether the elements of the coping appraisal (i.e., response costs of adaptive measures, response efficacy and self-efficacy) will increase the likelihood of forest owners adopting risk reduction measures.

Building on its strengths, a decision algorithm of forest owner adaptation behaviour based on a PMT framework can also be integrated with process-based forest models (e.g., CABALA, 3-PG). In this way, future adaptation pathways under evolving climatic and socio-economic uncertainty can be simulated with decision-making based on more realistic behaviour.

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References

1. Brown, C.; Alexander, P.; Holzhauer, S.; Rounsevell, M.D. Behavioral models of climate change adaptation and mitigation in land-based sectors. *Wiley Interdiscip. Rev. Clim. Change* **2017**, *8*, e448. [CrossRef]
2. Patt, A.G.; van Vuuren, D.P.; Berkhout, F.; Aaheim, A.; Hof, A.F.; Isaac, M.; Mechler, R. Adaptation in integrated assessment modeling: Where do we stand? *Clim. Change* **2010**, *99*, 383–402. [CrossRef]
3. Blanco, V.; Brown, C.; Holzhauer, S.; Vulturius, G.; Rounsevell, M.D. The importance of socio-ecological system dynamics in understanding adaptation to global change in the forestry sector. *J. Environ. Manag.* **2017**, *196*, 36–47. [CrossRef] [PubMed]
4. Rammer, W.; Seidl, R. Coupling human and natural systems: Simulating adaptive management agents in dynamically changing forest landscapes. *Glob. Environ. Change* **2015**, *35*, 475–485. [CrossRef]
5. Yousefpour, R.; Temperli, C.; Jacobsen, J.B.; Thorsen, B.J.; Meilby, H.; Lexer, M.J.; Lindner, M.; Bugmann, H.; Borges, J.G.; Palma, J.H. A framework for modeling adaptive forest management and decision making under climate change. *Ecol. Soc.* **2017**, *22*, 40. [CrossRef]

6. Burton, I.; Diringer, E.; Smith, J. *Adaptation to Climate Change: International Policy Options*; Pew Center on Global Climate Change: Arlington, VA, USA, 2006.
7. Inderberg, T.H.; Eriksen, S.; O'Brien, K.; Sygna, L. *Climate Change Adaptation and Development*; Routledge: London, UK; New York, NY, USA, 2015.
8. Pielke, R.A., Jr. Rethinking the role of adaptation in climate policy. *Glob. Environ. Change* **1998**, *8*, 159–170. [CrossRef]
9. Smit, B.; Pilifosova, O. Adaptation to climate change in the context of sustainable development and equity. *Sustain. Dev.* **2003**, *8*, 9.
10. Jones, R. *A Risk Management Approach to Climate Change Adaptation*; New Zealand Climate Change Centre: Wellington, New Zealand, 2010; pp. 10–25.
11. Holman, I.P.; Brown, C.; Carter, T.R.; Harrison, P.A.; Rounsevell, M. Improving the representation of adaptation in climate change impact models. *Reg. Environ. Change* **2019**, *19*, 711–721. [CrossRef]
12. Seidl, R.; Aggestam, F.; Rammer, W.; Blennow, K.; Wolfslehner, B. The sensitivity of current and future forest managers to climate-induced changes in ecological processes. *Ambio* **2016**, *45*, 430–441. [CrossRef]
13. MPI. *Situation and Outlook for Primary Industries*; Ministry for Primary Industries: Wellington, New Zealand, 2021; pp. 44–47.
14. NZSF. *New Zealand Superannuation Fund Climate Change Report 2020*; Ministry of Social Development: Wellington, New Zealand, 2020.
