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Integrating spatial and biomass planning for the United States

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ABSTRACT

Biomass is low-carbon energy and has tremendous potential as an alternative to fossil fuels. However, the significant role of biomass in future low-carbon energy portfolio depends heavily on its consumption. The paper presents a first attempt to examine the spatial-temporal patterns of biomass consumption in the United States (US), using a novel method-spatial Seemingly Unrelated Regression (SUR) model, in order to strengthen the link between energy planning and spatial planning. In order to obtain the robust parameters of spatial SUR models and estimate the parameters efficiently, an iterative maximum likelihood method, which takes full advantage of the stationary characteristic of maximum likelihood estimation, has been developed. The robust parameters of models can help draw a proper inference for biomass consumption. Then the spatial-temporal patterns of biomass consumption in the US at the state level are investigated using the spatial SUR models with the estimation method developed and data covering the period of 2000–2012. Results show that there are spatial dependences among biomass consumption. The presence of spatial dependence in biomass consumption has informative implications for making sustainable biomass polices. It suggests new efforts to adding a cross-state dimension to state-level energy policy and coordinating some elements of energy policy across states are still needed. In addition, results consistent with classic economic theory further proves the correctness of applying the spatial SUR models to investigate the spatial-temporal patterns of biomass consumption.

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1. Introduction

Rapidly growing concerns about the threat of global climate change caused by fossil fuel use and the national energy security have motivated the development of domestic renewable energy sources in the United States (US) [1]. Biomass is low-carbon energy and has tremendous potential as an alternative to fossil fuels. It is receiving increasing attention as scientists, policy makers, and growers search for clean, renewable energy alternatives [2]. Biomass has been identified as the single largest source of renewable energy in the US, accounting for half of all renewable energy consumption by 2009 and contributing about 4.1% of the total US energy consumption (which is about 100 EJ; Exajoule, 1 EJ $= 10^{18}$ J) [3]. In 2013, biomass accounted for about half of all renewable energy consumed and 5% of total US energy consumed. According to the proposal of the US Government Advanced Energy Initiative (AEI), 30% of 2005 petroleum use in the transportation sector is suggested being domestically generated from renewable bioethanol by 2030 [4]. In the western US, the region's energy policy is increasingly encouraging the use of biofuels from biomass [5]. Biomass is also widely used as renewable energy source in developing countries. According to the International Energy Agency (IEA) data in 2012, China has the productivity of about 5 billion tons per year for biomass.

The transition of fossil fuel-based energy to renewable energy has merited a lot of attention in recent years. Wang et al. [6,7] explore the contribution of energy crops, as alternative to conventional energy, to Great Britain (GB) electricity and heat demands by 2050, taking into account climate change. Nunes et al. [8] analyze the use of biomass as an energy alternative for the Portuguese textile dyeing industry from the political, economic, social and technological aspects. Safian [9] examines the sustainable energy planning in Hungary, in which renewable energy replaces fossil fuel to reduce the dependence on fossil fuel, from environmental point of view. The radical shift of energy provision towards the use of renewable energies, however, still needs new efforts and should take account of the spatial dimensions of renewable energies [10]. Effective spatial planning is crucial for cost-effective and sustainable development of biomass energy resources due to its diffuse nature.

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However, the link between spatial planning and renewable energy planning is still underdeveloped [10]. In order to implement the sustainable biomass energy systems, there is an emerging need to integrate biomass consumption into spatial planning.

The Seemingly Unrelated Regression (SUR) model is well-known in the econometric literature [11], and has been applied to agricultural economics [12], aquaculture economics [13], and forestry for modelling tree growth [14]; and recently to medical study [15]. It can explain the variation of a set of dependent variables in terms of the variation of general and specific independent variables and error terms specific to each individual, and can measure the temporal corrections across observations. The extensions to SUR model have been proposed to account for the spatial and temporal correlations across observations (i.e. spatial SUR model) [16,17], and have been used to estimate the vehicle crash rates in 169 cities in China over the period 1999–2002 [16]. In this paper, we present a first attempt to use the spatial SUR model as a framework to investigate the spatial-temporal patterns of biomass consumption in the US, with the aim to provide spatial-temporal information for interregional energy policy and thus for the sustainable biomass energy systems. The spatial SUR model is very well suited to such issues, because biomass consumption in neighboring areas tends to be spatially correlated [18] and biomass consumption in the same area tends to demonstrate the temporal correlation.

2. Materials and methods

The spatial-temporal patterns of biomass consumption in the US are examined using the spatial SUR model which is typically used to analyze a system of multiple equations with cross-equation parameter restrictions and correlated error terms. The SUR model was first suggested by Zellner [19] and was frequently used in economics to simultaneously estimate such things as investment functions, arbitrage asset pricing models, and demand equations of different economic units (e.g. firms and countries) for time series data. The SUR models have been recently extended to include spatial elements in the form of spatial lag [16] or autocorrelated disturbances [17] or both [16] (hereafter called spatial SUR models). In contrast, relatively small efforts have been put to develop the estimation methods of spatial SUR model. Because the spatial SUR models are good at analyzing the spatial dependence over time, it is important to investigate the estimation method for spatial SUR model. We present an iterative Maximum Likelihood (ML) estimation method to estimate the parameters of spatial SUR models.

