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# Projected social costs of $CO_2$ emissions from forest losses far exceed the sequestration benefits of forest gains under global change

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ABSTRACT

Forest cover gains and losses occur in response to complex environmental and anthropogenic pressures. Yet the impact of forest gains and losses on the provision of ecosystem services differs markedly. Here we investigate the social costs of potential forest carbon change in Australia's intensive agricultural region from 2015 to 2050 using spatial forest cover change and forest carbon models combined with climate and socioeconomic projections. More than 24,000 possible scenarios were used to identify the trend and lower and upper bounds of forest cover/carbon change. Net deforestation (3.5 million hectares, Mha) under the lower bound forest cover (LBFC) projection was around one-third less than net reforestation (4.8 Mha) under the upper bound forest cover (UBFC) projection by 2030. However, the $CO_2$ emissions (1.3 Gigatons of $CO_2$, $GtCO_2$) from deforestation were more than double the sequestration (0.5 $GtCO_2$) from reforestation. The social costs (up to 134 billion dollars) of the LBFC were almost five times the benefits of the UBFC (up to 28 billion dollars). The asymmetry decreased over time but persisted to 2050. This shows the markedly different social costs of potential forest carbon losses and gains under global change, evidence which can be useful to policymakers, stakeholders, and practitioners.

## 1. Introduction

The environmental and economic impacts of forest loss through deforestation and forest gain through reforestation and natural regeneration (hereafter simply *reforestation*) are significantly different. Deforestation, particularly of mature forests, typically involves an immediate and significant loss of ecosystem services that could take decades or centuries to recover—sometimes previous ecosystem function is entirely lost (Poorter et al., 2016). In recent years, $CO_2$ fertilization, climate change, and policies to reforest or reduce deforestation in some countries have led to transitions from net forest loss to gains or, as it is sometimes referenced, a *greening of the Earth* (Lambin and Meyfroidt, 2010; Zhu et al., 2016). However, the long-term potential to maintain this greening trend and consequent forest ecosystem services may be constrained by environmental and anthropogenic factors. For instance, limited soil nutrient availability (Wieder et al., 2015), plant acclimation reducing $CO_2$ fertilization effects (Booth et al., 2012), and ineffective forest policy (Marcos-Martinez et al., 2018; Simmons et al., 2018b) could limit, or even reverse, the greening trend.

In addition, even the most conservative estimates of global food demand and agricultural intensification forecast net forest cover loss to 2050 (Tilman et al., 2011). Increasing cropland scarcity and improvements in agricultural land productivity could intensify clearing pressure on remnant primary forests in marginal agricultural land (Lambin and Meyfroidt, 2011). Greenhouse gas (GHG) emissions from primary forest loss cannot be fully compensated by the small annual increments of $CO_2$ sequestration from new forests or forest regrowth. Therefore, even if forest cover expands in some regions, the continuing loss of primary forests could reduce global forest carbon stocks (Corlett, 2014). Net $CO_2$ emissions associated with these dynamics could produce significant

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long-term, global impacts on society through net damages to agricultural productivity, infrastructure, human health, and ecosystem services from climatic change (Interagency Working Group, 2016).

While the future fortunes of forests are uncertain, there is consensus across integrated assessment systems models with land-use components that long-term human and environmental processes pose significant challenges to terrestrial ecosystems and their associated services (Popp et al., 2017). However, this modelling typically involves an extensive set of assumptions about global futures and responses that are not always grounded in empirical research. Estimates of the magnitude and direction of potential environmental and socioeconomic outcomes vary significantly across models (Alexander et al., 2017; Robinson et al., 2014). Differences in modelling specifications, assumptions, and parameterization can even result in contradictory impact estimates (Baldos and Hertel, 2016; Nelson et al., 2014). Large-scale empirical assessments of the drivers and ecosystem services implications of forest cover change can improve the parameterization of sectoral agricultural and forestry models and reduce the variability of impact assessments (Nelson et al., 2014).

The policy relevance of large-scale empirical land-use and land-cover models has been documented for some regions. For instance, statistical models have highlighted that policy interventions in the U.S. may need to change significantly the underlying economic incentives of competing land-uses to modify trends in the provision of food, timber, biodiversity and other services (Lawler et al., 2014). Similar analyses have highlighted the relevance of forest policy for climate change mitigation in Europe (Ding and Nunes, 2014), the substantial environmental benefits of forest regrowth in degraded Chinese croplands (Yin et al., 2014), and the relevance of modelling the heterogeneous production capability of the natural environment for more efficient land-use planning in the U.K. (Bateman et al., 2013).

In Australia, agricultural intensification and expansion, and forest conservation policy failures have resulted in the degradation of globally relevant ecosystems (Steffen et al., 2009) and deforestation at higher rates than in other developed countries (Hansen et al., 2010). This has prompted a growing body of research on the ecosystem services implications of land-use, climate change, and regulations in this country (Bryan and Crossman, 2013; Pittock et al., 2012). However, most of this literature has been at catchment scale or theoretical and conceptual, rather than empirical (Alamgir et al., 2014; Pittock et al., 2012). Empirically-based assessments of the interactions between forests and agricultural land could reduce information gaps required to enhance more sophisticated Australian land-use sector models (Bryan et al., 2016; Connor et al., 2015). Therefore, this study aims to: (1) investigate the range of potential forest carbon stock change under long-term environmental and socioeconomic pressures in Australia; and (2) approximate the monetary cost to society of the potential forest carbon losses and gains.

## 2. Study area

Australia accounts for around 3% of the global forest area (Australian National Greenhouse Accounts, 2013). However, most of its forests are significantly degraded or fragmented due to rapid agricultural expansion and intensification (Bradshaw, 2012). Plantation forests account for around 1.6% (2 Mha) of the total forest area, and the rest is mostly natural *Eucalyptus* and *Acacia* forests (Montreal Process Implementation Group, 2013). Around one-third of Australia's forests are within privately managed land in the agriculturally intensive region (Fig. 1) (Kanowski, 2017). Land-use in this region is dominated by livestock grazing and cereal cropping but also contains areas of high-value, irrigated agriculture (Bryan et al., 2014). Most of the Australian crop and livestock gross value is produced here (around 99% and 90%, respectively) (ABARES, 2012) and around 60% of the agricultural output from this region is exported (ABS, 2012). Agricultural expansion has resulted in significant deforestation and biodiversity loss in recent decades (Brooks et al., 2006; Hansen et al., 2010) with GHG emissions from deforestation accounting for around 25% of the total domestic emissions (Bradshaw, 2012). The linkage of Australian agricultural production with international markets undergoing rapid economic, dietary, and demographic change in a context of productive land scarcity and climatic change pressures (Hatfield-Dodds et al., 2015) ensures relevancy of lessons learned for other regions.

