Global high-resolution land-use change projections: A Bayesian multinomial logit downsampling approach incorporating model uncertainty and spatial effects

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Abstract

Using econometric models to estimate land-use change has a long tradition in literature. Recent contributions show the importance of including spatial information and of using a multinomial framework to take into account the inter-dependencies between land-use classes. Few studies, however, agree on the relevant determinants of land-use change and there are no contributions so far comparing determinants on a global scale. Using multiple datasets of land-use change between 2000 and 2010 – standardized to 5 arc minute resolution – and taking into account the transitions between forest, cropland, grassland and all other land covers, we estimate a Bayesian multinomial logit model, using the efficient Pólya-Gamma sampling procedure introduced by Polson et al. (2013). To identify and measure the determinants of land-use change and the strength of spatial separation, our model implements Bayesian model selection through stochastic search variable selection (SSVS) priors and flexible spatial lags of the explanatory variables. In a second step, we combine our parameter estimates with aggregated satellite-based land-use change results from the partial equilibrium agricultural model GLOBIOM and project our model in ten-year intervals up to 2100 on a spatially explicit scale along multiple shared socio-economic pathways.

1. Introduction

Global agricultural models such as GLOBIOM are calibrated to provide realistic projections on country or above (regional) level, even if they include spatial dynamics at a finer resolution. This is due to computational and calibration constraints. There is a strong interest, however, in exploring and visualizing agricultural climate change projections at a considerably finer resolution (e.g. 5 arcminutes). These should be consistent with regional scale models. To obtain meaningful downscaled results at such a resolution, it is necessary to resort to a set of explanatory variables, which are easily available at the high resolution level and to relate these to observed land-use change. This paper puts forward a multinomial logit (MNL) model to estimate the contribution of variables and quantify the impact on land-use change – between the classes grassland, cropland, forest and other land – based upon multiple satellite-based land-use change maps.

2. A multinomial logit land-use change model

Consider J distinct land-use classes, with each land-use class denoted by \(\mathcal{J} = \{1, \ldots, J\}\). Our area of interest is divided into independent parcels \(i \in \mathcal{I}\), which are referred to as so-called simulation units (SimUs). Let us denote our main object of interest, the percentage of SimUs dedicated to land-use class \(j\) in a parish in a given time. – their impacts on land-use change – between the classes grassland, cropland, forest and other land – based upon multiple satellite-based land-use change maps.

3. Estimation and prior set-up

The Pólya-Gamma distribution Polson et al. (2013) can be used to sample directly from the MNL in Eq. (1). The main tactic employed is to introduce a Pólya-Gamma random variable into the joint distribution in such a fashion that the marginal resulting from the joint distribution leaves the original model in tact.

For this purpose the likelihood of all the coefficients of land-use class \(j\), \(\delta_j = \{\beta_j, \theta_j, \gamma_j\}\), can be written conditional on \(\delta_j\), where \(\delta_j\) denotes the \(2K + 1\) by \(J\) parameter matrix \(\delta_j\) without the \(J\)th column (Holmes and Held, 2012).

\[
L(\delta, \theta, \gamma, \beta, \sigma^2) = \prod_{i,s} \left( \int_{\mathbb{R}} e^{\phi_{i,s} \theta} \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{\phi_{i,s}^2}{2\sigma^2}} \right)^{y_{i,s} - 1} \frac{1}{\left(1 + e^{-\phi_{i,s} \gamma - \theta^T \delta_j + \beta}\right)}
\]

where \(\phi_{i,s} = \beta_j + \theta_j \sum_{k=1}^{2K} C_{i,k,s} \gamma_k + \sum_{l,j=1}^{J} L_{i,j} \delta_{j,l} / 2\). This gives the likelihood of the \(i\)th unit given the \(j\)th class.

Given the conditional likelihood Eq. (2), and an additional set of priors, we can easily formulate a Gibbs sampler for our model. The rest of our prior set up and the particular elicitation is as follows:

\[
\delta_j \sim N(\mu_j, \Sigma_j), \quad \mu_j \sim N(0, I), \quad \sigma^2 \sim IG(2, 1),
\]

where \(\Sigma_j\) is the covariance matrix of \(\delta_j\). We model the deterministic part of the land-use change: chiefly, while past values of land-use (and surrounding land-use) are undoubtedly important, other factors such as proximity to market seem to also play a central role in most regions. Second, we show the influence of spatial proximity per region on land-use change. Third, we demonstrate the applicability of our method by downsampling GLOBIOM land-use projections along multiple SSP scenarios.

5. Downscaling land-use projections

We use our coefficient estimates to downscale land-use change projections from GLOBIOM. The projections are available in ten-year time steps from 2000 until 2100 and along three Shared Socio-Economic Pathways (SSSP), which provide an exogenous framework for the agricultural model on socio-economic developments. SSP1 represents sustainable development, SSP2 is a middle of the road scenario, while SSP3 is characterized by continued divergence in economic growth. For the projections we use the posterior mean of \(\gamma_{ij}\) denoted as \(\gamma_{ij}\) from Eq. (1). To arrive at \(\gamma_{ij}\), we take the past observations on land-use and update the yield and population density variables and set \(\sigma^2\) so that the regional average composition of land-use change corresponds to GLOBIOM’s regional projections. As an example of our projections Fig. 1 show the differences in cropland for SSP1-3 in the period 2010-2100.

6. Concluding remarks

First, our results offer valuable insight into the dynamics of land-use change: chiefly, while past values of land-use (and surrounding land-use) are undoubtedly important, other factors such as proximity to market seem to also play a central role in most regions. Second, we show the influence of spatial proximity per region on land-use change. Third, we demonstrate the applicability of our method by downsampling GLOBIOM land-use projections along multiple SSP scenarios.

References

For a full list of references see online supplementary material. For the data used in this study please refer to the online supplementary material. For more information on the methods and implementation please refer to Table 2. Table 2 lists our explanatory variables.