Forest transition in developed agricultural regions needs efficient regulatory policy

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Highlights

We examined the robustness of forest transition in a developed country context.
We provide evidence of forest transition in Australia's intensive agricultural region.
Changes in land clearing laws were significantly associated with this transition.
Forest policy changes could hasten, delay, or even reverse forest transitions.
Effective forest policy across regions is needed to avoid deforestation hotspots.

Abstract

The shift from net forest loss to gain—*forest transition*—has been associated variously with economic development, market-driven reforestation, forest policy, and globalization. Evidence shows that governments can expedite forest transition, although economic and institutional failures can distort policy incentives. This study addresses the paucity of spatially explicit empirical research on the robustness of the forest transition hypothesis in a developed country context and identifies factors that may hasten, delay, or even reverse forest transition. We applied spatial-econometric analysis to high-resolution forest cover, climatic, socioeconomic, physiographic, and State-jurisdiction data for the Australian intensive agricultural zone from 1988 to 2014. While environmental and physiographic factors explained the spatial distribution of forests, net forest cover change was significantly associated with trends in farm-output prices inducing deforestation in Queensland, the State with less effective land clearance regulations. Changes in land clearing regulations in Queensland were significantly associated with the national forest cover trends that resulted in forest transition in Australia around 2008. Yet when land clearing regulations and their enforcement were subsequently relaxed in 2012, significant forest cover loss was once again observed in that State, particularly in remnant forests. We conclude that if forest regulatory protection is not effective, net forest loss could resume or increase, even in developed countries, in response to growing incentives for forest conversion to agriculture.

Keywords: Forest transition; spatial panel econometrics; Australia; agricultural expansion; policy; climate.

1. Introduction

Agricultural expansion in recent decades has resulted in a significant net loss of forest cover in tropical and sub-tropical regions (Gibbs et al., 2010; Matthew C Hansen, Stehman, & Potapov, 2010). Over the same period, net gains in forest cover have occurred in boreal and temperate forests, tropical savannahs, and shrublands (Liu et al., 2015). Although some of those gains have been attributed to carbon dioxide fertilization and climate change (Zhu et al., 2016), market and governmental incentives are also important drivers of net forest expansion (Mather, 2007). The switch from net forest loss to gain is called *forest transition* (Mather, 1992). This process has been documented in both developed (Mather, 1992; Rudel et al., 2005) and developing countries (Mather, 2007; Redo, Grau, Aide, & Clark, 2012), allowing the identification of multiple non-exclusive and often overlapping pathways to forest transition. For instance, the *economic development pathway* relates rural to urban migration, increasing agricultural input productivity and efficient land governance with land-sparing resulting in net forest gain (Mather, 1992; Redo et al., 2012; Rudel et al., 2005). The *forest scarcity pathway* is associated with market-driven expansion of forest plantations and forest conservation and expansion policy to address growing social preferences and pressures for increased provision of forest ecosystem services (Lambin & Meyfroidt, 2010; Mather, 2007; Rudel et al., 2005). The *State-led pathway* involves forest policy to address issues unrelated to the forestry sector (e.g., protection of aboriginal tribes living in forested regions, or promotion of eco-tourism) (Lambin & Meyfroidt, 2010). Net forest gains achieved by the displacement of deforestation to other countries through international trade or by reduced land pressures due to international remittances to rural regions represents the *globalization pathway* (Lambin & Meyfroidt, 2010; Meyfroidt, Rudel, & Lambin, 2010). The institutional, socioeconomic, and environmental conditions associated with these pathways are usually complementary, yet their presence does not guarantee forest transition. Market, policy, and institutional failures can delay transition (Barbier, Burgess, & Grainger, 2010)—e.g., some States in the USA lagged behind others, not reaching forest transition until the early 2000s (Kauppi et al., 2006). In recent decades, parts of North America, Europe and Australia—affluent regions with strong land-use governance—have experienced substantial net forest cover loss at rates comparable to those observed in the tropical forests of developing nations (M C Hansen et al., 2013; Matthew C Hansen et al., 2010; Kauppi et al., 2006). Emerging evidence portends net forest reductions—potentially even in regions where forest cover has until recently remained stable or increased (Ceddia, Sedlacek, Bardsley, & Gomez-y-Paloma, 2013; Matthew C Hansen et al., 2010)—as global population grows and becomes more affluent, diets change, and demand for food and biofuel production intensifies (Laurance, Sayer, & Cassman, 2014).

In this paper, we examined factors that may hasten, delay, or even reverse forest transition in a developed country experiencing overlapping processes associated with the multiple pathways to forest transition. First, we assembled a unique, high-resolution spatiotemporal dataset of forest cover, and human and environmental variables influencing forest cover change in Australia's intensive agricultural region (Fig. 1) during the period 1988–2014. We then investigated the occurrence of forest transition and, by applying spatial panel econometric methods, quantified the influence of various biophysical, socioeconomic, and institutional factors on pixel-level forest cover dynamics. Additionally, we discuss the implications of the results for forest transition processes, and the relevance of high-resolution data and the joint analysis of forest cover gains and losses to better inform forest policy and forest conservation strategies at multiple scales.

2. Materials and Methods

2.1. Australian forests

Consistent with the Australian definition of forest (National Forest Inventory, 1998), we defined forest cover as land with at least 20% of canopy cover—either primary or secondary vegetation—with potential to reach at least two meters in height (Lehmann, Wallace, Caccetta, Furby, & Zdunic, 2013). Under this definition land that has temporarily lost tree cover is still considered as part of the forest estate even if the vegetation has not reached the height threshold during the time of data collection (Montreal Process Implementation Group for Australia and National Forest Inventory Steering Committee, 2013). Australia has approximately 125 million hectares (Mha) of forest, comprising approximately 3% of the world's forests and ranking seventh in terms of forested area by country (Australian National Greenhouse Accounts, 2013). Most of this forest cover is native, with only 2 Mha of industrial plantations (Montreal Process Implementation Group for Australia and National Forest Inventory Steering Committee, 2013). Around 55% of the Australian native forests are managed under long-term leased or privately owned land, 35% are publicly owned and managed and around 10% are owned and managed by indigenous groups (Kanowski, 2017). Around one-third of the privately managed forests are located in the intensive agricultural region. Forest loss and fragmentation has had large negative effects on bird, small mammal, reptile, and plant diversity in Australia (Bradshaw, 2012). Deforestation has also constituted an important source of greenhouse gas emissions accounting for around 22% of Australia's emissions in 1990 and 7% in recent years (Australian National Greenhouse Accounts, 2013; Bradshaw, 2012).