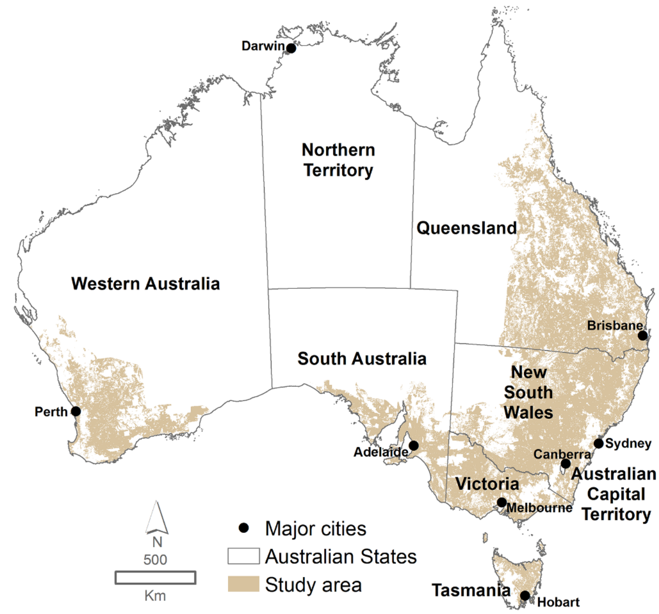


**Fig. 1.** Study region. The study area is the Australian intensive agricultural region which accounts for around 90% of the national agricultural gross value. Protected land, hydrological features, urban areas, fire scars, plantation areas, and pre-European settlement native grassland and bushland regions were excluded from the analysis.

Our analysis focuses on investigating forest cover change driven by landowners' decisions in this region. Therefore, we excluded from the study area: protected forests, forest loss due to wildfires and other non-agriculture/forest land (e.g. urban areas, hydrological features). We also excluded land with pre-European vegetation dominated by shrubs and grasses since land abandonment or restoration efforts in those regions are unlikely to result in forest regrowth due to natural constraints (e.g. limited water/nutrient availability). Plantation forests, identified through georeferenced data (ABARES, 2014), were also removed since their clearing follows different criteria than deforestation within agricultural land and would require a different modelling approach (Van Kooten et al., 1995).

## 3. Methods and data

We first estimated a statistical model with historical forest cover, climatic, socioeconomic, and physiographic data (Fig. 2) which was then coupled with projections of drivers of forest gains and losses and used to project forest cover change from 2015 to 2050. The carbon stock implications of representative forest cover change scenarios were assessed and the social costs of $CO_2$ (SC-$CO_2$) emissions/sequestration estimated. In the following sections, we use the term carbon emissions to refer to the release of $CO_2$ from forest biomass during deforestation and carbon sequestration to represent the storage of atmospheric $CO_2$ in biomass.