15. Eriksson, L. Risk Perception and Responses Among Private Forest Owners in Sweden. *Small-Scale For.* **2014**, *13*, 483–500. [CrossRef]
16. Vulturius, G.; André, K.; Swartling, Å.G.; Brown, C.; Rounsevell, M.D.; Blanco, V. The relative importance of subjective and structural factors for individual adaptation to climate change by forest owners in Sweden. *Reg. Environ. Change* **2018**, *18*, 511–520. [CrossRef]
17. Käyhkö, J. Climate risk perceptions and adaptation decision-making at Nordic farm scale–a typology of risk responses. *Int. J. Agric. Sustain.* **2019**, *17*, 431–444. [CrossRef]
18. Lodin, I.; Eriksson, L.O.; Forsell, N.; Korosuo, A. Combining Climate Change Mitigation Scenarios with Current Forest Owner Behavior: A Scenario Study from a Region in Southern Sweden. *Forests* **2020**, *11*, 346. [CrossRef]
19. Villamor, G.B.; van Noordwijk, M. Gender specific land-use decisions and implications for ecosystem services in semi-matrilineal Sumatra. *Glob. Environ. Change* **2016**, *39*, 69–80. [CrossRef]
20. Amadou, M.L.; Villamor, G.B.; Kyei-Baffour, N. Simulating agricultural land-use adaptation decisions to climate change: An empirical agent-based modelling in northern Ghana. *Agric. Syst.* **2018**, *166*, 196–209. [CrossRef]
21. Schrieks, T.; Botzen, W.J.W.; Wens, M.; Haer, T.; Aerts, J.C.J.H. Integrating Behavioral Theories in Agent-Based Models for Agricultural Drought Risk Assessments. *Front. Water* **2021**, *3*, 686329. [CrossRef]
22. Bonabeau, E. Agent-based modeling: Methods and techniques for simulating human systems. *Proc. Natl. Acad. Sci. USA* **2002**, *99*, 7280–7287. [CrossRef]
23. Heppenstall, A.J.; Crooks, A.T.; See, L.M.; Batty, M. *Agent-Based Models of Geographical Systems*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2011.
24. Dickinson, T. *The Compendium of Adaptation Models for Climate Change*; Environment Canada: Ottawa, ON, Canada, 2007.
25. Acosta-Michlik, L.; Espaldon, V. Assessing vulnerability of selected farming communities in the Philippines based on a behavioural model of agent's adaptation to global environmental change. *Glob. Environ. Change* **2008**, *18*, 554–563. [CrossRef]
26. Verburg, P.H.; Alexander, P.; Evans, T.; Magliocca, N.R.; Malek, Z.; Rounsevell, M.D.; van Vliet, J. Beyond land cover change: Towards a new generation of land use models. *Curr. Opin. Environ. Sustain.* **2019**, *38*, 77–85. [CrossRef]
27. Müller-Hansen, F.; Schlüter, M.; Mäs, M.; Donges, J.F.; Kolb, J.J.; Thonicke, K.; Heitzig, J. Towards representing human behavior and decision making in Earth system models–an overview of techniques and approaches. *Earth Syst. Dyn.* **2017**, *8*, 977–1007. [CrossRef]
28. Kwon, H.R.; Silva, E.A. Mapping the landscape of behavioral theories: Systematic literature review. *J. Plan. Lit.* **2020**, *35*, 161–179. [CrossRef]
29. De Castro, P.A.L.; Teodoro, A.R.B.; de Castro, L.I.; Parsons, S. Expected utility or prospect theory: Which better fits agent-based modeling of markets? *J. Comput. Sci.* **2016**, *17*, 97–102. [CrossRef]
30. Groeneveld, J.; Müller, B.; Buchmann, C.M.; Dressler, G.; Guo, C.; Hase, N.; Hoffmann, F.; John, F.; Klassert, C.; Lauf, T.; et al. Theoretical foundations of human decision-making in agent-based land use models—A review. *Environ. Model. Softw.* **2017**, *87*, 39–48. [CrossRef]
31. Schlüter, M.; Baeza, A.; Dressler, G.; Frank, K.; Groeneveld, J.; Jager, W.; Janssen, M.A.; McAllister, R.R.; Müller, B.; Orach, K. A framework for mapping and comparing behavioural theories in models of social-ecological systems. *Ecol. Econ.* **2017**, *131*, 21–35. [CrossRef]
32. Villamor, G.; Van Noordwijk, M.; Le, Q.B.; Lusiana, B.; Matthews, R.; Vlek, P.L. Diversity deficits in modelled landscape mosaics. *Ecol. Inform.* **2011**, *6*, 73–82. [CrossRef]
33. Gawith, D.; Hodge, I.; Morgan, F.; Daigneault, A. Climate change costs more than we think because people adapt less than we assume. *Ecol. Econ.* **2020**, *173*, 106636. [CrossRef]
34. Markowitz, H.M. Portfolio selection. *J. Financ.* **1952**, *7*, 77–91.
35. Kahneman, D.; Tversky, A. Prospect theory: An analysis of decision under risk. *Econometrica* **1979**, *47*, 263–291. [CrossRef]

36. Tanaka, T.; Camerer, C.F.; Nguyen, Q. Risk and time preferences: Linking experimental and household survey data from Vietnam. *Am. Econ. Rev.* **2010**, *100*, 557–571. [CrossRef]
37. Ingold, K.; Zimmermann, W. How and why forest managers adapt to socio-economic changes: A case study analysis in Swiss forest enterprises. *For. Policy Econ.* **2011**, *13*, 97–103. [CrossRef]
38. Madge, C. The Social Learning Processes involved in incorporating wildfire risk reduction strategies into forest harvesting plans in Northern Saskatchewan. Master's Thesis, Dalhousie University, Halifax, NS, Canada, 2021.
