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Research article

Diversification of forestry portfolios for climate change and market risk mitigation

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ABSTRACT

Investments in forestry are long-term and thus subject to numerous sources of risk. In addition to the volatility from markets, forestry investments are directly exposed to future impacts from climate change. We examined how diversification of forest management regimes can mitigate the expected risks associated with forestry activities in New Zealand based on an application of Modern Portfolio Theory. Uncertainties in the responses of *Pinus radiata* (D. Don) productivity to climate change, from 2050 to 2090, were simulated with 3-PG, a process-based forest growth model, based on future climate scenarios and Representative Concentration Pathways (RCPs). Future timber market scenarios were based on RCP-specific projections from the Global Timber Model and historical log grade prices. Outputs from 3-PG and the market scenarios were combined to compute annualized forestry returns for four *P. radiata* regimes for 2050–2090. This information was then used to construct optimal forestry portfolios that minimize investment risk for a given target return under different RCPs, forest productivity and market scenarios. While current *P. radiata* regimes in New Zealand are largely homogenous, our results suggest that regime diversification can mitigate future risks imposed by climate change and market uncertainty. Nevertheless, optimal portfolio compositions varied substantially across our range of scenarios and portfolio objectives. The application of this framework can help forest managers to better account for future risks in their management decisions.

1. Introduction

Tree planting is regarded as one of the most effective nature-based solutions for the climate crisis (Griscom et al., 2017), but the imminent shifts in climate conditions may hamper the success of this type of activity (Sperry et al., 2019). While higher carbon dioxide concentrations in the atmosphere may increase forest growth under certain circumstances (Norby and Zak, 2011), less-predictable climatic impacts, e.g., changes in the frequency of extreme droughts, rainfall and wind, may jeopardize the health and productivity of existing and future forests (Gea-Izquierdo et al., 2017; Sperry et al., 2019). Consequently, the forestry sector's exposure to risk is expected to increase substantially in a warmer world (Anderegg et al., 2020; Nordström et al., 2019). Application of Modern Portfolio Theory (MPT; Markowitz, 1952; Pfaff, 2016; Würtz et al., 2015) can potentially help forest managers to understand and cope with the future uncertainty imposed by climate change, as well as markets, to their businesses through the diversification of investments, management regimes, and tree species (Crowe and Parker, 2008; Hyytiäinen and Penttinen, 2008; Zinkhan and Cubbage, 2003).

The foundations of MPT are based on the optimal diversification of investments (Markowitz, 1952). In standard MPT applications, expected investment returns (and their volatilities) are treated as random variables and optimized for the construction of investment portfolios. Generally, the objective of portfolio optimization is (i) the maximization of returns given an acceptable level of risk or (ii) the minimization of risk for a given return target. In standard portfolio application, expected returns are commonly defined as the average historical returns of investment assets, whereas risks are a function of the assets' volatility, expressed as standard deviations and covariances (Pfaff, 2016; Würtz

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et al., 2015). While portfolio selection is dependent on the objectives of the investors, all optimal portfolios represent equally optimal trade-offs between the expected returns and risk. Standard MPT applications focus on "traditional" financial assets, e.g., government bonds or stocks, but applications to other fields such as forestry, agriculture, and environmental services can be found in the literature (Matthies et al., 2015; Mills and Hoover, 1982; Nalley et al., 2009; Redmond and Cubbage, 1988; Weng et al., 2013).

Forestry is an important economic activity in New Zealand, worth NZD 6.9 billion in annual export revenue (New Zealand Forest Owners Association, 2019). Most of New Zealand's commercial timber harvest comes from 1.6 million ha (~5% of New Zealand's land area) of *Pinus radiata* (D. Don) plantation forests (New Zealand Forest Owners Association, 2019). These forests are expected to expand in the near future (New Zealand Productivity Commission, 2018; West et al., 2020a). Projections suggest that New Zealand's transition pathway to a low-carbon economy will require an average of 44,000–90,000 ha of new forests to be planted each year over the next 30 years and many programmes and incentives were recently made available by the government in order to achieve this target (West et al., 2020b). Nevertheless, future climate uncertainty is likely to impose additional challenges for the establishment of new forests in the country (Anderegg et al., 2020). Some of these challenges are likely to result from more frequent pest and disease outbreaks, extreme weather events such as droughts (and wildfires), increased weed competition, loss of topsoil due to erosion, and changes in rainfall patterns (Dunningham et al., 2012; Frame et al., 2020; Ministry for the Environment, 2018; Ramsfield et al., 2016; Watt et al., 2019). Further, while nearly 85% of all wood products from the country are exported (New Zealand Forest Owners Association, 2019), New Zealand's forestry sector is a relatively small, price-taker player in the global economy (Daigneault, 2019), which increases its exposure to market risk. Combined, climate change and market uncertainty could jeopardize the country's economic sector substantially.

Given the long-term characteristic of forestry investments (with the time from planting to harvesting usually over 25 years), decisions taken by forest managers today will shape the future of their businesses over the next decades. Given the expected future impacts of climate change on forests (Anderegg et al., 2020; Gea-Izquierdo et al., 2017; Sperry et al., 2019), simulation models are often recognized as critical decision-making tools for forestry (Nordström et al., 2019). One model often used to examine the impacts of climate change on forest growth is 3-PG (*Physiological Principles in Predicting Growth*; Gupta and Sharma, 2019). This ecophysiological process-based model predicts forests' net primary productivity, transpiration, respiration, and growth based on various biological and environmental parameters and climate variables (Landsberg and Waring, 1997). Absorbed photosynthetically active radiation is calculated as a function of photosynthetically active radiation and leaf area index. Water balance is simulated based on input, output and storage. Water movement in the soil discriminates between water in the root and non-root zones. In 3-PG, a combination of suboptimal temperatures, high vapour pressure deficits, infertile soil fertility, and water availability in the soil limits photosynthesis, affecting growth and biomass allocation (see Landsberg and Waring, 1997, for details).

