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Agricultural land-use dynamics: Assessing the relative importance of socioeconomic and biophysical drivers for more targeted policy

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ABSTRACT

A detailed understanding of multiple human and environmental factors influencing land allocations among agricultural uses can facilitate more efficient and targeted land policy. To show this, we used a comprehensive dataset of socioeconomic, physiographic, and climatic indicators to investigate potential determinants of land-use in Australia's intensive agricultural region during the period 1992–2010. We applied a seemingly unrelated regressions land-use shares spatial error model with random effects coupled with variance decomposition analysis to identify the statistical significance, direction and magnitude of observed associations between land-use and its drivers.

Population: density, rainfall, equity ratio, and access to markets were the most influential policy-relevant land-use factors. Land allocations to cereals and livestock production were significantly influenced by spatiotemporal rainfall and temperature variability. Improved pastures, cereals, annual and perennial crops plantations were larger in regions with better access to markets. Increases in equity ratio (i.e., better financial position) were associated with larger land allocations to improved pastures and annual crops and smaller extensive grazing area. Marginal associations were detected between land-use and output prices, and higher population density was associated with lower shares for all high value agricultural land-uses. The results suggest that improved transportation infrastructure, zoning regulations, and mechanisms to reduce farm debt exposure and risks from climate variability could have significant impact on the configuration of the Australian agricultural landscape.

1. Introduction

Anthropogenic land-uses have substantially degraded global natural resources (Bradshaw, 2012; Foley et al., 2005; Vitousek et al., 1997) generating a tremendous growth in food, fiber, shelter, and fuel, but at a cost to soil and water quality, endemic biodiversity, and other ecosystem services (Dupouey et al., 2002; Lunt, 2002; McAlpine et al., 2009). Global population growth, urbanization, changing consumption patterns, and climate change are expected to challenge the ability of the land system to satisfy increasing demands for food, energy and natural resources (Foley et al., 2011; Garnett, 2013; Seale et al., 2003; Steffen et al., 2011). Given the significance of land-based ecosystem services and the opportunity to influence highly-valued outcomes with policy, there is substantial ongoing effort directed at understanding the human and biophysical drivers of land-use change (Bryan et al., 2015; Havlik et al., 2012; Rosegrant et al., 2008).

Until recently, the scope of land-use studies was limited to local or regional scales (Meiyappan et al., 2014). Patchy coverage and non-linear interactions between human and environmental land-use drivers limit the usefulness of local scale case studies for national policy and impact analysis (Ay et al., 2014; Kok and Veldkamp, 2001; Veldkamp and Lambin, 2001). Growing availability of large-scale high-resolution land-use data has contributed to the recent emergence of national-scale econometric land-use analyses. Examples include estimating the impact on ecosystem services from land-use change in the United States (Lawler et al., 2014; Lubowski et al., 2006; Radeloff et al., 2012); identifying the drivers of deforestation in Indonesia (Wheeler et al., 2013); quantifying climate change influence on agricultural output and returns in Israel (Kaminski et al., 2013), and assessing the impact of urbanization on Chinese farm land (Li et al., 2013).

Associations between climate and land-use on national level studies have been documented using high resolution spatiotemporal data (Kaminski et al., 2013; Li et al., 2013). Nevertheless, the study of other land-use drivers has been relatively coarse at that scale. The influence of soil characteristics on land allocations has been indirectly assessed through proxies such as average wheat

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yield (Chakir and Le Gallo, 2013), and estimated yield potential (Li et al., 2013). Spatiotemporal differences in net revenue have been used to assess national landscape dynamics in the USA (Lubowski et al., 2008) and France (Chakir and Le Gallo, 2013).

While the study of associations between land-use and coarse financial and soil quality indicators provides valuable information, simulations based on those types of analysis have found that policies that alter the net profitability among competing land-uses appear to have only minor effects on land allocations (Lawler et al., 2014; Radeloff et al., 2012). This low responsiveness has been attributed to socioeconomic, and environmental factors influencing land-use not included in the analyses (Lawler et al., 2014; Radeloff et al., 2012).