### 3.1. Empirical forest cover change model

#### 3.1.1. Spatial statistical model

Our model assumes that landholders allocate their land between

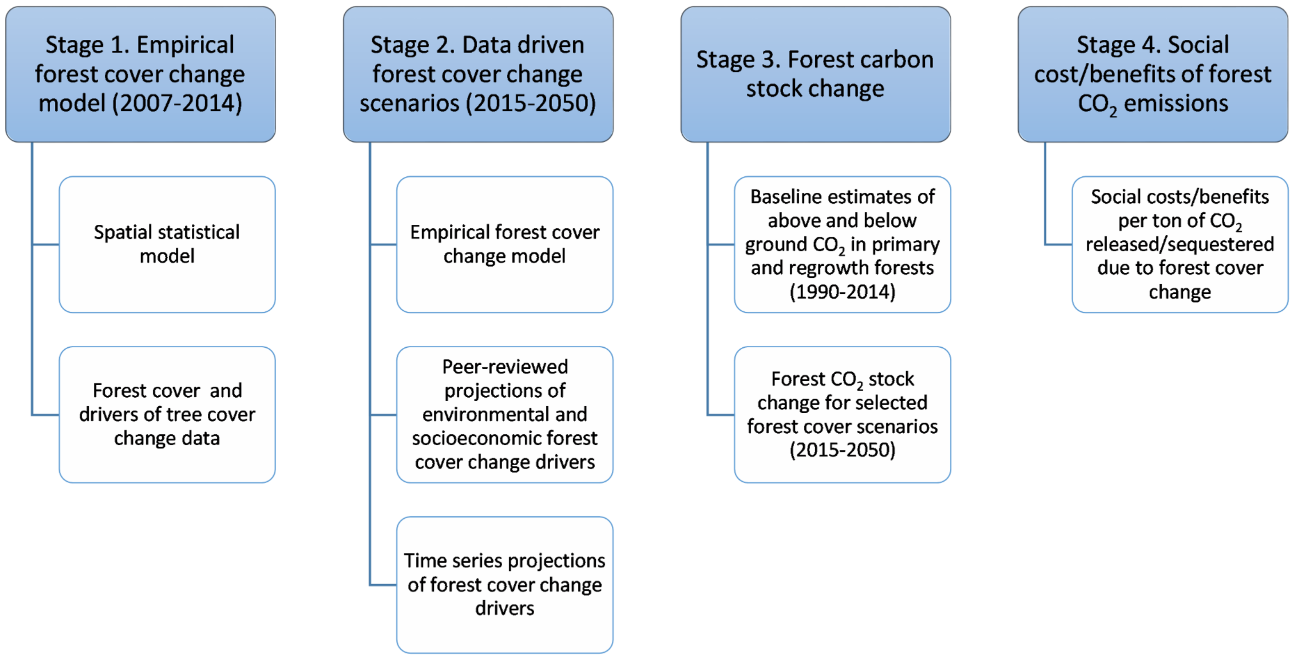


**Fig. 2.** Modelling stages to estimate the social cost of forest carbon dynamics under data-driven scenarios.

forest and non-forest cover as to maximize their expected payoffs. Such payoffs are determined by the observed and expected states of socio-economic, institutional, and environmental parameters (Plantinga, 1996). Information for some relevant parameters is readily available and can be explicitly modelled (e.g. agricultural prices, topographic data). Other determinants cannot be accounted for with available data. Consequently, it is necessary to control for the effect of unmeasured and unobserved landholder– and land–specific characteristics (e.g. preference for forest conservation, land productivity constraints). In addition, forest cover change is spatially dependent, being influenced by the forest cover patterns and environmental and socioeconomic characteristics of adjacent land (Simmons et al., 2018a). To account for the impacts of forest cover change drivers, unobserved heterogeneity and spatial effects, we applied a spatial panel with random effects analysis similar to models previously used to investigate forest cover change dynamics in Australia (Marcos-Martinez et al., 2018; Simmons et al., 2018b). An extended description of the model is presented in the Supplementary Data.

#### 3.1.2. Forest cover data and drivers of forest cover change

In our analysis, forests are defined as land with at least 20% of existing or potential canopy cover—either primary or secondary vegetation—and with the potential to reach at least two meters in height (Lehmann et al., 2013). We used annual (2007–2014) forest and non-forest data (25-meter resolution), generated through the supervised classification of Landsat imagery, with an overall accuracy of around 93% (Caccetta et al., 2012). Transition rules were applied to correct one and two-year misclassified forest cover change that deviated from long-term forest cover dynamics (Marcos-Martinez and Baerenklau, 2015). The binary forest/non-forest data was used to track annual forest gains and losses during the study period and to construct 1.1 km grid cell resolution forest cover index layers that represent the net proportion of land forested per observation year. The resulting dataset consists of 1.12 million cells per year, totalling around 9 million observations during the study period.

Physiographic data (elevation, slope, soil characteristics, temperature, and precipitation) were used to control for land and climate characteristics influencing payoffs from forest/non-forest land allocations. To account for economic drivers of forest cover change, we used time-series agricultural price index data and spatially explicit information on the profitability of observed agricultural land-use for a baseline year (2005–2006) during the study period. We used the Accessibility and Remoteness Index of Australia (ARIA) (GISCA, 2001) to account for population pressure on forest clearing. Categorical land tenure variables were included to control for differences in forest cover change among indigenous, private, leasehold, multiple-use, and Crown land. We also included categorical variables for tree and shrub height to account for land-specific characteristics that determine native vegetation growth form. Uncertainty in economic and climatic parameters was approximated by the standard deviations of the agricultural price index, temperature, and rainfall. Supplementary Table S1 describes the variables and sources used to calibrate our empirical model.

### 3.2. Data-driven forest cover change scenarios

We used peer-reviewed climate, population, and agricultural productivity projections and time-series forecasts for the period 2015–2050. Impacts of potential climate change were explored using ensembles of projections from three global circulation models: the Canadian Earth Systems Model (CanESM2) (Chylek et al., 2011), the Model for Interdisciplinary Research on Climate (MIROC5) (Watanabe et al., 2010), and the Max-Planck-Institute Earth System Model (MPI-ESM-LR) (Giorgetta et al., 2013) (Table 1). The ensembles correspond to global temperature rising 2, 3 and 6 degrees C by 2100 under emissions and abatement strategies corresponding to the Representative Concentration Pathways (RCPs) 2.6, 4.5, and 8.5 (Van Vuuren et al., 2011).

To account for potential changes in agricultural productivity influencing the profitability of agricultural uses, we used three productivity scenarios that capture historical trajectories observed between 1970 and 2010 in Australia: no change (0%), medium (1.5%) and high (3%) productivity increase per year (CSIRO, 2015) (Fig. 3b). Changes in productivity were assumed to result in similar percentage increases in agricultural profitability. Australian population projections to 2101 (ABS, 2013) were used to assess the impact on forest cover of low (1.28%), medium (1.66%) and high (2.17%) rates of land accessibility improvements per year through changes in the ARIA (Fig. 3d).

For the remaining temporal variables, we estimated innovation

**Table 1**
Global climate change and domestic uncertainties.

*Global climate projections*
- CanESM2: Moderately hotter climate projections, but relatively neutral climate change projections for Australia.
- MIROC5: Coolest and wettest climate projections, with most wetting occurring outside the study area.
- MPI-ESM-LR: Warmer and slightly wetter climate.
- RCPs: 2.6, 4.5, and 8.5 (low climate warming on track to 2 °C, mid climate 3 °C by 2100, and high climate 6 °C by 2100, respectively).

*Domestic uncertainties*
- Agricultural productivity: 0%, 1.5% and 3% per year simple increase in total factor productivity.
- Agricultural prices: 1st to 99th forecasted percentile based on historical data.
- Agricultural price variability: slight decrease, 50th percentile; medium increase, 75th percentile; and high increase, 95th percentile projections based on observed data.
- Climate variability: Historical trend, two standard deviations of maximum temperature and rainfall by 2050.
- Land accessibility: small (1.28%), medium (1.66%) and large (2.17%) annual improvement in connectivity across Australian communities (percentages defined by population projections).

state-space models for exponential smoothing calibrated with annual historical data (1985–2014) (Hyndman and Athanasopoulos, 2014). The fitted models were used to estimate the distribution and average trajectories of percentile forecast paths. To explore potential impacts of agricultural prices over a wide range of possible trajectories we generated percentile projections (Fig. 3a). Impacts of price variability were investigated using three possible trajectories of the standard deviation of agricultural prices: slight decrease relative to 2014 values, 50th percentile path; medium increase, 75th percentile; and high increase, 95th percentile (Fig. 3c). Annual pixel-level standard deviations of maximum temperature and rainfall observed from 1985 to 2014 were used to construct three spatially explicit projections of climate variability: continuation of the observed trend, and trend plus and minus two standard deviations (Fig. 3e,f).