Previous studies in the environmental field have applied MPT to inform the selection of species for reforestation under current and future climate scenarios (Crowe and Parker, 2008; Weng et al., 2013). The theory has also been used to examine investment trade-offs between forestry and "traditional" financial assets such as stocks, bonds, and real estate (Hyytiäinen and Penttinen, 2008), as well as to shed light on the selection of forest management regimes (Reeves and Haight, 2000), land-use decisions and diversification (Knoke et al., 2011; Mills and Hoover, 1982). More recent studies applied MPT to investigate the risks and returns associated with payments for ecosystem services (PES) programs; Matthies et al. (2015) examined portfolio options comprised of business-as-usual forest management, investments in equities and bonds, and enrolment in PES schemes with postponed harvesting in Finland, whereas Monge et al. (2016) applied MPT to evaluate the potential impacts of PES for forest carbon sequestration and nitrogen leaching mitigation on diversification of farm activities.

Here, we apply MPT to examine how diversification of forest management regimes in New Zealand can reduce the exposure of the forestry sector to climate change and market risk. Unlike standard MPT applications, where the expected investment returns and risks are based on historical (*ex-post*) information (Würtz et al., 2015), our analysis is focused on simulated (*ex-ante*) forest productivity responses to climate change, as well as forecasted changes in market prices. Consequently, this study also differs from previous MPT applications to forestry available in the literature (e.g., Hyytiäinen and Penttinen, 2008; Matthies et al., 2015; Monge et al., 2016; Reeves and Haight, 2000).

2. Methods

2.1. Future climate scenarios

Forest productivity responses to climate change were based on 2020–2090 projections from the global climate models adopted by the Intergovernmental Panel on Climate Change (IPCC; Stocker et al., 2014) for our study site, the Ashley Forest, in the South Island of New Zealand (43° 10′ 59″ S, 172° 34′ 00″ E). The 10,270-ha site is characterized by elevations ranging 140–865 m above sea level, a historical mean annual rainfall of 800 mm and a mean annual temperature of 10.8 °C (Meason and Mason, 2014).

Climate projections are based on four Representative Concentration Pathway (RCP) scenarios (Moss et al., 2010). The approximate total radiative forcing at 2100 relative to 1750, which defines these pathways, are 2.6 W m^{-2} for RCP2.6, 4.5 W m^{-2} for RCP4.5, 6.0 W m^{-2} for RCP6.0, and 8.5 W m^{-2} for RCP8.5. The RCPs include one mitigation pathway (RCP2.6), which implies the removal of some of the CO_2 present in the atmosphere (generally aligned with the Paris Agreement goals; Peters and Hausfather, 2020), two stabilisation pathways (RCP4.5 and RCP6.0) and one pathway with very high greenhouse gas emissions (RCP8.5).

Detailed projections at a 5-km grid for the Ashley Forest region were produced by downscaling the output from the six IPCC Fifth Assessment's global climate models: BCC-CSM1.1, CESM1-CAM5, GFDL-CM3, GISS-E2-R, HadGEM2-ES, and NorESM1-M (Ministry for the Environment, 2018; Stocker et al., 2014). The downscaled climate data, for each RCP scenario, served as input for the forest growth model 3-PG (Landsberg and Waring, 1997; Fig. 1). Following Coops et al. (2010), we did not allow atmospheric CO_2 concentrations associated with the RCPs to change over time (Meinshausen et al., 2011), as this variable was found to be highly sensitive to soil fertility, which affects phenology, photosynthetic capacity and allocation of growth above and below ground in 3-PG.

2.2. Forest productivity under climate change

We employed the 3-PGpjs version of the 3-PG model (v.2.7; Sands, 2010), to simulate three *P. radiata* productivity scenarios (i.e., low, medium and high; m^3 ha^{-1}) under climate change. The 3-PG model has been previously calibrated with *P. radiata* field data from the Ashley Forest and nearly forests in the Canterbury region of New Zealand (Meason and Mason, 2014). Mean monthly forecasts for precipitation, days with sub-zero temperatures, and minimum and maximum temperatures for the study site, under each RCP, were derived from the global climate model projections (for 2020–2090) and used as 3-PG input data (Figs. 1 and 2).

We used 3-PG to simulate wood volumes at harvest (m^3 ha^{-1}) for 2020–2090, under 25–30-year rotations. Yet, we define 2050 as the beginning of our study period, as that is the year when the simulated hectares planted in 2020, under 30-year rotations (i.e., our longest simulated rotation), reach harvest age. In the 3-PG simulations, one