From a methodological perspective several approaches have been implemented to reduce estimation biases in land-use research. Spatial discrete choice models allow us to control for spatially correlated land-use decisions (Li et al., 2013). Nested logit models facilitate the study of land-use change between correlated (close substitutes) options (Lubowski et al., 2006). Spatial panel data analysis allow the estimation of unobserved heterogeneity and spatial dependence in the error and dependent variables (Wheeler et al., 2013). Discrete choice dynamic programing models provide an option to control for stochastic variables, forward looking behavior, irreversibility of decisions and option values (De Pinto and Nelson, 2008; Marcos Martinez, 2013). In this paper, to control for several estimation bias sources (spatial error correlation, unobserved heterogeneity, cross-equation error correlation, and at some degree excess zero issues), we implemented seemingly unrelated panel data regressions with random effects and spatially correlated errors for aggregated data (Baltagi and Pirotte, 2011; Chakir and Le Gallo, 2013).

We explored patterns of land-use in Australia's intensive agricultural region related to four major groups of explanatory variables: temporally invariant characteristics of soil and topography; economic and institutional factors influenced by global and Australian markets and policy; climatic factors that vary systematically across space and randomly across time; and social variables that vary slowly over decades with demographic and social trends. We first assembled a dataset quantifying agricultural land-use allocations and twenty explanatory variables influencing land-use during the years 1992, 1993, 1996, 1998, 2000, 2001, 2005, and 2010. We then assessed the statistical significance and relative importance of those predictors by coupling a state-of-the-art spatial panel model with random effects with a variance decomposition analysis. Finally, we evaluated the ability to predict land-use allocations for 2010. The contributions of this paper are twofold. First, we provide empirical evidence on how spatiotemporal differences in Australian agricultural land allocations have been associated with fluctuations in relevant human and environmental land-use drivers. Second, we show that a systematic and comprehensive assessment of the statistical and relative importance of socioeconomic and biophysical land-use predictors can allow more efficient and targeted land-use policy at a national scale.

2. Methods

2.1. Land-use shares model

The land-use shares model is an approach to analyze landscape dynamics when household or parcel level data is not available (see Wu and Brorsen, 1995; Miller and Plantinga, 1999; Wu and Adams, 2002; Wu and Li, 2013 for a detailed description of the model). This model assumes that risk-neutral and forward-looking landowners distribute their land between alternative uses to maximize the expected payoff over a long time horizon (Chakir and Le Gallo, 2013; Plantinga, 1996). The aggregate outcomes of such farm-level decisions configure the landscape at higher spatial scales (e.g., counties, districts, states).

To analyze associations between changes in potential land-use drivers and aggregated land-use dynamics, the land-use shares model represents land allocated to land-use j, for $j \in J$, in region r, for $r = 1, \ldots, N$, at time t, for $t = 1, \ldots, T$, as a set of J land-use logistic share equations $s_{rjt} = \frac{\exp(\boldsymbol{\beta}_j \mathbf{X}_{rjt})}{\sum_{k=1}^{J} \exp(\boldsymbol{\beta}_k \mathbf{X}_{rkt})} + \varepsilon_{rjt} \forall j \wedge k \in J$, normalized with respect to a residual land category, s_{rlt}. In this equation, $\boldsymbol{X_{rjt}}$ is a vector of non-stochastic, region-specific (e.g., rainfall, temperature, elevation, soil type), and land-use specific variables (e.g., prices, costs) that impact the profitability of competing land-uses, $\boldsymbol{\beta_j}$ is a vector of unknown coefficients, and ε_{rjt} is an error term with zero-mean and finite variance that accounts for unobserved variables. For computational convenience, this model is transformed to a logarithmic specification, $y_{rjt} = \ln\left(s_{rjt}/s_{rlt}\right) = \left(\boldsymbol{\beta}_j - \boldsymbol{\beta}_l\right)\mathbf{X}_{rt} + u_{rjt}$, where u_{rjt} is the modified error term and $\boldsymbol{\beta}_l = 0$ for model identification—i.e., l is assumed as the baseline land-use. Under this transformation the change in y_j with respect to a marginal change in covariate z is dependent on the change in both s_j and the normalizing share s_l with respect to a marginal change in z.