2.2. Forest cover index data.

We used data from the Australian National Carbon Accounting System – Land Cover Change Program (NCAS-LCCP) which consists of a forest/non-forest classification at 25-meter resolution for 19 epochs (1988, 1989, 1991, 1992, 1995, 1998, 2000, 2002, 2004, and annually from 2005–2014). This forest cover mapping was based on the supervised classification of more than 7000 Landsat MSS, TM and ETM+ images and validated using around 800 historical aerial photographs, 1000 IKONOS images, expert knowledge, ground-based surveys and forest plantation information (Caccetta et al., 2012). Global errors were around 3% for observations identified as *definite* forest or non-forest, and 12% including *not well-identified* observations (Caccetta et al., 2012). To further increase the accuracy of the data we applied transition rules to identify and remove temporary (one and two period) forest cover change that deviated from long-term forest cover dynamics at the pixel level which were illogical on both economic and tree-physiology grounds (Marcos Martinez & Baerenklau, 2015).

We focused our analysis on Australia's intensive agricultural region which accounts for more than 99% and 92% of the national gross value of crops and livestock, respectively (Marcos-Martinez, Bryan, Connor, & King, 2017). Protected areas, hydrologic features (e.g., rivers, lakes), and other non-agriculture/forest land (e.g., urban areas, roads) within such region were removed from the forest cover dataset along with forest cover change caused by wildfires using fire-scar mapping (Fig. 1). The binary 25m resolution forest/non-forest data was used to compute 1.1 km grid cell resolution forest cover index layers that represents the proportion of land in forest status during each observation year. The resulting dataset consists of 1.38 million observations per epoch, totaling more than 26 million data points. This forest cover index value was used as the dependent variable for our study of net forest cover change and forest transition.

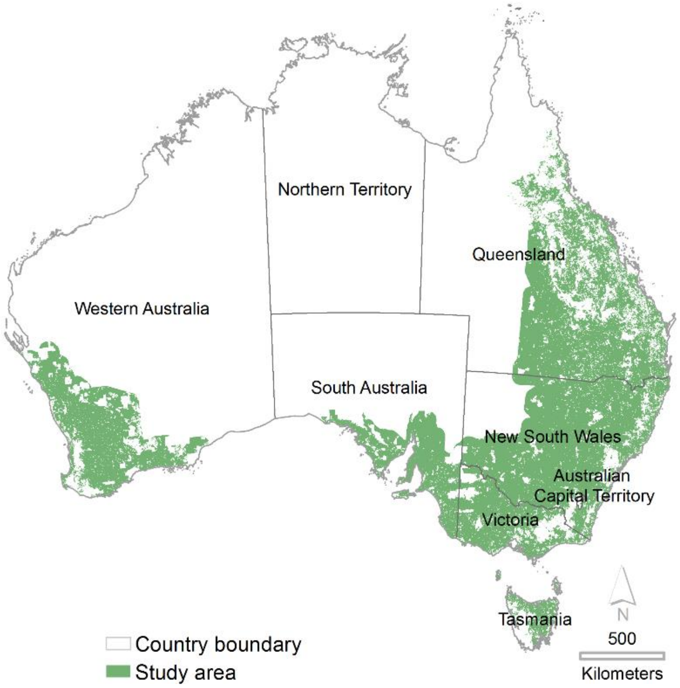

Fig. 1. Study area. The study area is net of protected land, hydrological features, urban areas, fire scars and other land types not influenced by landowners' decisions.

2.3. Explanatory variables.

Spatiotemporal data were assembled on a wide range of biophysical, socio-economic, and institutional factors that literature shows influence forest cover change (Ferretti-Gallon & Busch, 2014) (Supplementary Material, *SM*, Table S1). We grouped those variables into four categories: 1) temporally invariant, spatial (e.g., soils, land tenure); 2) spatially and temporally varying (e.g., climate); 3) spatially invariant, temporal (e.g., market prices); and 4) binary indicators and interaction variables (e.g., farm output price index for each State) (see Table 1 for a list of the variables included in each category and *SM* for description and sources).

Five-year moving averages of price indices for timber and agricultural products were developed to account for output price expectations influencing net forest cover dynamics. Average agricultural price variation during the previous five years was also included to capture the effects of price uncertainty but the variance of timber prices was excluded from the analysis due to collinearity issues. To capture the opportunity costs from conversion of non-forest to forest land, we used spatial information on the profits from the agricultural uses observed in 2005-06 (Marinoni et al., 2012), with forested areas assigned zero profit. We used the Accessibility and Remoteness Index of Australia (ARIA) (GISCA, 2001) as an indicator of local human population pressure and transportation costs (see Table S1 for an extended description of the ARIA). Elevation, slope, and soil characteristics were included to account for topographic factors impacting land productivity.

Since climate variability has been shown to influence land use decisions and land values (Mukherjee & Schwabe, 2015), we computed both five-year moving averages and standard deviations of the total annual rainfall and average daily maximum temperature (Jones, Wang, & Fawcett, 2009). Spatially explicit data on forest ownership and management is available only for one reference year, 2013 (ABARES, 2014b). While changes in landownership occurred during the study period, changes in land tenure type were insignificant or non-existent during the study period (Kanowski, 2017). To control for potential differences in forest management strategies under different forms of land tenure, we included time-invariant indicator variables for indigenous ownership, private ownership, leasehold, multiple use land, and other Crown land (land managed by State governments) (ABARES, 2014b). Indicators of native vegetation height observed before pre-European settlement (1788) were included to control for unobserved spatial characteristics influencing forest growth (Geoscience Australia, 2004).

Forest transitions occur at multiple spatial scales and country-level analysis may overlook dissimilar forest cover patterns across State jurisdictions (Mather, 2007; Redo et al., 2012). This is particularly relevant for our study since in Australia the primary responsibility for land use and forest policy rests at the subnational (State and Territory) level. Therefore, indicator variables were used to control for State-specific unobserved variables influencing forest cover dynamics (e.g., local attitudes to agricultural/forest land, or State-based regulations). State indicators were interacted with the index of prices received by landowners to capture constraints to market signals due to State-specific factors. Summary statistics for the non-categorical variables are presented in Table S2. An analysis of variance inflation factors indicated no further multicollinearity issues.