The three climate ensembles combined with the different projections of forest cover change drivers resulted in over 24,000 plausible forest cover change scenarios. Out of that set of possible future forest cover, we identified the scenarios that resulted in the lower and upper bound forest cover projections and their associated socioeconomic and environmental determinants (Table 2). To assess the implications of a business-as-usual-scenario we also modelled the social costs of forest carbon change corresponding to a trend forest cover scenario that reflects mid climate change projections and historical, long-term Australian socioeconomic trends.

### 3.3. Spatially explicit estimates of forest carbon stock change

Historical and projected aboveground forest carbon gain per hectare was estimated using tree yield formulas calibrated to the average growth conditions of native Australian trees and bounded by pixel-specific Forest Productivity Index data (Kesteven et al., 2004). To estimate below-ground biomass, we mapped the root-to-shoot ratios for major Australian vegetation groups (Hunt, 2015) using the estimated pre-1750 major vegetation groups distribution data (Geoscience Australia, 2004) (Supplementary Table S2). The carbon fraction of above-ground and below-ground biomass was estimated following studies of Australian vegetation that report that on average 49% of the tree mass is composed of carbon (Supplementary Table S3) (Commonwealth of Australia, 2016).

To estimate annual forest carbon change from regrowth and deforestation of climax and secondary forests we first estimated pixel-specific forest carbon stocks in 1990 under the assumption that on average around half of the Australian forests in that year were mature stands at their maximum carbon stock potential (Bradshaw, 2012). The remaining percentage was assumed to contain carbon stocks equivalent to a 30-year old forest stand, on average (i.e. not yet achieving maximum stock potential). The baseline forest carbon stock was updated annually to account for differences in emissions from first-time clearing of mature forests and clearing of regrowth, and for carbon stock increases from regrowth. The Supplementary forest carbon stocks section present a formulaic description of the methodology used to estimate pixel specific forest carbon change.

### 3.4. Social costs of carbon emissions from potential forest gains and losses

Through their impact on climate change, $CO_2$ emissions affect agricultural and forestry productivity, unmanaged ecosystems, coastal developments, human health, energy consumption, and water resources (Tol, 2002). While the impacts from climate change are spatially heterogeneous, significant net global costs are expected (Cai et al., 2016). Due to the long-term persistence of GHG emissions in the atmosphere, the capacity of terrestrial and ocean systems to absorb emissions is gradually decreasing (Solomon et al., 2009). Hence, the marginal global cost to society per additional unit of $CO_2$ emissions (SC-$CO_2$) is expected to increase during the next decades.

To estimate the social impacts of forest carbon stock change under the selected forest cover change scenarios we used estimates from the U.S. Interagency Working Group (IWG) (2016). These estimates are based on three global integrated assessment models (IAMs) that account for potential climate change impacts – both benefits and costs – of small increases in regional temperature across multiple economic sectors (e.g. real state, agriculture, human health, energy) and ecosystems.

The IWG computes the intertemporal flow of net economic costs from the year a ton of $CO_2$ is released to 2300. Different intergenerational discount rates are then applied (2.5%, 3%, and 5%) to allow comparison of the stream of benefits and costs estimated to 2300. The SC-$CO_2$ is also estimated for a scenario that approximates extreme climate impacts by using the 95th percentile of the climate damage estimates generated by the IAMs at a 3% discount rate.

## 4. Results

### 4.1. Empirical forest cover change model

Forest cover change from 2007 to 2014 was significantly influenced by factors that directly or indirectly impact the profitability of agricultural activities. The empirically calibrated model explained around 98% of the spatiotemporal patterns of forest cover change observed during this period. A one percent increase in agricultural prices was associated with a 1.8% decrease in forest cover. Spatially explicit differences in agricultural profitability (not accounted for by physiographic parameters) were negatively associated with forest cover. However, the forest cover response to a one percent change in this variable was relatively low (−0.08%). Spatiotemporal changes in annual maximum temperature and rainfall were positively related to forest cover changes (1.26% and 0.72% forest cover change to a 1% change in each variable, respectively). This corresponds to the spatial distribution of forest in Australia with more trees in wet areas and less agricultural conversion pressure for forests in warm, dry climates. Percent changes in rainfall and temperature variability were associated with 0.04% and −0.08% changes in forest cover, which reflect the potential impact of climate variability on tree growth (e.g. through heat/water stress). Land close to protected areas had greater forest cover, a potential result of spillover effects of forest conservation areas. Private land had 3.8% less forest cover that land in other tenure types, on average, a potential result of more stringent land clearing regulations for other tenure types. Land with physiographic characteristics that are challenging for agricultural production (high slope and bulk