39. Ricco, G.; Schultz, C.A. Organizational learning during policy implementation: Lessons from US forest planning. *J. Environ. Policy Plan.* **2019**, *21*, 275–287. [CrossRef]
40. Vulturius, G.; Gerger Swartling, Å. Overcoming social barriers to learning and engagement with climate change adaptation: Experiences with Swedish forestry stakeholders. *Scand. J. For. Res.* **2015**, *30*, 217–225. [CrossRef]
41. Von Neumann, J.; Morgenstern, O. *Theory of Games and Economic Behavior*, 3rd ed.; Princeton University Press: Princeton, NJ, USA, 1953.
42. Gebetsroither, E.; Kaufmann, A.; Gigler, U.; Resetarits, A. Agent-based modelling of self-organisation processes to support adaptive forest management. In *Agent-Based Computational Modelling*; Springer: Berlin/Heidelberg, Germany, 2006; pp. 153–172.
43. Tversky, A.; Kahneman, D. Advances in prospect theory: Cumulative representation of uncertainty. *J. Risk Uncertain.* **1992**, *5*, 297–323. [CrossRef]
44. Bohensky, E. Learning dilemmas in a social-ecological system: An agent-based modeling exploration. *J. Artif. Soc. Soc. Simul.* **2014**, *17*, 2. [CrossRef]
45. Reed, M.S.; Evely, A.C.; Cundill, G.; Fazey, I.; Glass, J.; Laing, A.; Newig, J.; Parrish, B.; Prell, C.; Raymond, C. What is social learning? *Ecol. Soc.* **2010**, *15*, r1. [CrossRef]
46. Scheller, F.; Johanning, S.; Bruckner, T. *A Review of Designing Empirically Grounded Agent-Based Models of Innovation Diffusion: Development Process, Conceptual Foundation and Research Agenda*; University of Leipzig: Leipzig, Germany, 2019.
47. Leahy, J.E.; Reeves, E.G.; Bell, K.P.; Straub, C.L.; Wilson, J.S. Agent-based modeling of harvest decisions by small scale forest landowners in Maine, USA. *Int. J. For. Res.* **2013**, *2013*, 563068. [CrossRef]
48. Kostadinov, F.; Holm, S.; Steubing, B.; Thees, O.; Lemm, R. Simulation of a Swiss wood fuel and roundwood market: An explorative study in agent-based modeling. *For. Policy Econ.* **2014**, *38*, 105–118. [CrossRef]
49. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Processes* **1991**, *50*, 179–211. [CrossRef]
50. Karppinen, H.; Berghäll, S. Forest owners' stand improvement decisions: Applying the Theory of Planned Behavior. *For. Policy Econ.* **2015**, *50*, 275–284. [CrossRef]
51. Scalco, A.; Ceschi, A.; Shiboub, I.; Sartori, R.; Frayret, J.-M.; Dickert, S. The implementation of the theory of planned behavior in an agent-based model for waste recycling: A review and a proposal. In *Agent-Based Modeling of Sustainable Behaviors*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 77–97.
52. Regasa, D.T.; Akirso, N.A. Determinants of climate change mitigation and adaptation strategies: An application of protection motivation theory in konta District, South Western Ethiopia. *Eur. Rev. Appl. Sociol.* **2019**, *12*, 49–73. [CrossRef]
53. McEligot, K.; Brouse, P.; Crooks, A. Sea Bright, New Jersey reconstructed: Agent-based protection theory model responses to Hurricane Sandy. In Proceedings of the 2019 Winter Simulation Conference (WSC), National Harbor, MD, USA, 8–11 December 2019; pp. 251–262.