2.4. Econometric model.

To evaluate the determinants of forest cover change, we applied a model that assumes risk-neutral landowners estimate the net present payoff of forested vs. non-forested land and allocate land to maximize their expected payoffs (Marcos-Martinez et al., 2017). Expected payoffs are dependent on the state of biophysical, socioeconomic, and institutional, parameters during the decision-making period. With imperfect information on the multiple factors influencing forest cover across all observations, we modelled the proportion of forested land across N spatial units and T time periods as being comprised of both a systematic component that can be modeled with observed data, and an error term which incorporates unobserved spatial interactions among neighboring land, unobserved heterogeneity across observations, and random errors. Based on the results of an iterative spatial Hausman test, we applied a *spatial panel with random effects* model (Kapoor, Kelejian, & Prucha, 2007) (see *SM* for a full formulaic description).

2.5. Implementation.

For datasets with a large number of observations, spatial econometric models are computationally intensive and may become intractable even with only a few time periods. To address this issue, we applied a bootstrapping method that generated random (although still containing some residual spatial correlation due the observed forest/non-forest patterns) samples, and computed the spatial panel regressions. Average parameter estimates and 95th percentile confidence intervals were computed from regressions applied to 1,000 samples each consisting of 10,000 observations over 15 periods—a total of 150,000 records per sample.

We approximated the spatial interactions among unobserved covariates using sample-specific, row-standardized Sphere of Influence spatial weights matrices that were based only on geographical distance. The choice of spatial weights matrix configurations (e.g., contiguity, inverse distance weights) had no appreciable effect on our results. Non-categorical data and the dependent variable were log-transformed to constrain the forest cover index estimates to the [0,1] interval. The relative effect of the categorical variables was computed using the Halvorsen and Palmquist adjustment for categorical variables in semi-logarithmic equations. Out-of-sample estimation was applied to quantify how well the model predicted spatially and temporally forest cover. Best linear unbiased predictors were estimated for the period 2011–2014 using the bootstrapped marginal effects computed with the 1988–2010 data. Additional notes on this methods and implementation can be found in the *SM*.

Preliminary versions of our model included interactions between timber prices and state indicators and time dummies to control for temporal differences in land clearing regulations and forest incentives. Yet the corresponding parameter estimates were not statistically significant, and in some cases generated convergence problems and thus we chose the more parsimonious approach and excluded those parameters from our analysis. The bootstrapped estimation was implemented in R (R Core Team, 2017) using cloud computing resources (RStudio Team, 2016). We used the libraries splm (Millo & Piras, 2012) for spatial panel regressions, spdep (Bivand & Piras, 2015) for spatial weighs matrix generation and spatial autocorrelation tests, and doParallel (Revolution Analytics & Weston, 2015) for parallel computing. Although the parameter estimates and 95% confidence intervals converged after 300 iterations, the regression was applied to 1,000 samples to better approximate the distribution of the parameters.

3. Results

3.1. Forest cover dynamics.

From 1988 to 2007, net forest cover loss in the study area was 4.02 million hectares (Mha) (Fig. 2A), whereas from 2008 to 2014 net forest cover increased by 2.05 Mha. Nearly all of the change occurred in the State of Queensland which, despite gains since 2008, experienced a net loss of 2.74 Mha during the period 1988–2014. This represented a 19% reduction of the forest cover observed in that State in 1988 (Fig. 2B). The rest of the study area saw comparatively small changes relative to the 1988 forest stock with net losses in Western Australia (0.13 Mha) and Tasmania (0.05 Mha) and moderate to small net gains in New South Wales (0.52 Mha), Victoria (0.35 Mha) and South Australia (0.15 Mha) (Fig. 2A). These trends resulted in forest transition within the study area during the period 2008-09 (Fig. 2C).

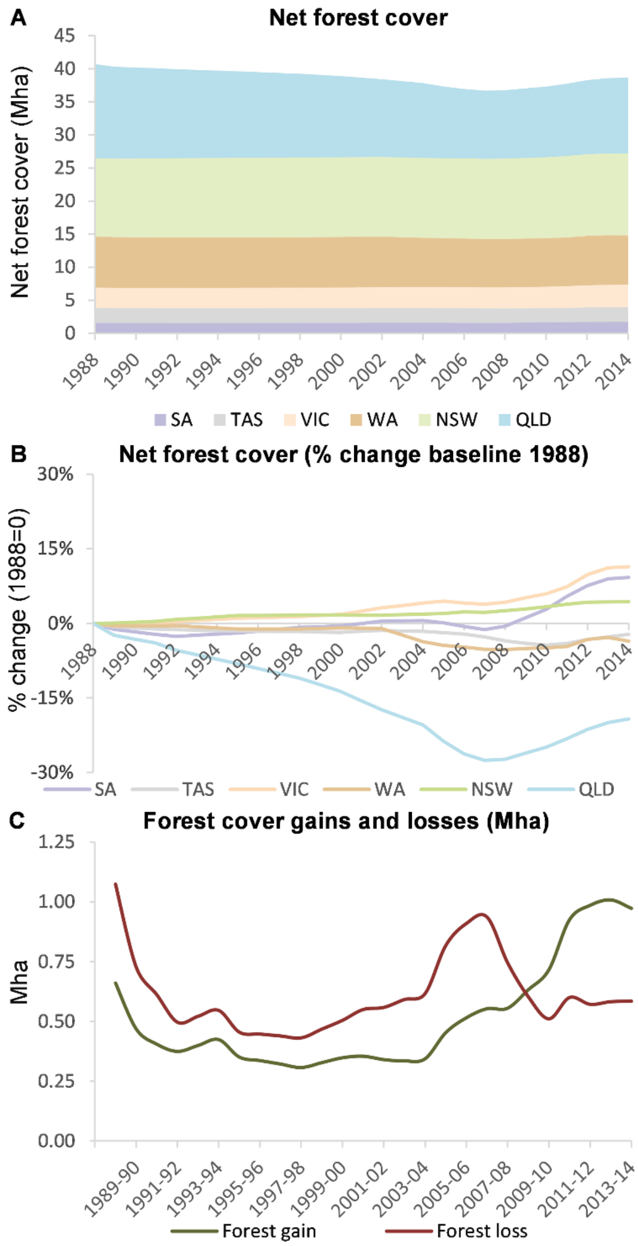

Fig. 2. Forest cover dynamics in Australia 1988–2014. A. Net forest cover by State in Mha. B. Percent change in forest cover relative to 1988. C. Inter-annual forest cover gains and losses.