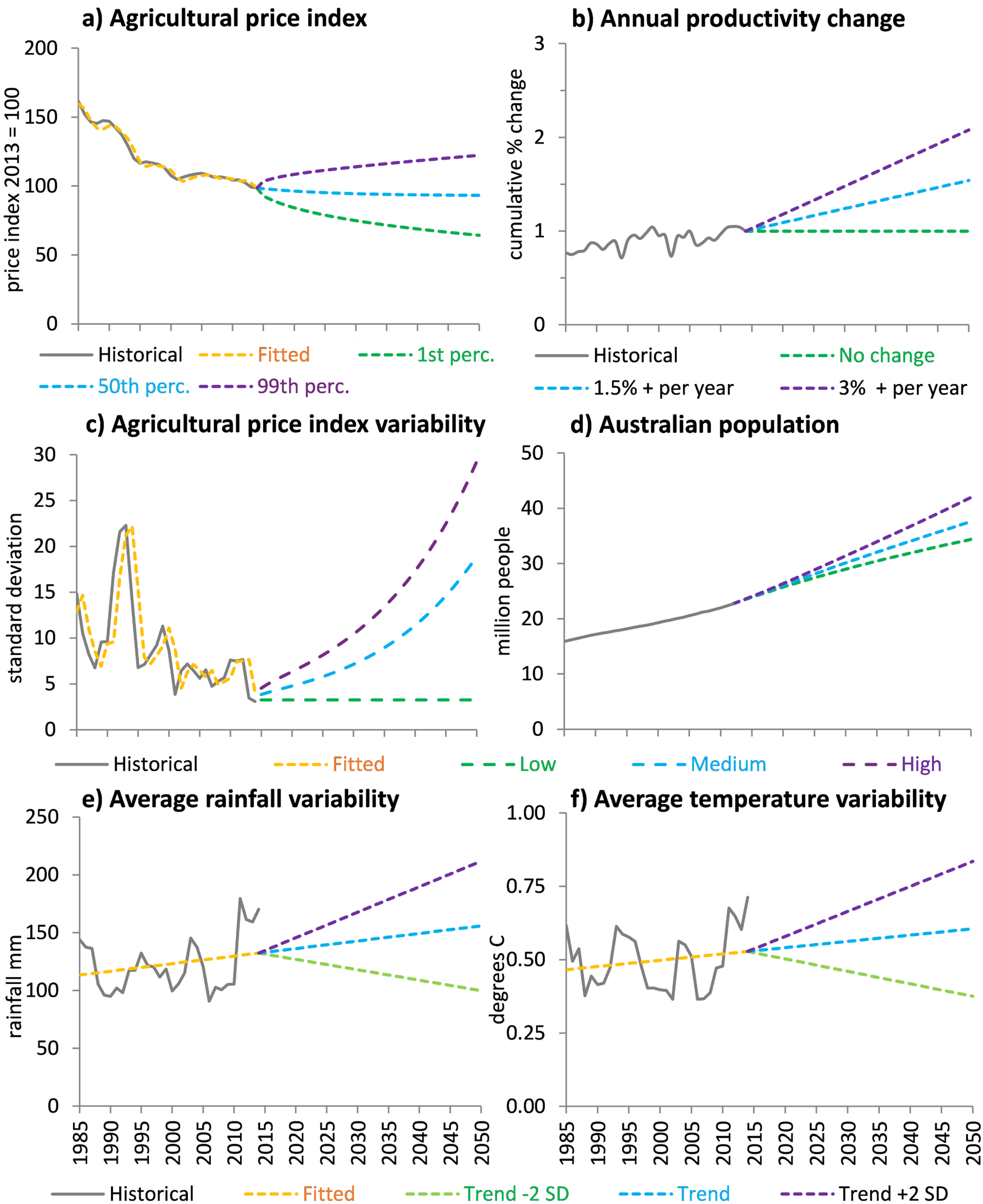


**Fig. 3.** Projections of socioeconomic factors and climate variability. a) Agricultural price index percentile projections. b) Annual rates of agricultural productivity change. c) Five-year moving standard deviation of the agricultural price index. d) Australian population growth trends. e, f) Average projected change in the standard deviation of rainfall and maximum temperature. Note: b) and d) are based on exogenously determined projections; therefore the corresponding graphs do not include fitted lines.

density, low soil content and pH) had greater forest cover. Other modelled variables did not have a statistically significant association with forest cover change. All coefficient estimates from the spatial panel regression are presented in the Supplementary Table S4.

*4.2. Projection of forest cover change drivers and key drivers of forest cover change*

The projection of agricultural prices and price variability were

**Table 2**
Characteristics of the data-driven forest cover change scenarios.

| Parameters | Forest cover projections | | |
|---|---|---|---|
| | Lower bound | Trend | Upper bound |
| *Climate projections* | | | |
| Representative Concentration Pathway: | 2.6 | 4.5 | 8.5 |
| *Domestic uncertainties* | | | |
| Agricultural productivity (annual % increase in total factor productivity): | 3.0% | 1.5% | 0.0% |
| Agricultural price index (percentile): | 99th | 50th | 1st |
| Agricultural price variability (percentile) | 95th | 75th | 50th |
| Climate variability (standard deviation, SD, of maximum temperature and rainfall): | Historical trend plus two SD | Historical trend | Historical trend minus two SD |
| Accessibility (improvement in connectivity across Australian communities to 2050): | 2.17% | 1.66% | 1.28% |

based on time series forecasting models that closely approximated historical patterns ($R^2 = 0.98$ and 0.56, respectively). Similarly, the modelled climate variability projections approximated the spatial variation of maximum temperature and rainfall across the study area (see maps in Supplementary Fig. S1). Due to the uncertainty of future values for each of the projected temporally dependent variables, the bounds of the corresponding projections gradually diverge over time (Fig. 3).

Within the range of modelled scenarios, changes in agricultural prices outweighed the influence of other modelled parameters—including climate—on our forest cover projections. The empirical agricultural price projections to 2050 ranged from a 24% increase to a 35% decrease relative to 2014 (Fig. 4). With other variables at their long-term mean, a 1% change in prices resulted in a 0.97% response in projected forest cover on average (Fig. 4). Across the range of forest cover projections, neither price variability nor climate variability had a strong influence on forest cover change projections.

### 4.3. Social costs of projected forest carbon gains and losses

Forests in the margins of the agricultural zone and in semi-arid regions were more responsive to projected socioeconomic and environmental pressures than forests in other regions (e.g. forests near irrigated

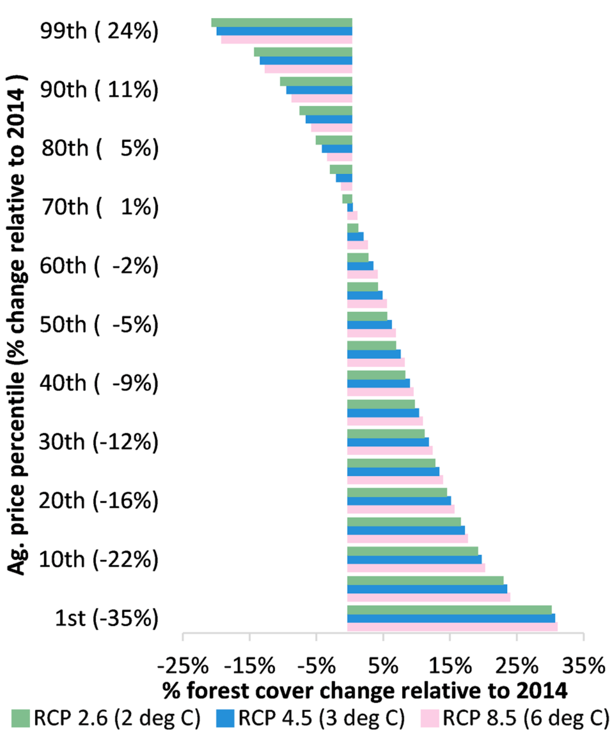


**Fig. 4.** Forest cover change to 2050 across forecasted agricultural price percentiles and climate ensembles with other variables at their long-term mean.