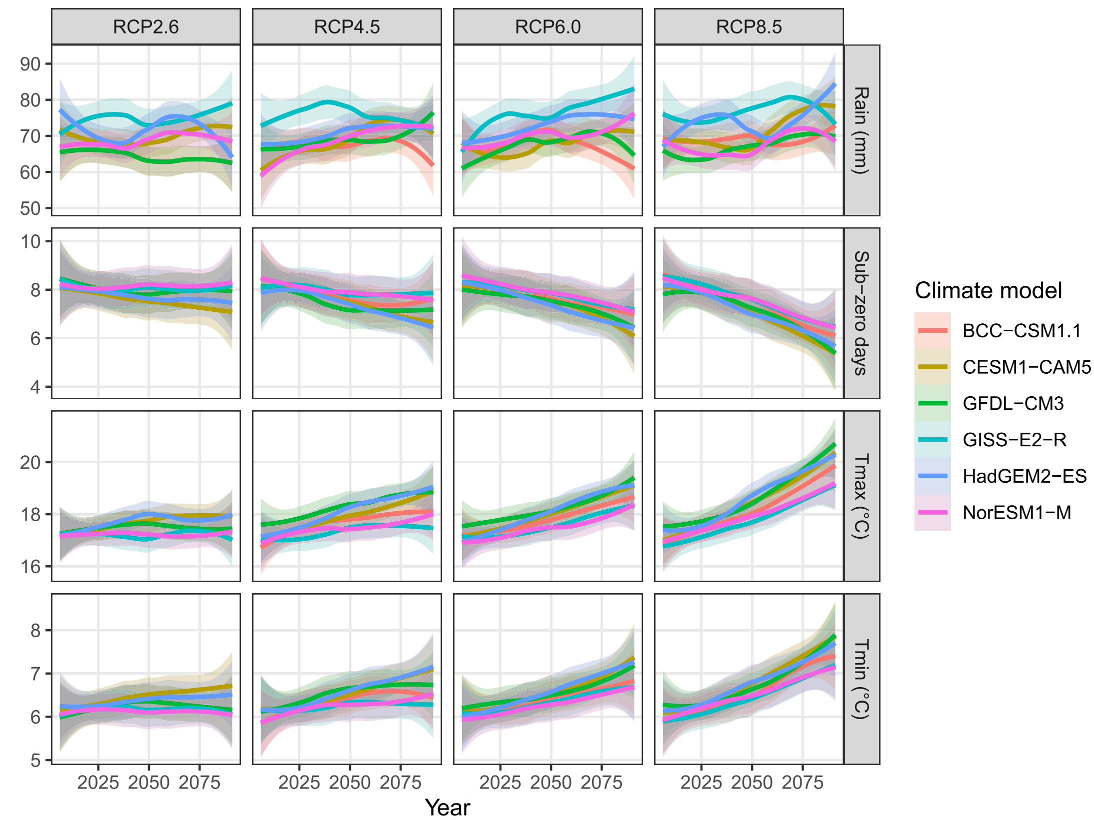

Fig. 1. Climate scenario trends for the Ashley Forest site per global climate model and Representative Concentration Pathway (RCP). Panels represent monthly averages. Sub-zero days are the number of days per month with sub-zero temperatures. Shaded areas represent 95% confidence intervals.

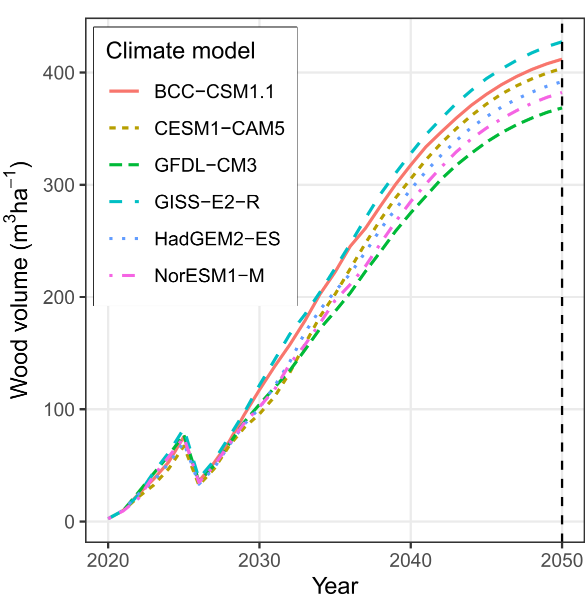

Fig. 2. Example of *Pinus radiata* growth simulations from the 3-PG model for a hypothetical hectare planted in 2020 based on forecasts from six global climate models under a given Representative Concentration Pathway. The dashed line represents the harvest year under a 30-year rotation regime. Drops in the growth curves around 2025 result from thinning.

hectare of forest, for each simulated regime, is planted each year from 2020 to 2090. These forest hectares grow in response to the climate conditions corresponding to the period between planting and harvesting (Figs. 1 and 2). For example, under 30-year rotations, the harvest volumes simulated for 2060, 2061 and 2062 correspond to forest hectares planted in 2030, 2031 and 2032, respectively, and exposed to the 2030–2060, 2031–2061 and 2032–2062 climatic conditions, respectively. We computed the mean expected volume at harvest, and 95% confidence intervals (CIs) around the mean, from the 3-PG simulations for each management regime and RCP. We then adopted the upper and lower limits of the CIs, as well as the mean, to represent high, low and medium forest productivity scenarios for our portfolio analyses, respectively (see Fig. 3 in the Results Section). We focus our results on fixed, 28-year rotations because this is the most commonly adopted rotation length for *P. radiata* plantations in New Zealand.

Two *P. radiata* regimes were simulated with 3-PG: T7S300 represents a forestry regime where thinning takes place in year seven ("T7") and the plantation stocking is reduced from 833 to 300 stems ha^{-1} ("S300"), whereas in T9S600, thinning happens in year nine ("T9") and stocking is reduced from 833 to 600 stems ha^{-1} ("S600"). While the 3-PG model cannot directly accommodate the effects of pruning on forest growth, we accounted for those by altering the log grade proportions associated with the harvested wood volumes from pruned and unpruned, T7S300 and T9S600 regimes (Table 1). Log grade proportions, based on the specifications from the AgriHQ market reports for New Zealand (i.e., minimum small-end diameter, maximum branch size and the range of allowable log lengths), were estimated with a yield calculator for *P. radiata* plantations developed by the New Zealand Forest Research Institute (Scion), based on Kimberley et al. (2005). Pruned regimes aimed at the production of high-value, P1 and P2 logs for the domestic market, whereas unpruned regimes favoured the production of S1/S2 and K-grade export logs (Table 1).

Fig. 3. Simulated 2050–2090 wood volumes at harvest from the 3-PG model for the Ashley Forest site for 28-year *Pinus radiata* rotations based on various global climate model projections per regime (panel rows) and Representative Concentration Pathway (RCP; panel columns). Dark red lines, corresponding to multi-model ensemble averages and 95% confidence intervals, represent the low, medium and high forest productivity scenarios (total m^3 of logs per ha) adopted for the portfolio analyses. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Log grade proportions associated with the wood volumes at harvest from the 3-PG simulations per forestry regime and rotation length.