3.2. Factors influencing forest cover dynamics.

The econometric model explained a high proportion of the net forest change variance (R-squared = 0.91), with most explanatory variables significant at the 95% level (Table 1). Nearly all of the temporally invariant physiographic, tenure and pre-European vegetation variables were statistically significant in explaining spatial differences in net forest cover. The marginal influence for a one percent change from the sample mean value for the non-categorical variables (Table 1) shows that greater forest cover across the study region was associated with higher slope, lower soil clay content and pH, and greater soil bulk density. This is consistent with past studies that highlight the impact of those factors on soil structure, management, productivity and suitability for agricultural uses (Ferretti-Gallon & Busch, 2014). The negative association between forest cover and elevation may be an artifact of the specific topographic relief of the study area as much of it is low-lying and most of the higher elevation is in tablelands, rather than mountains. These tablelands are typically in rain shadows and support grassy woodland ecosystems which have been extensively cleared for grazing.

From a land tenure perspective, privately owned land had less forest cover than any other tenure type. The lower levels of forest cover in indigenous land is more likely a result of biophysical characteristics (e.g., infertile soils, arid climate) that limit forest growth than indigenous land management practices. Areas supporting low and medium height pre-European vegetation tended to have less forest cover, possibly because the native vegetation was easier to clear for agriculture.

Distance from protected areas was inversely related to forest cover, possibly due to protected area network spillover effects or the fact that conservation areas are more often located in areas at low risk of deforestation (e.g., in steep or infertile land) (Andam, Ferraro, Pfaff, Sanchez-Azofeifa, & Robalino, 2008). The positive effect of remoteness (high transportation costs) on forest cover is consistent with past findings (Ferretti-Gallon & Busch, 2014). While the timber price index was not statistically significant, one might expect this for a number of reasons. Harvesting of native forests is selective across the majority of the study area (i.e., only individual trees of commercial value are removed without impacting significantly the forest canopy). In addition, most of the timber used by the domestic wood-processing industry is provided by plantation forests (Bradshaw, 2012) where harvesting is typically constrained by contractual commitments and forest stand age, rather than short-term price fluctuations. Highly profitable agricultural areas had less net forest cover while increased variability of farm output prices corresponded with increased forest cover.

Climate variables in our study represent the combined influence of spatially and temporally varying climate conditions on forest cover. Increased precipitation was associated with more forest cover, a reflection of how the vast majority of Australian agriculture (by area) takes place in dryland Mediterranean to semi-arid climates. The negative association between forest cover and maximum temperature corresponds to the observed spatial distribution of forests in Australia with fewer trees on average in warm, dry climates than in cool, wet areas (Table 1). The results also reflect the negative impact that large inter-annual temperature variability could have on tree growth (e.g., through heat/water stress). These results are consistent with estimates of the impact of climatic variation on farmland conversion in China (Li, Wu, & Deng, 2013), forest loss in Indonesia (Wheeler, Hammer, Kraft, Dasgupta, & Blankespoor, 2013), and agricultural land price models in the USA (Mukherjee & Schwabe, 2015).

The State jurisdiction variables explained otherwise unaccounted-for, State-level differences influencing forest cover. The results generally corresponded with observed differences in existing forest cover relative to South Australia, the default category due to the effective deforestation laws in the State and resulting relatively low forest cover change during the study period (Fig. 2). Exploration of alternative specifications gave support to interacting farm output prices and State-level binary variables. This allowed quantifying heterogeneous forest cover response across states to agricultural price fluctuations. The influence of farm output price changes on forest cover was not statistically significant for Western Australia and Tasmania (Table 1). Consistent with agricultural intensification and land-use governance studies (Ceddia et al., 2013; Redo et al., 2012), farm output price increases—coupled with productivity improvements (Hatfield-Dodds et al., 2015)—were associated with forest cover gains in States with more effective land clearance regulations (i.e., Victoria, New South Wales, and South Australia). In Queensland however, net forest cover response to changes in farm output prices was comparatively strong and negative.

Table 1. Percent change in net forest cover per 1% change in each continuous variable or relative to the reference category.

Variable	Coefficient	Std. dev.	[95% Conf. Interval] Lower bound	Upper bound	
Intercept	3.4839	2.1239	-0.4262	7.7884	
Temporally invariant, spatial					
Topography and soil features					
Slope	0.8496	0.0390	0.7655	0.9258	*
Elevation	-0.3276	0.0434	-0.4123	-0.2444	*
pH	-1.1399	0.8841	-3.5914	-0.2482	*
Clay content	-0.9044	0.0982	-1.1009	-0.7081	*
Bulk density	0.5794	0.3856	-0.4421	1.1208	
Tenure (reference category private land)					
Other crown land	4.7360	0.2225	4.2798	5.2123	*
Leasehold land	1.8571	0.1034	1.6433	2.0611	*
Multiple-use land	3.0302	0.1782	2.6506	3.3864	*
Indigenous land *(reference category non-indigenous land)*	-0.3732	0.1182	-0.6050	-0.1392	*
Pre-European vegetation (reference category Tallest Stratum Growth Form: tall trees >30m)					
Low trees <10m	-2.4423	0.1943	-2.8184	-2.0675	*
Medium trees <18-30 m	-1.9460	0.1602	-2.2588	-1.6357	*
Tall shrubs >2 m	0.4863	0.2415	0.0110	0.9358	*
Socioeconomic (short-term invariant)					
Remoteness/Accessibility index	0.1483	0.0515	0.0488	0.2504	*
Agricultural profits	-0.0935	0.0056	-0.1045	-0.0828	*
Spatial and temporally varying					
Rainfall (5-year moving averages)	0.3919	0.0648	0.2652	0.5210	*
Maximum temperature (5-year moving averages)	-3.4360	0.5679	-4.5688	-2.3751	*
Rainfall variability (5-year moving Std. Dev.)	-0.0258	0.0159	-0.0574	0.0043	
Maximum temperature variability (5-year moving Std. Dev.)	-0.0381	0.0129	-0.0628	-0.0112	*
Euclidean distance to protected areas	-0.6194	0.0439	-0.7044	-0.5291	*
Spatially invariant, temporal					
Timber price index	0.0500	0.0310	-0.0140	0.1103	
Farm output prices	0.7605	0.1915	0.3748	1.1376	*
Variance of the farm output prices	0.0092	0.0043	0.0007	0.0175	*
Binary indicators and interactions *(reference category South Australia)*					
New South Wales (NSW)	1.7960	0.9527	-0.0901	3.7627	
Victoria (VIC)	-4.1459	1.3523	-6.6627	-1.7231	*
Queensland (QLD)	20.0801	1.1261	17.2739	22.7012	*
Western Australia (WA)	5.0681	1.1680	2.5382	7.2250	*
Tasmania (TAS)	5.8505	1.6211	2.4969	8.9227	*
Farm output prices in NSW	0.2189	0.2138	-0.2055	0.6477	
Farm output prices in VIC	1.1715	0.3072	0.5932	1.7698	*
Farm output prices in QLD	-3.2923	0.2441	-3.7517	-2.7819	*
Farm output prices in WA	-0.7771	0.2594	-1.2406	-0.2363	*
Farm output prices in TAS	-0.8582	0.3646	-1.5318	-0.1208	*
Spatial error correlation	0.0044	0.0046	-0.0016	0.0170	
Share of individual effects in the residuals	0.8779	0.0516	0.8698	0.8865	*
Share of idiosyncratic effects in the residuals	0.1221	0.0516	0.1134	0.1302	*
Pseudo R-squared	0.9054				