54. Hengst-Ehrhart, Y. Knowing is not enough: Exploring the missing link between climate change knowledge and action of German forest owners and managers. *Ann. For. Sci.* **2019**, *76*, 94. [CrossRef]
55. Laakkonen, A.; Zimmerer, R.; Kähkönen, T.; Hujala, T.; Takala, T.; Tikkanen, J. Forest owners' attitudes toward pro-climate and climate-responsive forest management. *For. Policy Econ.* **2018**, *87*, 1–10. [CrossRef]
56. Holt, J.R.; Butler, B.J.; Borsuk, M.E.; Markowski-Lindsay, M.; MacLean, M.G.; Thompson, J.R. Using the Theory of Planned Behavior to Understand Family Forest Owners' Intended Responses to Invasive Forest Insects. *Soc. Nat. Resour.* **2021**, *34*, 1001–1018. [CrossRef]
57. Karppinen, H. Forest owners' choice of reforestation method: An application of the theory of planned behavior. *For. Policy Econ.* **2005**, *7*, 393–409. [CrossRef]
58. Clarke, M.; Ma, Z.; Snyder, S.A.; Hennes, E.P. Understanding invasive plant management on family forestlands: An application of protection motivation theory. *J. Environ. Manag.* **2021**, *286*, 112161. [CrossRef]
59. Rogers, R.W. A protection motivation theory of fear appeals and attitude change1. *J. Psychol.* **1975**, *91*, 93–114. [CrossRef]
60. Rogers, R.W. Cognitive and psychological processes in fear appeals and attitude change: A revised theory of protection motivation. In *Social Psychophysiology: A Sourcebook*; Guilford: New York, NY, USA, 1983; pp. 153–176.
61. Milne, S.; Sheeran, P.; Orbell, S. Prediction and intervention in health-related behavior: A meta-analytic review of protection motivation theory. *J. Appl. Soc. Psychol.* **2000**, *30*, 106–143. [CrossRef]
62. Bubeck, P.; Botzen, W.J.W.; Kreibich, H.; Aerts, J.C.J.H. Detailed insights into the influence of flood-coping appraisals on mitigation behaviour. *Glob. Environ. Change* **2013**, *23*, 1327–1338. [CrossRef]
63. Grothmann, T.; Patt, A. Adaptive capacity and human cognition: The process of individual adaptation to climate change. *Glob. Environ. Change* **2005**, *15*, 199–213. [CrossRef]
64. Ghasemi, B.; Kyle, G.T.; Absher, J.D. An examination of the social-psychological drivers of homeowner wildfire mitigation. *J. Environ. Psychol.* **2020**, *70*, 101442. [CrossRef]

65. Truelove, H.B.; Carrico, A.R.; Thabrew, L. A socio-psychological model for analyzing climate change adaptation: A case study of Sri Lankan paddy farmers. *Glob. Environ. Change* **2015**, *31*, 85–97. [CrossRef]
66. Tapsuwan, S.; Rongrongmuang, W. Climate change perception of the dive tourism industry in Koh Tao island, Thailand. *J. Outdoor Recreat. Tour.* **2015**, *11*, 58–63. [CrossRef]
67. Le Dang, H.; Li, E.; Nuberg, I.; Bruwer, J. Understanding farmers' adaptation intention to climate change: A structural equation modelling study in the Mekong Delta, Vietnam. *Environ. Sci. Policy* **2014**, *41*, 11–22. [CrossRef]
68. Hailegiorgis, A.; Crooks, A.; Cioffi-Revilla, C. An agent-based model of rural households' adaptation to climate change. *J. Artif. Soc. Soc. Simul.* **2018**, *21*, 4. [CrossRef]
69. Wens, M.; Johnson, J.M.; Zagaria, C.; Veldkamp, T.I. Integrating human behavior dynamics into drought risk assessment—A sociohydrologic, agent-based approach. *Wiley Interdiscip. Rev. Water* **2019**, *6*, e1345. [CrossRef]
70. Keshavarz, M.; Karami, E. Farmers' pro-environmental behavior under drought: Application of protection motivation theory. *J. Arid Environ.* **2016**, *127*, 128–136. [CrossRef]
71. An, L. Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecol. Model.* **2012**, *229*, 25–36. [CrossRef]
72. Berrang-Ford, L.; Ford, J.D.; Paterson, J. Are we adapting to climate change? *Glob. Environ. Change* **2011**, *21*, 25–33. [CrossRef]
73. Negri, D.H.; Gollehon, N.R.; Aillery, M.P. The effects of climatic variability on US irrigation adoption. *Clim. Change* **2005**, *69*, 299–323. [CrossRef]
74. Thomas, D.S.; Twyman, C.; Osbahr, H.; Hewitson, B. Adaptation to climate change and variability: Farmer responses to intra-seasonal precipitation trends in South Africa. *Clim. Change* **2007**, *83*, 301–322. [CrossRef]
75. Blennow, K.; Persson, J.; Tome, M.; Hanewinkel, M. Climate change: Believing and seeing implies adapting. *PLoS ONE* **2012**, *7*, e50182. [CrossRef]
76. Lindell, M.K.; Perry, R.W. *Behavioral Foundations of Community Emergency Planning*; Hemisphere Publishing Corporation: London, UK, 1992.