Regime	Rotation length (years)	P1 (%)	P2 (%)	S1/S2 (%)	S3 (%)	K (%)	Pulp (%)	Waste (%)
Pruned T7S300	25	24.1	11.6	–	0.2	39.2	9.9	15.0
	26	24.3	10.4	–	0.2	40.6	9.5	15.0
	27	24.6	9.3	–	0.1	41.7	9.2	15.0
	28	24.7	8.4	–	0.1	42.8	8.9	15.0
	29	24.8	7.6	–	0.1	43.8	8.7	15.0
	30	24.7	7.0	–	0.1	44.7	8.5	15.0
Pruned T9S600	25	8.7	15.1	0.4	13.2	23.9	23.7	15.0
	26	9.6	14.3	1.0	13.6	24.0	22.5	15.0
	27	10.4	13.5	1.4	12.9	25.5	21.4	15.0
	28	11.2	12.7	2.4	13.3	25.3	20.1	15.0
	29	11.7	12.0	2.5	12.7	26.5	19.6	15.0
	30	12.5	11.3	3.0	11.6	27.7	19.0	15.0
Unpruned T7S300	25	–	–	1.7	0.1	72.6	10.6	15.0
	26	–	–	2.1	0.1	72.4	10.4	15.0
	27	–	–	1.9	0.1	73.0	10.1	15.0
	28	–	–	1.7	0.1	73.3	9.9	15.0
	29	–	–	2.1	–	73.1	9.7	15.0
	30	–	–	2.0	–	73.5	9.5	15.0
Unpruned T9S600	25	–	–	10.7	8.6	42.3	23.4	15.0
	26	–	–	10.5	8.6	43.7	22.3	15.0
	27	–	–	11.3	8.8	43.6	21.3	15.0
	28	–	–	11.0	7.9	45.4	20.7	15.0
	29	–	–	11.9	8.4	44.6	20.2	15.0
	30	–	–	12.6	8.0	44.7	19.7	15.0

2.3. Log price scenarios

The simulated wood volumes at harvest from 3-PG were converted to forestry returns based on the log grade proportions from Table 1 and log price scenarios. Price projections were constructed based on quantiles from 100 Monte Carlo simulations, following:

$$P_{gt} = P_{gt-1} + P_{gt-1}\left(u_{\psi} + \sigma_g Z_t\right) \tag{1}$$

$$Z_t = F^{-1}(p), p \in [0, 1] \tag{2}$$

where the monthly price (P_{gt}) of log grade g is a function of its previous value (P_{gt-1}) adjusted by a constant, RCP-specific (ψ), percentage drift (u_{ψ}) and a constant, log grade-specific, volatility (σ_g), modified by a stochastic parameter (Z_t; Equation (1)). The latter parameter is computed as the inverse of the normal cumulative distribution function F for a randomly generated probability p (Equation (2)). This formulation is used to model deterministic price trends while accommodating stochastic price fluctuations along with the forecasts.

Price trends (or drifts) were informed by 2015–2100 global roundwood price projections from Daigneault (2019) for five shared socio-economic pathways (O'Neill et al., 2014). These estimates result from an application of the Global Timber Model (Kim et al., 2018; Sohngen et al., 1999), adjusted for our study period. We assumed constant annual log price increments (u_c) of 0.67%, 0.59%, 0.21% and 1.35% under RCPs 2.6, 4.5, 6.0 and 8.5, respectively (see Daigneault, 2019, for details).

Fluctuation in price changes were based on the historical volatility of log prices (i.e., the 2000–2020-time series' standard deviations; σ_g) obtained from the AgriHQ monthly market reports and corrected for inflation based on New Zealand's Producers Price Index (Fig. S1).

Given the stochastic nature of the Z_t parameter, Equation (1) was estimated 100 times (based on Monte Carlo simulations) for each log grade and RCP. Log prices were monthly forecasted from 2020 to 2090 for P1, P2, S1/S2, S3, K and pulp log grades. Last, 25%, 50% and 75% price quantiles from the Monte Carlo simulations were adopted to represent low, medium and high log price scenarios for our portfolio analyses (see Fig. 4 in the Results Section).

2.4. Forestry portfolios

We combined the three log price scenarios (s_1; NZD m^{-3} per log grade) with the three forest productivity scenarios from 3-PG (s_2; m^3 ha^{-1} at harvest age per log grade), for each forestry regime (f), to compute annualized forestry returns ($A_{fys_1s_2\psi}$) for 2050–2090 per RCP (ψ), as:

$$\Pi_{fys_1s_2\psi} = \sum_{t=1}^{j}\sum_{g=1}^{6}\frac{P_{gts_1\psi}v_{fgts_2\psi} - \phi_{ft}}{(1+\theta)^t} \tag{3}$$

$$A_{fys_1s_2\psi} = \frac{\theta(\Pi_{fys_1s_2\psi})}{1-(1+\theta)^{-j}} \tag{4}$$

where j denotes the rotation length of forestry regime f, the internal summation term from Equation (1) (i.e., total "net" revenue) sums the value of each price P of each of the six log grades (g), in rotation year t under a given log price scenario s_1 (low, medium or high), and a respective wood volume v under a given forest productivity scenario s_2 (low, medium or high), discounting management costs ϕ (i.e., pruning cost). The total net revenue is then discounted to present value ($\Pi_{fys_1s_2}$), at calendar year y (corresponding to the harvest year), with discount rate θ, given the length of the forest rotation. Finally, the present values are converted to annualized forestry returns following Equation (4).

This exercise resulted in annualized forestry returns under nine combinations of log price and productivity scenarios per RCP for each regime. We then performed a series of portfolio analyses to select optimal mixes of forestry regimes that mitigate climate change and market risks based on the simulated 2050–2090 forestry revenue time series for each scenario and RCP. Pruning costs were assumed as NZD 1.5 $tree^{-1}$, taking place in years five and seven after planting. These were the only costs discounted from the forestry returns because they vary between pruned and unpruned regimes. Other forestry costs, assumed to be equal for all regimes, were disregarded because they would not affect the portfolio composition. Forestry returns were discounted with a rate of 6% $year^{-1}$ (adopted by the New Zealand Treasury).