* The 95% confidence interval does not include 0.

The dependent variable and all non-categorical variables are log-transformed. Bootstrapped results of 1000 samples with 10,000 observations over 15 periods (150,000 records per sample). The standard errors of the shares of individual and idiosyncratic effects are similar since both shares are complementary and constrained to add up to 1.

3.3. Out-of-sample validation

Out-of-sample validation also revealed high predictive accuracy. Predictions based on the coefficients reported in Table 1 and the values of the explanatory variables in 2011, 2012, 2013, and 2014 produced pseudo R-squared values of 0.87, 0.86, 0.84 and 0.83, respectively. The average root mean squared error for those periods was 0.12. Predictions and prediction errors were also mapped to visualize the model's capability to predict observed spatial forest cover patterns. The spatial distribution of the predictions matched the general patterns of the observed forest index values across the study region (Fig. 3). The overestimates for Queensland are likely a result of the limitations of the model, calibrated with 1988-2010 data, to account for changes in land clearing regulations in the State after 2012. Those regulatory changes resulted in significant deforestation rates (Evans, 2016).

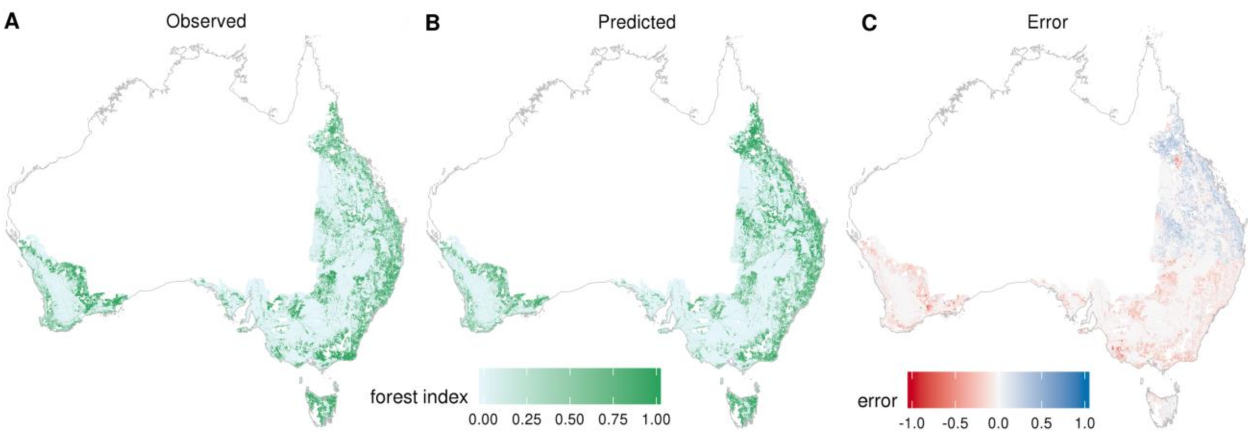

Fig. 3. Forest cover index in 2014: observed, predicted and prediction error.
A. Observed forest cover index. Proportion of 1.1 km cells with forest cover in 2014 in the study area. **B. Predicted forest cover index.** A and B share the same legend with greener values indicating higher forest density. **C. Prediction error.** Difference between observed and predicted 2014 forest cover index values. Red areas indicate underestimated forest cover; blue areas indicate overestimation.

4. Discussion

4.1. Forest cover dynamics and forest policy

The results suggest that the comparatively high rate of net forest cover loss in Queensland from 1988 to 2007 may have been attributable to changes in State land clearing regulations that, when coupled with economic and environmental factors, provided the motivation to clear significant areas of forests. The annual net forest cover growth rate in Queensland was negative from 1988 to 2007 (Fig. 4). When broad scale clearing in Queensland was banned at the end of 2006, net forest cover expanded at an increasing rate until 2012, at which point land clearing regulations and their enforcement were again relaxed (Evans, 2016) and significant forest cover loss was once again observed in Queensland, particularly in remnant forests (DSITI, 2015).

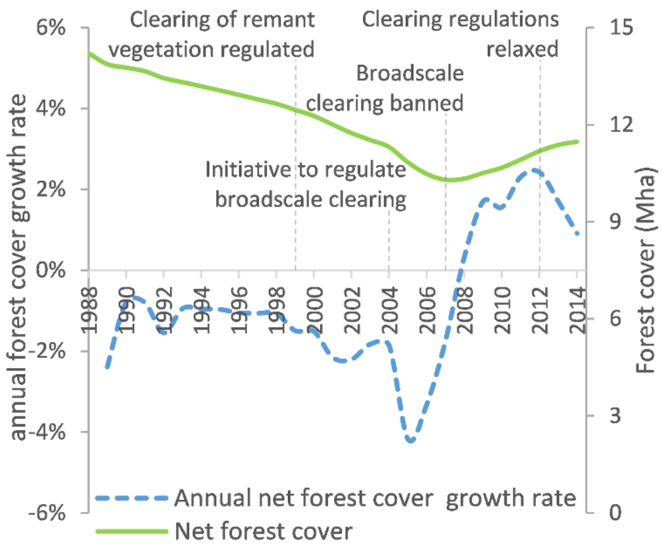

Fig. 4. Annual forest cover growth rate and land clearing regulations in Queensland 2007 – 2014.