Since the unobserved variables are expected to influence all land-use shares, cross-equation error correlation can reduce the efficiency of the parameter estimates (Srivastava and Dwivedi, 1979; Wu and Brorsen, 1995). To control for this, we jointly estimated the system of seemingly unrelated land-use share equations (Fiebig, 2001; Zellner, 1962). Furthermore, we addressed the challenge of inefficient parameter estimates and biased t-tests and goodness of fit arising when the unobserved variables are spatially correlated (Anselin and Rey, 1991) by implementing a spatial error model.

Following Chakir and Le Gallo (2013) and Miro and Piras (2012), we modelled the spatially autocorrelated disturbances as $\mathbf{u}_j = \left(\mathbf{I}_T \otimes \rho_j \mathbf{W}_j\right)\mathbf{u}_j + \boldsymbol{\omega}_j$, where $\boldsymbol{u_j}$ represents in vector form the unobserved variables influencing land-use j shares across all regions and periods, $\boldsymbol{I_T}$ is an identity matrix of dimension T, $\otimes$indicates the Kronecker product, $\boldsymbol{W_j}$ is a spatial weights matrix representing the connectivity of the N regions, ρ_j is the spatial autocorrelation coefficient, and $\boldsymbol{\omega}_j$ is a vector of non-spatially related disturbances.

Additionally, since data limitations hinder a complete assessment of the influence of inter-regional biophysical and socioeconomic differences on land-use dynamics, unobserved heterogeneity can also reduce the efficiency of the estimated parameters. Fixed or random effects could be used to account for unobserved regional differences and improve the efficiency of the parameter estimates (Hausman and Taylor, 1981). Nevertheless, a fixed effects approach would not allow the estimation of coefficients for relevant time-invariant factors such as soil characteristics. Overall, across all land-uses a spatial Hausman test failed to reject the null hypothesis of equal parameters in fixed and random effects regressions at the 5% significance level. Therefore, we estimated the idiosyncratic and region-specific components of $\boldsymbol{\omega}_j$ following a random effects approach. Under this procedure $\boldsymbol{\omega}_j = \left(\boldsymbol{\iota}_T \otimes \mathbf{I}_N\right)\boldsymbol{\mu}_j + \boldsymbol{\upsilon}_j$ where ι_T is a vector of ones of size T, $\boldsymbol{I_N}$ is an identity matrix of dimension N, and $\boldsymbol{\mu_j}, \boldsymbol{\upsilon_j}$ are vectors of random variables with zero means and covariance matrices $E\left(\boldsymbol{\mu}_j \boldsymbol{\mu}_l^{'}\right) = \sigma^2_{\mu_{jl}} \mathbf{I}_N$, $E\left(\boldsymbol{\upsilon}_j \boldsymbol{\upsilon}_l^{'}\right) = \sigma^2_{\upsilon_{jl}} \mathbf{I}_{TxN}$, and $E\left(\boldsymbol{\mu}_j \boldsymbol{\upsilon}_l^{'}\right) = E\left(\boldsymbol{\upsilon}_j \boldsymbol{\mu}_l^{'}\right) = 0$ (Chakir and Le Gallo, 2013).

The spatial weights matrix is one of the most important components of the spatial error model. Conceptually, its structure should approximate the strength of interacting biophysical, economic and social processes influencing land-use decisions across spatial units (Corrado and Fingleton, 2012). However, empirical