We adopt the formulation proposed by Markowitz (1952), and the notation by Pfaff (2016), in which the portfolio selection, based on N jointly distributed assets (in our case, the four forestry regimes), is defined as:

$$\arg\min_{\omega} \sigma_W^2 = \omega^T \Sigma \omega \tag{5}$$

s.t.

$$\omega^T i = 1 \tag{6}$$

$$\omega^T \mu = \bar{r} \tag{7}$$

where portfolio risk, or variance σ_W^2, is defined as $\omega^T\Sigma\omega$, and Σ denotes the positive semi-definite variance-covariance matrix of the 2050–2090 forestry regimes' revenues (see Fig. 5 in the Results Section). In turn, portfolio target return $\bar{r}$ is defined by the scalar product of the ($N \times 1$) weight and return vectors ω and μ, respectively, where i is the ($N \times 1$) vector of ones. Constraints imply full investment of capital (Equation (4)) for a given target return (Equation (5)). The solution to the Markowitz portfolio model[1] is then given by:

$$\omega^* = \bar{r}\omega_0^* + \omega_1^* \tag{8}$$

where,

$$\omega_0^* = \frac{1}{ab-c^2}\left(b\Sigma^{-1}\mu - c\Sigma^{-1}i\right) \tag{9}$$

$$\omega_1^* = -\frac{1}{ab-c^2}\left(c\Sigma^{-1}\mu - a\Sigma^{-1}i\right) \tag{10}$$

$$a = \mu^T\Sigma^{-1}\mu \tag{11}$$

$$b = i^T\Sigma^{-1}i \tag{12}$$

$$c = \mu^T\Sigma^{-1}i \tag{13}$$

Last, the portfolio standard deviation (i.e., risk) is calculated as:

$$\sigma = \sqrt{\frac{1}{ab-c^2}\left(a + b\bar{r}^2 - 2c\bar{r}\right)} \tag{14}$$

We used the expected 2050–2090 forestry returns to construct optimal portfolios for each combination of forest productivity and log price scenarios, per RCP. In this framework, portfolio risk is expressed as the volatility (i.e., standard deviation) of the forestry returns' time series for each combination of forest productivity, log price and RCP scenarios (see Fig. 5 in the Results Section). We constructed two sets of portfolios: (i) *cross-RCP* and (ii) *RCP-specific*. In the former set, portfolios were based on the average simulated 2050–2090 forestry returns (and their volatilities) across the RCPs, whereas in the latter, RCP-specific data were used. For both portfolio sets, target returns were set as the average expected 2050–2090 forestry returns across the four *P. radiata* regimes. Portfolios were constructed with the *fPortfolio* package (v.3042.83.1) available for R software (Würtz et al., 2015).

3. Results

The 3-PG simulations suggest that the T9S600 regime (with higher stocking after thinning) is likely to consistently produce an additional 14% (i.e., ~54 m^3 ha^{-1}) of wood compared to T7S300 across all RCPs, on average (Fig. 3). However, T9S600 logs are expected to present higher proportions of low-value log grades than T7S300. For example, while 25% and 9% of the pruned T7S300 logs are expected to belong to P1 (most valuable) and pulp (least valuable) grades, respectively, 11% and 21% of the pruned T9S600 logs are expected to belong to those respective grades (Table 1). Similarly, only 10% of the unpruned T7S300 logs are expected to belong to the pulp grade, compared to 21% for the unpruned T9S600 logs.

Real log price forecasts for 2050–2090 were consistent with the inherent value of the log grades, i.e., P1 > P2 > S1/S2 > S3/K > pulp prices (Fig. 4 & S1). The highest average prices of the time series were associated with P1 and P2 grades (ranging NZD 186–481 and 156–376 Mg^{-1} across the RCPs, respectively), followed by S1/S2 (NZD 128–329 Mg^{-1}). In conformance with the historical time series, there was substantial overlap between the average price ranges for S3 and K (NZD 111–274 and 106–261 Mg^{-1}, respectively). Pulp log forecasts were associated with the lowest average price (NZD 56–140 Mg^{-1}).

The combination of future log volumes and prices, with discounted pruning costs and other costs excluded, resulted in a substantial overlap of the annualized forestry returns across the management regimes and RCPs for 2050–2090 (Table S1, Fig. 5, S3 & S4). Unpruned T7S300 and T9S600 regimes were associated with average time-series returns of

[1] See Merton (1972) for an analytical derivation of the portfolio model.

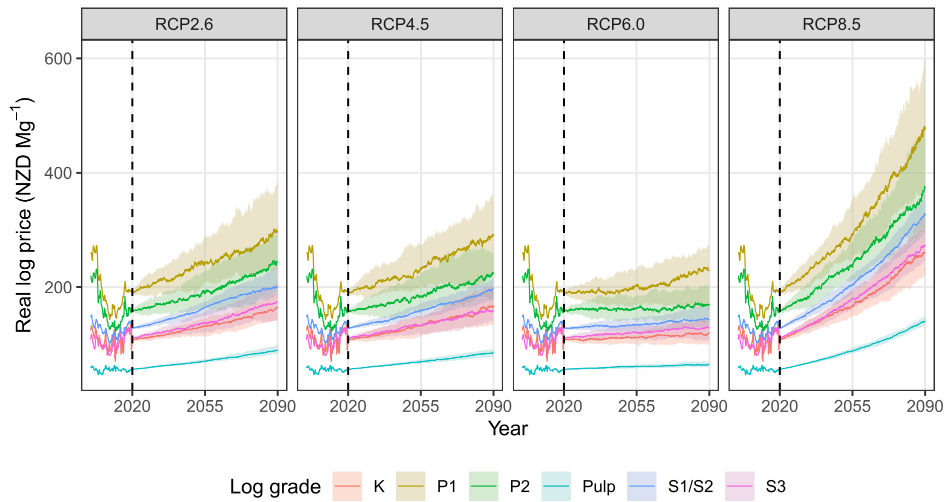

Fig. 4. Real historical log grade prices (2010–2020) and forecasts for 2020–2090. Lines and shaded areas represent 50% quantiles and 25–75% quantile intervals from 100 Monte Carlo simulations, respectively.