77. FAO. *Terms and Definition*; Food and Agriculture Organization: Rome, Italy, 2018. Available online: https://www.fao.org/3/I8661EN/i8661en.pdf (accessed on 27 December 2021).
78. MPI. *Situation and Outlook for Primary Industries*; Ministry for Primary Industries: Wellington, New Zealand, 2019; pp. 1–7.
79. Dunningham, A.; Kirschbaum, M.; Payn, T.; Meason, D. Chapter 7. Forestry: Long-term adaptation of productive forests in a changing climatic environment. In *Impacts of Climate Change on Land-Based Sectors and Adaptation Options. Technical Report to the Sustainable Land Management and Climate Change Adaptation Technical Working Group. MPI Technical Paper*; Ministry for Primary Industries: Wellington, New Zealand, 2012; pp. 293–346.
80. Meason, D.F.; Mason, W. Evaluating the deployment of alternative species in planted conifer forests as a means of adaptation to climate change—Case studies in New Zealand and Scotland. *Ann. For. Sci.* **2014**, *71*, 239–253. [CrossRef]
81. Moore, D.; Dunningham, A. Practical demonstration and up-scalling on climate change and green house gas emissions to farmers and growers. In *Report 1: Climate Change Messages from Workshops*; Scion: Rotorua, New Zealand, 2011.
82. Payn, T.W.; Barnard, T.; Clinton, P.; Spence, H.; Crawford, K. *Development of an Implementation Plan for Model Forests to Aid Climate Change Adaptation in New Zealand's Planted Forests*; New Zealand Forest Research Institute: Rotorua, New Zealand, 2009.
83. Dunningham, A.; Grant, A.; Wreford, A.; Kirk, N. *A Review of Climate Change Research in New Zealand Focusing on Forestry*; Ministry of Primary Industries: Wellington, New Zealand, 2018.
84. Brown, P. *Survey of Ruray Decision Makers*; Manaaki Whenua—Landcare Research: Wellington, New Zealand, 2017. [CrossRef]
85. West, T.A.; Salekin, S.; Melia, N.; Wakelin, S.J.; Yao, R.T.; Meason, D. Diversification of forestry portfolios for climate change and market risk mitigation. *J. Environ. Manag.* **2021**, *289*, 112482. [CrossRef]
86. Villamor, G.B.; Wakelin, S.J.; Dunningham, A.; Clinton, P.W. Climate change adaptation behaviour of forest growers in New Zealand: An application of protection motivation theory. *Clim. Change* **2022**. *Submitted*.
87. Battaglia, M.; Sands, P.; White, D.; Mummery, D. CABALA: A linked carbon, water and nitrogen model of forest growth for silvicultural decision support. *For. Ecol. Manag.* **2004**, *193*, 251–282. [CrossRef]
88. Watt, M.S.; Palmer, D.J.; Kimberley, M.O.; Höck, B.K.; Payn, T.W.; Lowe, D.J. Development of models to predict Pinus radiata productivity throughout New Zealand. *Can. J. For. Res.* **2010**, *40*, 488–499. [CrossRef]
89. Landsberg, J.J.; Waring, R.H. A generalised model of forest productivity using simplified concepts of radiation-use efficiency, carbon balance and partitioning. *For. Ecol. Manag.* **1997**, *95*, 209–228. [CrossRef]
90. Wilensky, U.; Rand, W. *An Introduction to Agent-Based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo*; MIT Press: Cambridge, MA, USA, 2015.
91. Smajgl, A.; Bohensky, E. Behaviour and space in agent-based modelling: Poverty patterns in East Kalimantan, Indonesia. *Environ. Model. Softw.* **2013**, *45*, 8–14. [CrossRef]
92. Voinov, A.; Bousquet, F. Modelling with stakeholders. *Environ. Model. Softw.* **2010**, *25*, 1268–1281. [CrossRef]
93. Augusiak, J.; Van den Brink, P.J.; Grimm, V. Merging validation and evaluation of ecological models to 'evaludation': A review of terminology and a practical approach. *Ecol. Model.* **2014**, *280*, 117–128. [CrossRef]