The statistically significant and positive association between net forest area and farm output prices in New South Wales, Victoria and South Australia, along with the observation that most area gained was from plantation forest expansion (Fig. 5), suggests that the result may be a response to federal incentives to establish forest plantations—mostly in the form of tax breaks after 1997 (Fin, Trusler, & Fin, 2010). These incentives were offered during a period when Australian agricultural productivity and the index of farm output prices were increasing (Hatfield-Dodds et al., 2015) and resulted in the planting of around 0.7 Mha of mostly short rotation hardwood between 1997–2007 (Burns, Vedi, Heyhoe, & Ahammad, 2009), and around 0.2 Mha between 2005-2011 (Montreal Process Implementation Group for Australia and National Forest Inventory Steering Committee, 2013). The impact of this incentive could have been greater with more certainty about the continuation of the incentive scheme, improved management of new forestry projects, and more accurate yield and timber price projections (Ferguson, 2014).

4.2. Implications for the environment and policy

While our results are consistent with findings from analyses focusing on tropical forests in developing countries, particularly with respect to the price, soil characteristics, and climate effects, they also suggest caution regarding complacency in the process of forest transition, in particular as it relates to developed countries. Forest transition hypotheses typically frame forest transition as a directional process (i.e. towards, and through transition), and ignore the possibility that these transitions can potentially be undone. However, even in developed countries where forest cover losses have declined or even reversed, lax environmental regulations coupled with inadequate incentives can allow forest cover loss to resume, and continue the associated ecological and environmental degradation. Such an outcome was observed in our study region. Forest cover loss occurred predominantly in Queensland's native *Eucalypt* and *Acacia* forests—the two most common forest types in Australia (Fig. 5A-B). Forest cover gains occurred mainly in forest plantation areas (Fig. 5B), and most of the non-forest land remained unchanged during the period of analysis. We stress, however, that there is a marked difference in the biodiversity and ecosystem services implications associated with the observed forest cover loss and gain (Fig. 1). The clearance of established remnant native forest generally results in an immediate and near complete local-scale loss of forest biodiversity and carbon storage services. Conversely, in many cases biodiversity improvement and carbon sequestration only accrue from forest restoration or natural regeneration decades or centuries after initial restoration activity, sometimes previous ecosystem function is fully lost (Poorter et al., 2016). An accurate characterization of the environmental services provided by forests of different age, composition, and structure is needed for effective conservation and adaptation policy (Bryan et al., 2015). The *Forest identity* concept (Kauppi et al., 2006)—which, in addition to changes in forest area, accounts for variations in accumulated biomass, growing stock, and sequestered carbon—could improve the characterization of the environmental impacts of forest transitions.

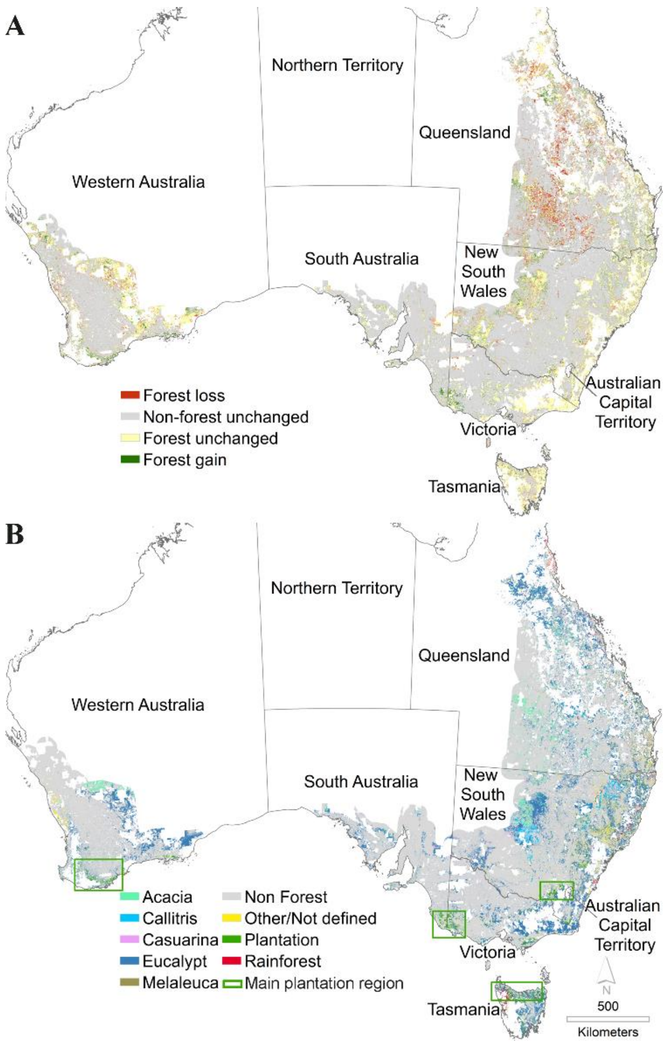

Fig. 5. Forest cover change and predominant vegetation in the study area.
A. Forest cover change between 1988 and 2014. B. Predominant forest type. Generated with data from (ABARES, 2014a)

The high net forest loss observed in Queensland highlights the need for coordinated land clearance regulations across geopolitical regions to avoid deforestation hotspots. The results indicate that socio-economic, technological and institutional development is not sufficient to guarantee forest cover transition and that efficient forest regulatory and incentive policy is also needed. This includes long-term certainty in the regulatory framework and avoiding temporary policy changes which tends to compromise forest regrowth or increase clearing of primary forests.