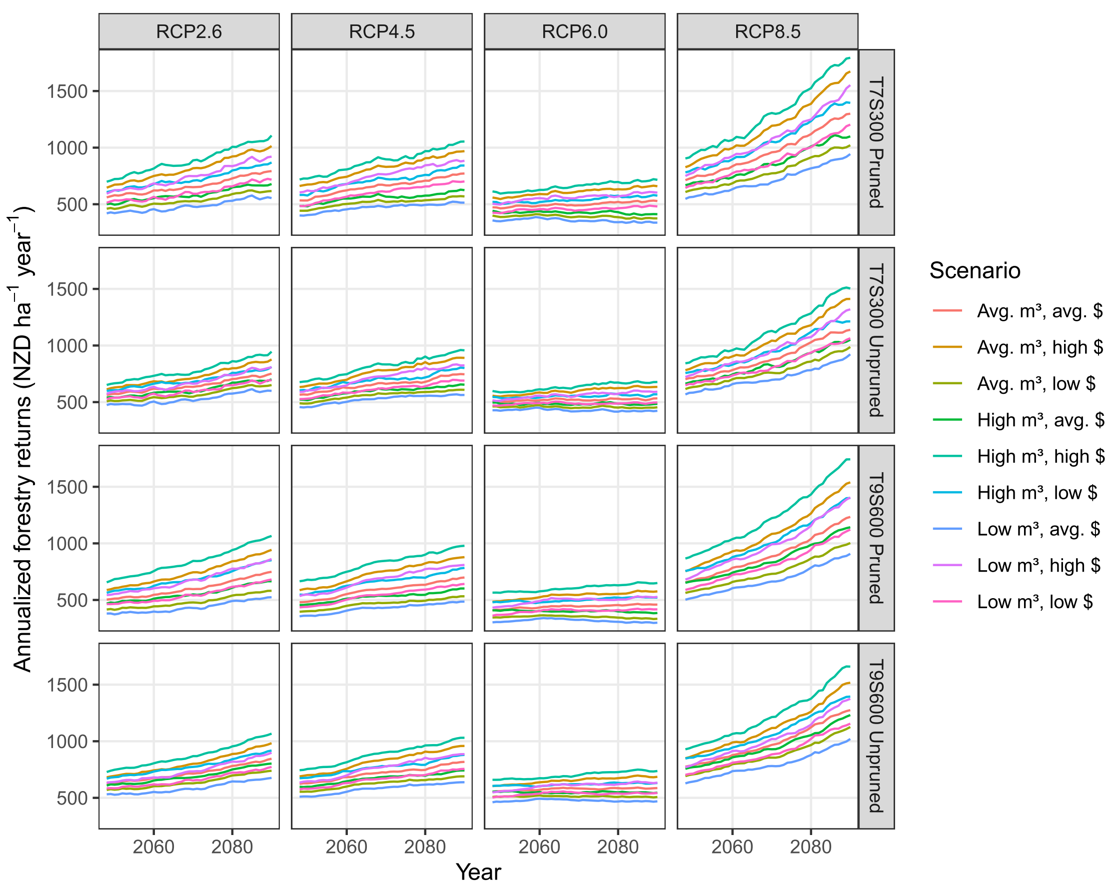

Fig. 5. Annualized forestry returns for the Ashley Forest site for 28-year *Pinus radiata* rotations per regime (panel rows) and Representative Concentration Pathway (RCP; panel columns). Time series in each panel represent a combination of low, average, and high forest productivity (m^3) and log price scenarios ($) per forestry regime.

NZD 533±45[2] to 924 ± 161 ha^{-1} year^{-1} and NZD 593 ± 49 to 1023 ± 175 ha^{-1} year^{-1}, respectively. Pruned T7S300 and T9S600 regimes presented average returns of NZD 517 ± 59 to 1011 ± 207 ha^{-1} year^{-1} and NZD 461 ± 48 to 947 ± 193 ha^{-1} year^{-1}, respectively.

Results from cross-RCP and RCP-specific portfolios suggest that regime diversification in *P. radiata* forests can reduce exposure to future market and climate change risks under all combinations of forest

[2] Standard deviation.

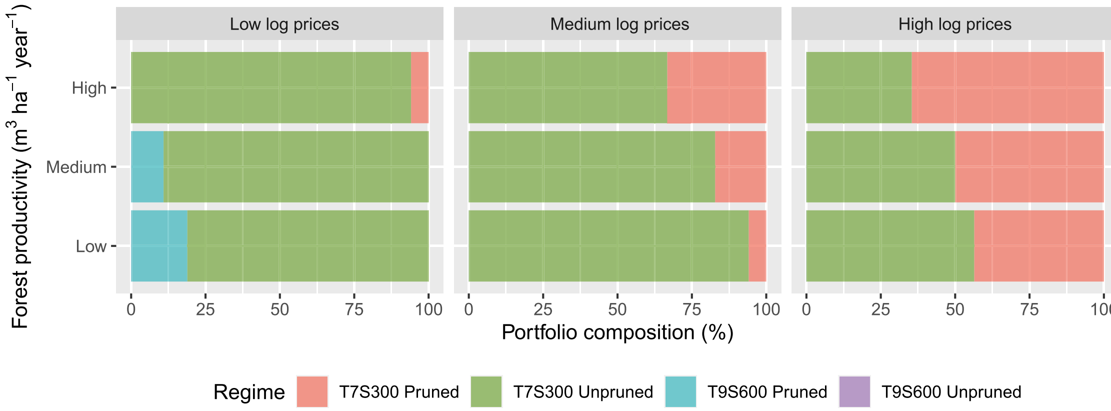

Fig. 6. Cross-RCP portfolios for 28-year *Pinus radiata* rotation regimes per forest productivity, log price, and Representative Concentration Pathway (RCP) scenarios. Each panel bar represents a unique portfolio.