2.1. General spatial SUR model

Consider the set of $N \times T$ equations:

$$y_{it} = X_{it}\beta_t + \varepsilon_{it} \tag{1}$$

where i is region ($i = 1, \ldots, N$) and t is time ($t = 1, \ldots, T$). N is the total number of regions and T is the total time. y_{it} is the dependent variable at time t and region i. $\boldsymbol{X}_{it}$ is a $1 \times K_t$ vector of explanatory variables and β_t is the $K_t \times 1$ coefficients vector associating with $\boldsymbol{X}_{it}$. K_t is the number of explanatory variables for each time period t. ε_{it} is the error term.

The above equation can be in stacked form as

$$y_t = X_t\beta_t + \varepsilon_t \tag{2}$$

where $y_t = \begin{pmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{Nt} \end{pmatrix}$, $X_t = \begin{pmatrix} X_{1t} \\ X_{2t} \\ \vdots \\ X_{Nt} \end{pmatrix}$ and $\varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{Nt} \end{pmatrix}$.

The general spatial SUR model, which includes both spatial lag and autocorrelated disturbances, can be expressed as

$$\begin{aligned} y_t &= X_t\beta_t + \gamma_t W_1 y_t + \varepsilon_t \\ \varepsilon_t &= \lambda_t W_2 \varepsilon_t + \mu_t \end{aligned} \tag{3}$$

where $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$ are standardized spatial weight matrices ($N \times N$), corresponding to the spatially lagged dependent variable and the disturbance, respectively. $\mu_t \sim N(0, \sigma_{tt}^2 I_N)$ and $E(\mu_t \cdot \mu_s') = \sigma_{ts}^2 I_N$. $\boldsymbol{I_N}$ is a $N \times N$ identity matrix.

The system can be further rewritten in stacked form as

$$\begin{aligned} y &= X\beta + \gamma W_1 y + \varepsilon \\ \varepsilon &= \lambda W_2 \varepsilon + \mu \end{aligned}$$

or

$$B(Ay - X\beta) = \mu \tag{4}$$

where $\boldsymbol{X} = \mathrm{diag}(\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_T)$, $\gamma = \mathrm{diag}(\gamma_1, \ldots, \gamma_T)$, $\lambda = \mathrm{diag}(\lambda_1, \ldots, \lambda_T)$, $\boldsymbol{A} = \mathrm{diag}(\boldsymbol{A}_1, \boldsymbol{A}_2, \ldots, \boldsymbol{A}_T)$ with $A_t = I - \gamma_t W_1$, and $\boldsymbol{B} = \mathrm{diag}(\boldsymbol{B}_1, \boldsymbol{B}_2, \ldots, \boldsymbol{B}_T)$ with $B_t = I - \lambda_t W_2$. γ reflects the direct spatial dependence among dependent variables and λ indicates the indirect spatial dependence among dependent variables. $\mu \sim N(0, \Omega)$ with $\Omega = E(\mu \cdot \mu') = \Sigma \otimes I_N$, $\otimes$ is the Kronecker product, and $\Sigma = \begin{pmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \cdots & \sigma_{1T}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 & \cdots & \sigma_{2T}^2 \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_{T1}^2 & \sigma_{T2}^2 & \cdots & \sigma_{TT}^2 \end{pmatrix}$.

A family of spatial SUR results when the subvectors of unknown parameters vector $\theta = [\gamma, \beta', \lambda, \boldsymbol{\Sigma}]$ are set to be zero. For example, if the vector $\gamma = 0$, the model specifications become the spatial SUR with spatially autocorrelated disturbance, while the model specifications are the spatial SUR with spatially autocorrelated dependent variables, if the vector $\lambda = 0$.

2.2. Spatial SUR estimation

As the error covariance matrix Ω is diagonal, a vector of homoskedastic random disturbances v following the standard normal and independent distributions can be found as

$$v = \Omega^{-\frac{1}{2}} \mu$$

where $\Omega^{-1/2}$ is the inverse of square root of matrix Ω. Hence Equation (4) becomes

$$\Omega^{-\frac{1}{2}}.B.(Ay - X\beta) = v \tag{5}$$

The Jacobian for the transformation from the vector of random variable v into the vector of random variables y is

$$J = \det(\partial v/\partial y) = \left|\Omega^{-\frac{1}{2}}\right|.\left|B\right|.\left|A\right| = \left|\Sigma\right|^{-N/2}.\left|B\right|.\left|A\right| \tag{6}$$

Therefore, the log-likelihood function for the joint vector of observations y is obtained as

$$L = -(NT/2).\ln(2\pi) - (N/2).\ln|\Sigma| + \ln|B| + \ln|A| - (1/2)v'v \tag{7}$$

with $v'v = (Ay - X\beta)'B'\Omega^{-1}B.(Ay - X\beta)$

The log-likelihood function contains a quadratic form in the disturbance v, which results in a well-behaved optimization problem. If the variance-covariance matrix for y is positively defined, the general asymptotic properties for the ML estimators will hold. In order to maintain the positive variance-covariance

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