4.3. Innovations, contributions, and caveats

Although the role of national forest policies (e.g., expansion of protected areas, incentives for forest plantation/conservation) in the path to forest transition has been discussed using country level statistics (Bae, Joo, & Kim Yeon-Su., 2012; Mather, 2007; Rudel et al., 2005), few studies have documented their impact using remotely sensed data (see Meyfroidt & Lambin, 2008; Plieninger *et al.*, 2012; Bruggeman *et al.*, 2016 for some examples). However, none have approached the level of detail in explanatory variables enabled by our high-resolution, spatiotemporal dataset. Such information coupled with our quantitative analysis facilitated deep socio-economic, environmental, and policy insights into forest cover dynamics associated with forest transition.

Limitations of the study include the potential influence of the *Millennium drought* (1997–2010)—the worst drought on record in Australia (Van Dijk et al., 2013). Annual rainfall in the study area during that period was 6% lower than the long-term (1988–2014) average, with some regions experiencing up to 23% less rainfall. Average maximum temperature was 1.1% (0.3 °C) higher than the long-term average during the drought, and inter-annual rainfall and maximum temperature variability were down 5% and 11%, on average. The drought contributed to increased tree mortality, wildfires, and agricultural land abandonment (Heberger, 2011). However, by using high-resolution spatiotemporal climate data, our statistical analysis was able to control for pixel-level effects of the drought. The results indicate that the net impact of the drought on forest cover dynamics was low, with forest cover trends during the drought deviating little from the pre-drought period in most Australian States (Fig. 1A). We caution that further studies are needed to move from the statistical associations found in this study to the identification of the causal effects of extreme climate events, protected areas, land clearing regulations and plantation forest incentives on net forest change and deforestation.

Despite the extensive set of socio-economic and environmental parameters used, unobserved heterogeneity (i.e. non-modeled variables) remained a significant component in our analysis. Unobserved land and landowner-specific characteristics influencing forest cover change include debt-to-asset ratios limiting agricultural expansion (Mugera & Nyambane, 2015), private benefits from forest conservation within agricultural farms (Polyakov, Pannell, Pandit, Tapsuwan, & Park, 2015), agricultural investments *locking* land cover into non-forest use for long time horizons (Regan et al., 2015), and varying risk aversion among landowners (Parks, 1995). We found limited evidence of the influence of non-modelled variables in neighboring land on forest cover patterns (i.e. low spatial error correlation). However, this does not compromise our statistical analysis since in the case of zero spatial effects our analysis would automatically reduce to bootstrapped non-spatial longitudinal regressions with random effects, without violating modelling assumptions, and maintaining the same forecasting function (Baltagi, Bresson, & Pirotte, 2012).

5. Conclusions

We have addressed a paucity of research on forest transition in modern industrialized agricultural settings, where net forest area has mostly been stable over the past several decades. We investigated how complex interactions between environmental and physiographic factors, land use regulations, and agricultural prices may create risk of net forest reductions in such regions. For the

Australian intensive agricultural region, we found that a net loss in forest cover occurred over the period 1988 to 2014. Most net forest loss was in the State of Queensland, the majority during the years prior to 2007 when the State land clearance regulations allowed broad-scale clearing of remnant vegetation. Small net forest cover gains in several other States with the same agricultural price pressures for forest land conversion indicates the combined influence of land clearance regulation and plantation forest incentives. The relatively stable land-cover configuration in those States represents an advanced stage of the forest transition process. The different forest cover change patterns observed between Queensland and the other States highlights the importance of incorporating spatial forest policy heterogeneity in the analysis of forest transitions.

The forest transition observed in the study area suggests transition via the *forest scarcity pathway* since it was closely related to State-jurisdiction policy to address pressures for conservation of remnant vegetation. We have shown that effective forest conservation policy is needed to hasten and maintain the path to net forest gains in the agricultural zones of developed nations. The results suggest that even in developed countries where forest cover loss has mostly declined or reversed, increased incentives to clear forests for agriculture (e.g., to meet rising global demand for food, achieve food self-sufficiency targets or produce biofuels) could delay forest transitions or even reverse past transitions. Such an outcome would also entail risks surrounding the degradation of biosequestered carbon stocks and other ecological and environmental forest services and values. Our findings emphasize that this risk is greatest where policy regulating deforestation is least developed and/or weakly enforced.

Supplementary Material to this article can be found online at https://doi.org/10.1016/j.forpol.2017.10.021. [Also attached after the references].

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Supplementary Material
Forest transition in developed agricultural regions needs efficient regulatory policy.

1. Explanatory variables

Table S1. Environmental, socio-economic and categorical variables associated with net forest cover change in Australia's intensive agricultural region during 1988-2014.

Variable	Description (source)	Unit	Resolution
Dependent variable, spatial and temporally varying			
Forest cover index	Proportion of 1 km cell forested.	%	1.1 Km
Temporally invariant, spatial			
Physiography			
Slope	Topographic gradient.	degree	95 m
Elevation	Meters above sea level (Gallant et al., 2011).	meters	95 m
pH	Upper 30 cm soil layer pH level (ACLEP, 2014).	-	250 m
Clay content	Upper 30 cm soil layer % clay content (ACLEP, 2014).	%	250 m
Bulk density	Upper 30 cm soil layer bulk density (ACLEP, 2014).	Mg/m3	250 m
Tenure			
Indigenous land	Indicator variable for indigenously owned land (Department of Agriculture and Water Resources, 2013).	binary	100 m
Private land	Indicator variable for privately owned land (ABARES, 2014).	binary	100 m
Leasehold land	Indicator variable for forests on privately managed leased land (ABARES, 2014).	binary	100 m
Multiple-use land	Indicator variable for public forests on State land managed for several uses e.g., wood harvesting, water supply, recreation (ABARES, 2014).	binary	100 m
Other crown land	Indicator variable for forests in land owned and managed by State governments and not in protected areas (ABARES, 2014).	binary	100 m
Pre-European vegetation (Geoscience Australia, 2004)			
Tallest Stratum Growth Form (TSGF) low trees	Indicator for average tree height < 10 m	binary	100 m
TSGF medium trees	Indicator for average tree height 10 to 30 m	binary	100 m
TSGF tall shrubs	Indicator shrubs taller than 2 m	binary	100 m
TSGF tall trees	Indicator for average tree height > 30 m	binary	100 m
Socioeconomic (short-term invariant)			
Accessibility and Remoteness Index of Australia (ARIA)	The ARIA uses the road distance and information on proximity to four categories of public and private services from 11,338 populated localities and urban centers to construct a grid with values ranging from 0 (high accessibility) to 12 (high remoteness)(GISCA, 2001).	score	1 km
Agricultural profits	Profit per hectare for agricultural land uses observed in 2005-06 (Marinoni et al., 2012).	2013 AU$/ha	1.1 km
Spatial and temporally varying			
Rainfall	Five-year moving averages of annual rainfall (Australian Bureau of Meteorology, 2015; Jones et al., 2009).	mm	0.05^o
Rainfall variability	Five-year moving standard deviations of annual rainfall.	mm	0.05^o
Maximum temperature	Five-year moving averages of annual maximum temperature (Australian Bureau of Meteorology, 2015; Jones et al., 2009).	^{o}C	0.05^o
Maximum temperature variability	Five-year moving standard deviations of annual maximum temperature.	^{o}C	0.05^o
Euclidean distance to protected areas	Annually updated Euclidean distance from each pixel to nearest protected status pixel (Department of the Environment, 2014).	km	1.1 km
Spatially invariant, temporal			
Timber price index	Five-year moving average weighted international hardwood and softwood price index (IMF, 2015).	2013 US$	
Farm output prices index	Five-year moving average of value weighted index of prices received for agricultural outputs (Australian National Greenhouse Accounts, 2013).	score	
Variance of the farm output prices index	Five-year variance of farm output prices index.	Score	
Binary indicators			
State	Indicator variable to account for unobserved State specific factors	binary	1.1 Km
State - farm output prices index	Interaction between agricultural price index and State indicators	2013 US$	1.1 Km