croplands or closer to major population centres) (Fig. 5). By 2030, a cumulative net forest loss of 3.5 Mha was projected relative to 2014 (the last year in our historical forest cover dataset) under the lower bound forest cover (LBFC) scenario. Emissions for this scenario were estimated to be 1.3 $GtCO_2$ at a social cost between 11 to 69 billion US dollars at discount rates between 2.5% to 5%. However, social costs increased to 134 billion dollars when low-probability, high-impact outcomes were considered (3% discount rate and 95th percentile of the distribution of SC-$CO_2$ estimates, Fig. 6c). Under the upper bound forest cover (UBFC) scenario, a net forest gain of 4.8 Mha was projected, sequestering 0.5 $GtCO_2$, with a social benefit between 2 and 28 billion dollars (Fig. 6).

By 2050, under the LBFC scenario a net forest loss of 8.7 Mha was projected, with emissions of 2.1 $GtCO_2$ (Fig. 5), and social costs between 16 and 203 billion dollars (Fig. 6c). Under the UBFC scenario net forest gains of 12.5 Mha were projected, sequestering 1.7 $GtCO_2$, with a social benefit of between 8 and 111 billion dollars (Figs. 5, 6c). The *trend forest cover* scenario projected a 7% (2.2 Mha) forest cover increase and stabilization of forest cover and carbon stocks at around 1990 levels (Fig. 6a) by 2050. This represents an increase in forest carbon stocks of around 8% (0.5 $GtCO_2$) relative to 2014 values (Figs. 5, 6b) and a social benefit ranging from 2 to 24 billion US dollars.

Under the LBFC scenario the largest net forest cover loss occurred during the period 2015–2020 (a change of −8.1% in forest cover) which resulted in a 9.7% reduction in forest carbon stocks. However, the carbon emissions during this period was around 1.7 times the emissions of the period 2010–2015. Such a change in the volume of emissions coupled with an increasing per ton cost of GHG emissions results in social costs ranging from 6 to 73 billion dollars depending on the discount rate. The projected rates of forest cover loss gradually diminished afterwards. Consequently, the rates of change in GHG emissions and associated social costs also decreased.

The largest change in forest cover under the UBFC scenario—an 11.3% increase—also occurred during the period 2015–2020. However, forest carbon stock only increased around 1.4% during this period—-mainly due to legacy forest regrowth. The temporally lagged uptake of $CO_2$ from forest regrowth and decreasing rates of forest cover growth resulted in a maximum inter-period rate of forest carbon stock change during the period 2030–2035, a 3.8% increase. The corresponding social benefits for the sequestered $CO_2$ during this period ranged from 2 to 11 billion dollars.

## 5. Discussion

The marginal effects of the topographic, environmental, and socioeconomic data estimated with the empirical forest cover change model are consistent with previous studies of Australian land cover change (Marcos-Martinez et al., 2018, 2017; Simmons et al., 2018b). For conciseness, we focus our discussion on the forest cover and forest carbon change projections and their social cost implications.