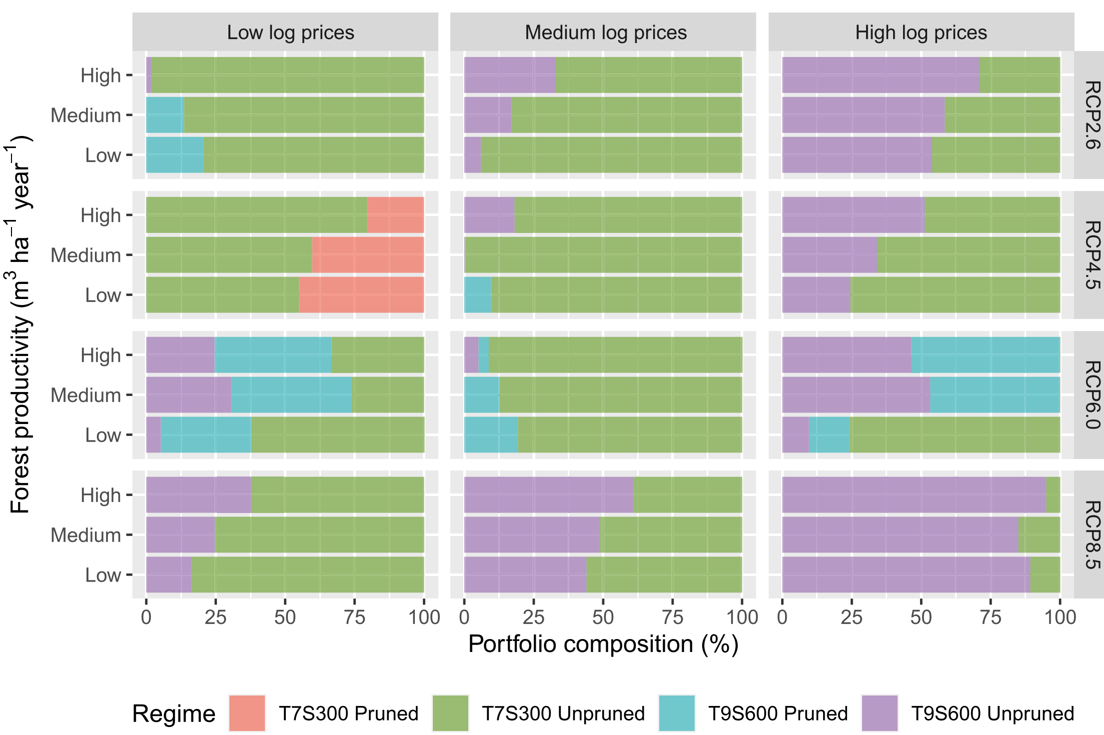

Fig. 7. RCP-specific portfolios for 28-year *Pinus radiata* rotation regimes per forest productivity, log price, and Representative Concentration Pathway (RCP) scenarios. Each panel bar represents a unique portfolio.

productivity, log price and RCP scenarios for 2050–2090 (Figs. 6 and 7, S5 & S6). Cross-RCP portfolios were majority composed of the unpruned T7S300 regime, mainly because of its lower volatility compared to the others, and the pruned regimes, with higher expected returns than the unpruned T7S300. While the pruned regimes presented higher volatility, they were necessary for the cross-RCP portfolios to meet their target return. For example, for 28-year rotations and both medium forest productivity and log prices, the cross-RCP portfolio presented average expected returns of NZD 696 ± 63 ha^{-1}. This value is higher than the returns from portfolios composed 100% of unpruned T7S300 (NZD 679 ± 64 ha^{-1}) and pruned T9S600 (NZD 634 ± 81 ha^{-1}) and, at the same time, it is associated with lower volatility than portfolios composed 100% of pruned T7S300 (NZD 698 ± 84 ha^{-1}) and unpruned T7S300 (NZD 750 ± 71 ha^{-1}). Similar patterns were observed under other combinations of forest productivity and log price scenarios (Fig. 6 & S5).

We observed substantial variation in portfolio composition among the RCPs (Fig. 7 & S6). Once again, many portfolios were largely composed of the unpruned T7S300 regime due to its low volatility. However, the former regime was replaced mainly by unpruned T9S600 with increasing forest productivity and log prices. In some cases, the unpruned T9S600 was replaced by slightly more profitable pruned regimes. For example, for medium productivity and high prices under RCP2.6 and 28-year rotations, our simulations suggest the pruned T7S300 regime to be associated with returns of NZD 1190 ± 252 ha^{-1} versus NZD 1127 ± 198 ha^{-1} for unpruned T9S600 (Fig. 5). Still, because pruned regimes were often associated with higher volatilities, they were left out from most of the RCP-specific portfolios when their presence was not necessary to meet the portfolio's target return.

We also found significant differences in the expected returns and risks of the portfolios among the RCPs (Table S2). While the average returns for the cross-RCP portfolios was NZD 704 $\pm$ 68 ha^{-1}, the averages varied from NZD 515 $\pm$ 14 to 964 $\pm$ 149 ha^{-1} among the RCP-specific portfolios. These differences were largely influenced by the forecasted log prices (Fig. 4).

4. Discussion

Results from our portfolio analysis suggest that the diversification of *P. radiata* regimes has the potential to mitigate future climate change and market risks. These results are aligned with a similar application of MPT for climate change adaptation in reforestation activities (Crowe and Parker, 2008). Optimal portfolio selection should reflect the objectives of forest managers. In this case study, forestry portfolios were largely composed of unpruned T7S300 regime, with the lowest time-series volatility, often complemented with the other regimes, associated with higher expected returns. The often-higher returns from the pruned regimes resulted from the further diversification of log grades (i.e., P1 and P2), associated with higher prices but also higher volatilities (Fig. 5, S1 & Table S1). If the price volatilities associated with P1 and P2 logs were lower in comparison with the unpruned log grades, or if the portfolio target returns were higher than the values we adopted, the share of unpruned T7S300 in the optimal portfolios would have reduced. This highlights the sensitivity of our portfolio selection framework to the correlation and price level of the log grade forecasts, particularly for pruned versus unpruned regimes. Price gaps between pruned and unpruned log grades prior to 2005 were substantial but have closed over the 2005–2015 period (largely influenced by the Chinese market demand for unpruned logs; Fig. S1). This demand has led many forest managers to abandon pruning operations (New Zealand Forest Owners Association, 2019). However, post-2015 price trends suggest that such a gap may increase again in the near future (Fig. S1).