Spatial data was transformed to 1.1 km resolution using majority or nearest neighbors' values for categorical variables, and spline interpolation for continuous data.

Table S2. Summary statistics for non-categorical variables

Variable	Unit	Mean	Std. dev.	Min	Max
Dependent variable					
Forest cover index	score	0.21	0.32	0	1
Socioeconomic					
Timber price index	2013 US$	239.73	42.92	168.45	334.28
Agricultural prices index	score (2013 = 100)	76.55	10.51	56.74	94.64
Variance of the agricultural prices index	score	41.09	29.53	3.61	120.49
Agricultural profits	2013 AU$ per hectare	29.81	76.17	0	485.51
Euclidean distance to protected areas	Km				
Accessibility/Remoteness index	score	8.55	4.61	0	12
Topography and soil features					
Slope	degree	1.85	3.38	0	48.48
Elevation	Meters above sea level	266.53	199.78	-5.63	1716.83
pH	-	6.10	0.95	0.6	9
Clay content	%	28.47	15.05	0	82
Bulk density	Mg/m3	1.42	0.17	0	2
Climate					
Rainfall (5-year mean)	mm	543.17	276.86	133.40	5058.70
Rainfall (5-year standard deviation)	mm	119.84	71.20	2.07	1778.40
Maximum temperature (5-year mean)	ºC	25.06	3.56	8.34	33.89
Maximum temperature (5-year Std. Dev.)	ºC	0.49	0.17	0.02	1.45

2. Econometric model

2.1. Expanded econometric model description

Our model takes a linear-in-parameters specification of the form $\mathbf{f}=\boldsymbol{\beta}'\mathbf{X}+\mathbf{u}$, with spatially autocorrelated errors represented as $\mathbf{u}=\left(\mathbf{I}_T\otimes\rho\mathbf{W}\right)\mathbf{u}+\boldsymbol{\omega}$, and unobserved heterogeneity modelled as $\boldsymbol{\omega}=\left(\boldsymbol{\iota}_T\otimes\mathbf{I}_N\right)\boldsymbol{\mu}+\boldsymbol{\upsilon}$. Here $\mathbf{f}$ is a vector of the proportion of forested surface across observations and time periods with $f_{n,t}\in\left[0,1\right]$; $\mathbf{X}$ is a matrix of pixel-specific and time-specific variables (e.g., rainfall and agricultural prices); $\boldsymbol{\beta}$ is a vector of coefficients that approximates the "true" associations between the covariates and the outcome; $\mathbf{u}$ is a vector of spatially correlated unobserved variables; $\mathbf{I}_T$ and $\mathbf{I}_N$ are identity matrices of dimension T and N; $\boldsymbol{\iota}_T$ is a vector of ones of size T; $\otimes$ indicates the Kronecker product; $\mathbf{W}$ is a spatial weights matrix of size N; ρ is the spatial autocorrelation coefficient; $\boldsymbol{\omega}$ is a vector of composite errors comprised of observation specific effects $\boldsymbol{\mu}$, and a random error vector $\boldsymbol{\upsilon}$ that follows a standard normal distribution (Elhorst, 2014; Kapoor et al., 2007; Millo and Piras, 2012). A random effects approximation to the unobserved heterogeneity $\boldsymbol{\omega}$ was selected based on results from an iterative Hausman test.

2.2. Best linear unbiased predictor for spatial longitudinal regressions with random effects.

We estimated the best linear unbiased predictors (BLUP) for the period 2011-2014 using the bootstrapped marginal effects calibrated with 1988-2010 data and computing predictions for all the observations in our study region. The BLUP for observation n at time $T+\tau$ is defined as,

$\hat{y}_{n,T+\tau} = \mathbf{X}_{n,T+\tau}\hat{\boldsymbol{\beta}}_{GLS} + \left(\frac{\sigma_\mu^2}{\sigma_1^2}\right)\left(\boldsymbol{\iota}_T' \otimes \boldsymbol{\eta}_n'\right)\hat{\boldsymbol{\varepsilon}}_{GLS}$, where $\hat{\beta}_{GLS}$ is the vector of generalized least squares (GLS) estimated coefficients, $\boldsymbol{\eta}_n'$ is the nth row of the identity matrix $\mathbf{I}_N$, $\sigma_1^2 = T\sigma_\mu^2 + \sigma_\upsilon^2$, $\hat{\varepsilon}_{GLS}$ is the vector of GLS disturbances, $\tau \in \{1, 2, ...\}$ indicates the number of periods after the last observation for the target prediction, σ_1^2, σ_μ^2, and σ_υ^2 are variance components of the model (Baltagi et al., 2012). The out of sample accuracy of the model was assessed computing pseudo R-squared values (Elhorst, 2014) and the standard errors of the prediction. Predictions and prediction errors were also mapped to identify the model's capability to predict observed spatial forest patterns(Marcos-Martinez et al., 2017).

3. References

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