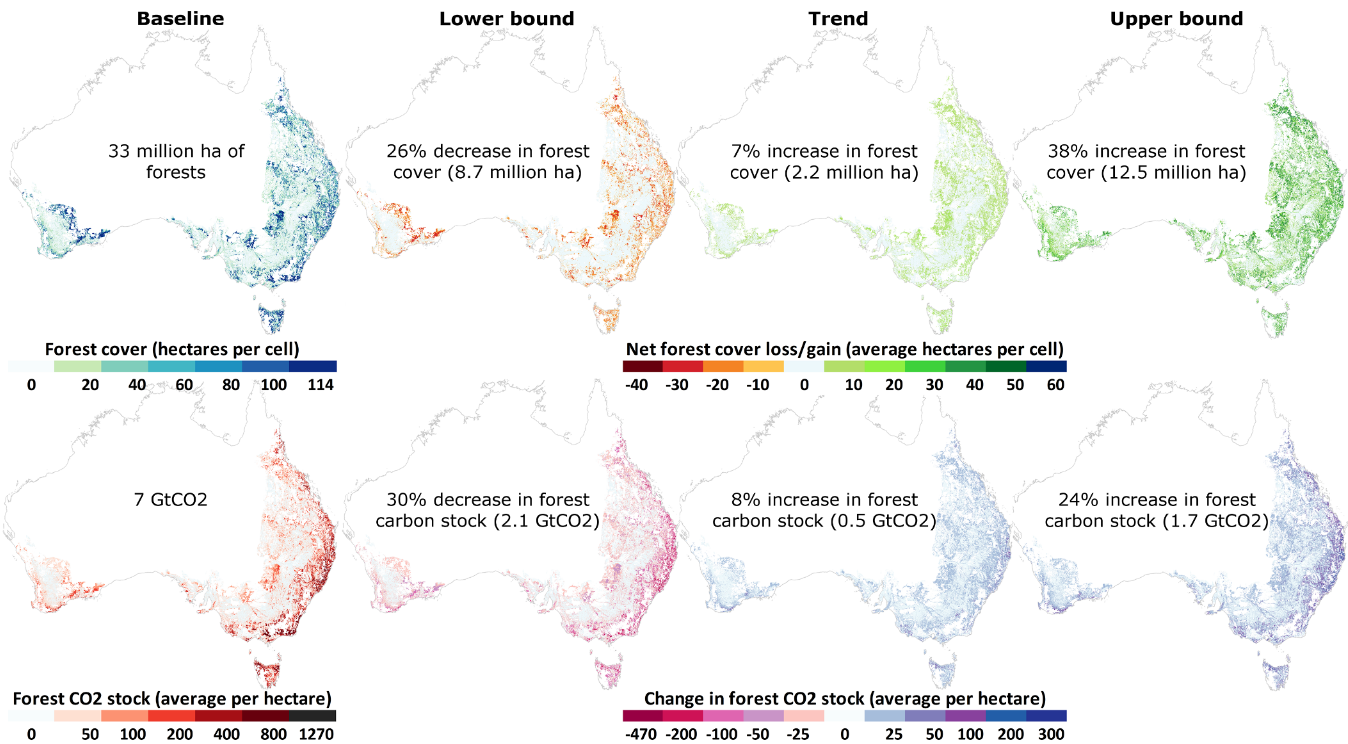


**Fig. 5.** Projections of forest cover and forest $CO_2$ stock change to 2050 (relative to 2014 values).

### 5.1. Social costs of carbon from forest gains and losses

Around 70% of all projected trajectories of socioeconomic and climate parameters resulted in net forest cover gains. In contrast, the majority of the modelled scenarios resulted in increased forest carbon emissions. Consequently, the social costs of the increased emissions from deforestation scenarios are considerably larger in magnitude than the social benefits from carbon sequestration from projected forest cover gains. Differences in the social costs of these carbon dynamics are amplified the less future climate change damages are discounted.

Such asymmetries are most pronounced when comparing the scenarios at the extreme bounds of the forest cover projections considered in this study (Fig. 6). The LBFC scenario involves net deforestation around one-third less in absolute terms than the reforestation projected under the UBFC scenario. However, the magnitude of the carbon emissions are more than double the sequestration (Fig. 6b), and the social costs are almost five times the benefits (Fig. 6c). The asymmetric impacts arise because carbon in new forests takes years to accumulate while the effect of forest loss on carbon emissions is immediate as the biomass is usually burned. In our analysis, the asymmetric social impacts of potential forest loss and gains decrease between 2030 and 2050 as forest biomass growth increased and projected deforestation rates decreased. However, the difference was still significant with the benefits of forest expansion in the UBFC scenario at around half the costs of comparable forest area loss projected in the LBFC scenario by 2050.

### 5.2. Policy implications

The trend and lower and upper bounds of the projections encompass price trajectories commonly used in land-use models: increasing agricultural prices (e.g. due to increasing food demand and extreme weather events) (Hatfield-Dodds et al., 2015); decreasing prices (e.g. due to large increases in agricultural productivity and resource efficiency (Baldos and Hertel, 2016), or long-term mean values (Nelson et al., 2014). The estimated forest cover response to changes in agricultural prices highlights the potential role of sustainable food production and consumption policies to reduce the intensity of trade-offs between food security, biofuel production, and environmental conservation policy (Obersteiner et al., 2016). It also provides some insights into the potential social benefits from forest expansion if food prices resume their long-term decreasing trend (Baldos and Hertel, 2016).

The modest marginal effect of climate on forest cover change in our analysis is consistent with studies documenting the emerging but still small influence of climate change on land-use and agricultural production relative to other drivers (Aleman et al., 2016). However, evidence suggests that if warming continues unabated, the climate system could be tipped into different states causing irreversible and significant social costs (Cai et al., 2016). Models that account for uncertain climate thresholds indicate that optimal climate policy requires urgent GHG emissions reduction at maximum technically feasible rates (Ackerman and Stanton, 2012). In Australia, the agriculture and forestry sector offers the largest emission abatement opportunity of any sector (van Oosterzee et al., 2014). Our results underscore that forest conservation within agricultural areas can help achieve carbon emissions abatement targets and more effectively reduce the costs of climate change damage.

Cool, temperate, and Mediterranean areas in the study region contain the largest concentration of forest carbon and have large biomass productivity potential (Fig. 5). In those regions, forest gains and losses have large social carbon impacts even under relatively low rates of change. However, the scale of deforestation observed in recent decades in low carbon density per unit area—mostly in semi-arid regions—has generated large volumes of carbon emissions (Bradshaw, 2012). The non-linear and spatially heterogeneous relationship between forest cover and carbon density could inform the design of low-cost spatially explicit forest conservation and reforestation policy (Aslam et al., 2017). This could be achieved through assessments of the cost-benefit implications of abatement efforts targeting land with large carbon stocks or high biomass productivity (potentially preferable for agriculture) versus large-scale abatement in low carbon density regions (e.g. low productivity grassland).