The timber market projections from Daigneault (2019) anticipate a 0.1–1.3% $year^{-1}$ increase in global timber prices from 2015 to 2100; which in turn is expected to result in at least a 50% increase in New Zealand's planted forest area and timber production over that period. These estimates are at the core of the log price scenarios adopted in this study. Economic equilibrium models, like the Global Timber Model employed by Daigneault (2019), arguably represent a more robust approach to simulate future market conditions than "standard" time-series analyses solely informed by historical data. Still, all long-term market forecasts are subject to criticism and the ones used in this study are no exception (McNees, 1992). The development and application of models like the Global Timber Model are complex and often rely on underlying economic assumptions that may not hold in the future (Hertel et al., 2019). Other forestry studies based on MPT have adopted stochastic price models based on time-series analysis of historical data to derive formulas for the means and covariances of price predictions (e.g., Reeves and Haight, 2000).

In addition to the log price forecasts, the simulated forest productivity responses to climate change are also important drivers of our results. Stand volumes at harvest modelled with 3-PG were most sensitive to precipitation and available soil water content and varied substantially across the six climate model projections. The output from the GISS-E2-R climate model was consistently associated with the highest modelled wood volumes from 3-PG, while the GFDL-CM3 climate model output was associated with the lowest (Fig. 3).

The unpruned and pruned T7S300 regimes were more sensitive to changes in the future climate across all four RCPs than the T9S600 regimes. For the higher stand density regime (T9S600), intraspecific competition for space and site resources (captured in 3-PG by "modifiers" and mortality functions) had a greater effect on limiting tree growth than the climate, thus annual variations were smaller than in the lower stand density regime (T7S300). Given that intraspecific competition for resources was lower in the latter regime, stand productivity was also more sensitive to annual changes in climate, especially precipitation, which resulted in larger variations in the wood volumes at harvest.

Previous studies have modelled potential CO_2 fertilisation effects on *P. radiata* in New Zealand. Watt et al. (2019) estimated a 19–37% increase in productivity across the country, in contrast to a 106% increase from Meason and Mason (2014). Although the 3-PG model can simulate CO_2 fertilisation effects, this was not done for this study due to the uncertainty of the magnitude of these effects (Coops et al., 2010). For example, previous studies found increases in leaf photosynthetic rates due to higher CO_2 concentrations in the atmosphere to be short-lived, while others reported impacts on site productivity to diminish over time (Ainsworth and Long, 2005; Girardin et al., 2016; Karnosky, 2003; Lo et al., 2019; Norby and Zak, 2011). This is likely due to other environmental limitations to growth, e.g., soil nutrients, soil water, etc. (Norby et al., 2010; Peñuelas et al., 2011; Reich et al., 2018). By disregarding the raising in CO_2 concentrations associated with the RCPs, our 3-PG simulations shed more light on the potential future impacts of other climate variables on forest productivity in our study site.

The use of more complex forest growth models, e.g., CABALA (Battaglia et al., 2004), could result in improvements in forest productivity simulations, and potentially validate the results presented in this study. Further, some of these alternative models may better capture and discriminate the effects of competing management regimes, as well as the potential impact of abiotic and biotic factors disregarded in 3-PG, on forest productivity under climate change (Meason and Mason, 2014; Medlyn et al., 2011). Further, while our findings are also site-specific, other studies based on the application of MPT to forestry found site characteristics (e.g., fertility levels) to affect portfolio composition (Matthies et al., 2015). Hence, future work should explore a range of site conditions and potentially spatially-explicit growth models to better assess the risks imposed by climate change to forestry in New Zealand and elsewhere (Nordström et al., 2019).

Lastly, our application of MPT is somewhat unique in the literature. Standard MPT studies from the field of finance often focus on a single source of risk uncertainty, i.e., the assets' volatility. Portfolios are thus (*ex-post*) constructed based on observable historical prices of assets and their covariances (Würtz et al., 2015). In contrast, our portfolios are based on (*ex-ante*) forest productivity and log price forecasts, inherently associated with additional sources of uncertainty. Ultimately, consideration of the additional uncertainty from model simulations and future scenarios would inflate the standard deviations and covariance matrices (i.e., risk measures) used for portfolio optimization. In this study, we accounted for the additional uncertainty issue by adopting multiple forest productivity and log price scenarios per and across RCPs. Nevertheless, other studies have taken a different approach to address the uncertainty beyond historical volatilities, with the combination of MPT and uncertainty theory (Li and Xu, 2009; Tanaka et al., 2000; Wang et al., 2019). Exploration of these methods represents a promising research direction to further examine the impacts of future climate change on forestry decisions.

5. Conclusions

We proposed a modeling framework based on MPT to examine how diversification of forest management regimes can mitigate the risks imposed by climate change and markets on New Zealand's forestry sector. Overall results suggest that future risks can be mitigated through the diversification of management regimes, but the optimal mix of regimes in the portfolios is anticipated to vary across future climate and log price scenarios. Future studies are encouraged to contrast the results from portfolio analyses with the decisions from forest managers and explore alternative forestry regimes, tree species and study sites. Application of the MTP framework proposed in this study, with further consideration for additional sources of risk and uncertainty (e.g., from plant diseases and pest outbreaks), can help forest managers to mitigate the expected negative impacts of climate change and market shifts on the forestry sector.

Credit author statement

Conceptualization: TAPW, NM, RTY, DM; Data curation: TAPW, SS, NM, SJW, DM; Formal analysis: TAPW, SS, DM; Methodology: TAPW, SS, SJW, RTY, DM; Project administration: TAPW; Visualization: TAPW; Writing - original draft: TAPW, SS, NM, DM; Writing - review & editing: TAPW, SS, NM, SJW, RTY, DM.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

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