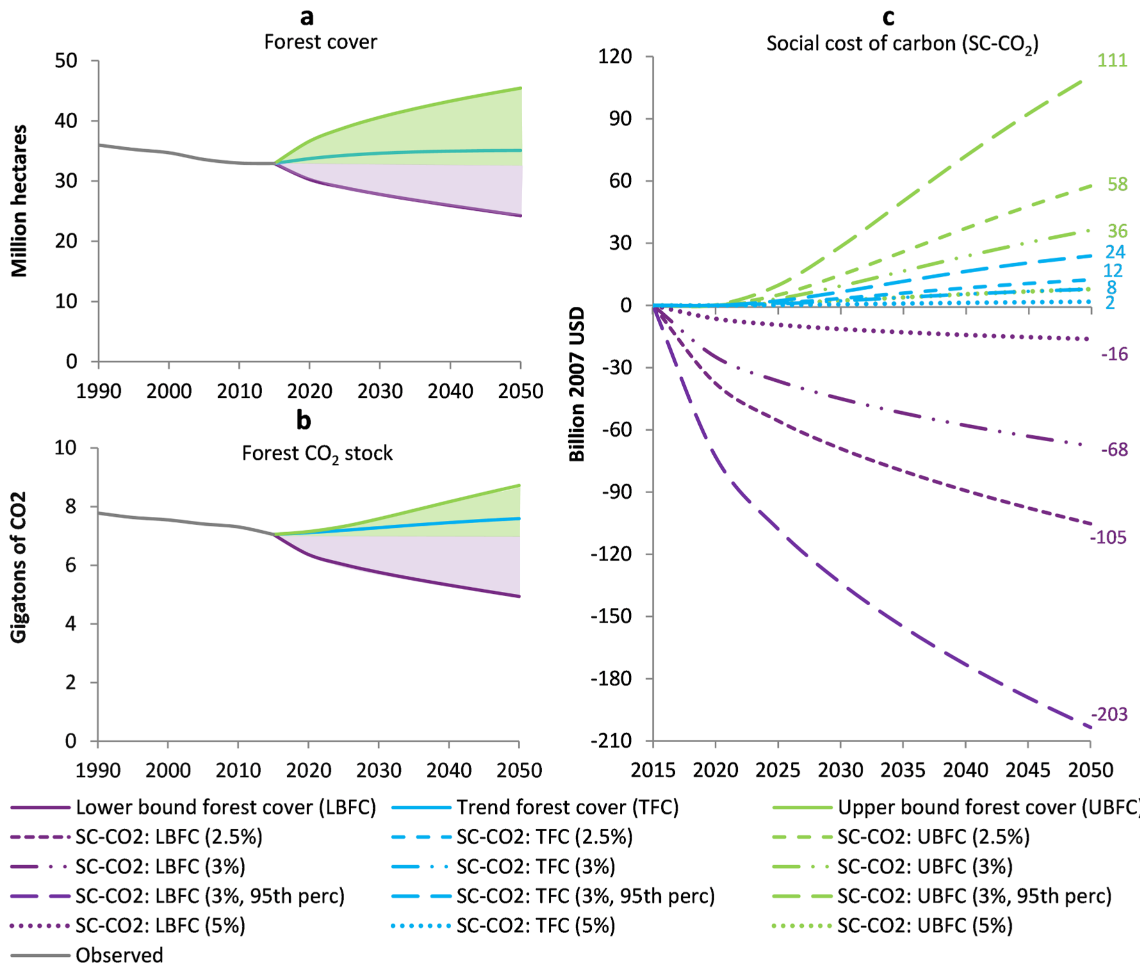


**Fig. 6.** Projected range of forest cover and carbon stock change in Australia's intensive agricultural region. a. Observed and projected forest cover. b. Changes in forest $CO_2$ stock. c. Social costs (negative values) and benefits (positive values) of $CO_2$ emissions/sequestration at 2.5%, 3%, 3% (at the 95th percentile of the distribution of SC-$CO_2$ estimates) and 5% discount rates.

*5.3. Contributions and caveats*

Conservation policy must be based on expectations about future environmental and socioeconomic conditions that are highly uncertain. If those expectations are limited to a small set of possible futures, they may not provide evidence that is appropriate for conditions that eventually arise (Peterson et al., 2003). We show that the trends and patterns of multiple global and domestic land-use drivers can be used to estimate the social cost implications of forest cover and forest carbon change over a large range of plausible futures. In addition to informing forest and land-use policy, the results could inform the calibration of forest and agricultural land interactions in domestic sectoral agricultural models. Our approach could be expanded to account for other benefits that forest ecosystems provide (Albert et al., 2017; Costanza et al., 2017). The value of provisioning, cultural and supporting services could significantly outweigh the societal benefits of forest carbon sequestration (Ninan and Inoue, 2013), particularly for services without close substitutes (Ehrlich and Mooney, 1983).

In our projections, we assumed that forest clearing could occur across any of the modelled land tenure types. While forests in publicly-owned land (e.g. multiple use land and other Crown land) are less likely to be cleared, deforestation in those regions still occurs (DSITI, 2015; Lindenmayer et al., 2015). For instance, logging of native forests in State land under the Regional Forests Agreements is a significant source of greenhouse emissions and biodiversity loss in Australia (Sweeney, 2016). We also assumed that the relatively strict vegetation clearing regulations observed between 2007 and 2014 influence clearing behaviour similarly throughout the projection period (2015–2050). While our analysis captures the effect of clearing regulations during the model calibration period (Evans, 2016; Marcos-Martinez et al., 2018), changes to such regulations could lead to forest cover change well outside of the ranges presented here (Simmons et al., 2018c).

One of the limitations of our analysis relates to emission reduction mechanisms (e.g. carbon markets) which were under development and not widely adopted in Australia during the model calibration period (van Oosterzee et al., 2014). The potential impacts of those instruments, which were not examined, could play a significant role on emissions abatement and biodiversity conservation if society is prepared to absorb their costs (Bryan et al., 2016). Another gap in our modelling is that $CO_2$ emissions from agricultural uses and wildfires were omitted which could increase the social cost of emissions from forest loss and the benefits from forest gains (Martinez-Harms et al., 2017). The projections of socioeconomic or environmental factors are based only on the time series structure or system dynamics of each variable. While on average some correlation exists among the trajectories of the modelled forest cover change drivers, we evaluated the forest cover change implications of all possible joint trajectories to explore a wide range of possible outcomes. We recognize that other forecasting techniques are available (e.g. Monte Carlo simulation, geometric Brownian motion). However, innovation state-space time series models were selected due to their ability to automatically estimate the error, trend and seasonal structure for a wide range of time series data (Hyndman et al., 2008). These assumptions and limitations could impact the magnitude of the estimated social costs of forest carbon stock change but are unlikely to alter the general conclusions.

## 6. Conclusion

A better understanding of the heterogeneous manner in which land managers respond to economic, policy, and environmental change could help improve the management of forest resources and their ecosystem services. Based on historical data, our simulation of the effects of future economic and environmental scenarios on forest cover in Australia indicates a slight increase in forest cover and forest carbon stock under trend trajectories of climate change, and agricultural productivity and profitability. Greater agricultural productivity growth, lower agricultural prices and lower climate change pressure could see even more forest area and carbon stock gains (upper bound forest cover scenario). Conversely, should stagnant agricultural productivity and higher growth in agricultural prices eventuate, as illustrated by the lower bound forest cover scenario, a loss of forest area and net carbon emissions are projected. The social cost of climate change damage from carbon emissions of the lower bound forest cover scenario are substantially higher than the social benefits of avoided climate change damage from sequestration realised under the upper bound forest cover scenario. This asymmetric impact underscores the significantly higher social costs of deforestation, the limited ability of reforestation to offset these costs, and the clear implications for forest policy. The results could allow the identification of communities, ecosystems, and regions that may be more vulnerable to global change dynamics impacting the configuration of land-use. Such information may provide policymakers the opportunity to more proactively understand, adapt, and mitigate climate change impacts.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2019.100935.

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