INTRODUCTION

The economic accessibility of biomass resources is a key attribute in the potential viability of a bioenergy or bioproducts industry. One aspect of the economic accessibility of biomass energy crops is landowners’ willingness to supply biomass, which is usually measured by landowners’ private reservation price (RP) (Mooney, Barham, & Lian, 2015). RP can be defined as the feedstock price at which landowners become willing to supply a bioenergy crop, which can be influenced by a range of factors including potential yields (i.e., tons per hectare) of biomass crops, agronomic costs needed to produce biomass, and opportunity costs of the land-use change (i.e., the potential profitability of alternative land uses).

The significance of RP is well recognized in the literature. Mooney et al. (2015) find the median RP for corn stover ranging from $116 to $590 per dry ton and the median RP for switchgrass (Panicum virgatum) ranged from $135 to $228 per dry ton in Wisconsin. Jiang, Zipp, et al. (2018) assess
landowners’ willingness to supply bioenergy crops on marginal lands in the northeastern United States. Results suggest that RP is likely to be lower on economically marginal lands with mean prices from $168 to $229 per dry ton. Qualls et al. (2012) assess factors influencing RP among producers in the southeast United States. They predict RPs of $44 to $132 per dry ton for switchgrass. On nonindustrial private forestlands in the southern United States, factors such as tract size, tree diameter class, demographic factors, and forest management objectives were all significant in determining RP, with large tracts of small-diameter trees managed for timber production expressing lowest RP (Shivan & Sayeed, 2012).

There is a growing interest in determining the spatial dependence of RP for bioenergy crops with recognition of the need to identify spatial agglomerations where landowners are more willing to grow bioenergy crops (Skevas, Skevas, & Swinton, 2018; Swinton, Tanner, Barham, Mooney, & Skevas, 2017). This paper fills this gap in the literature by making three contributions—(a) building a comprehensive spatial dataset of landowners’ preferences; (b) comparing estimates of landowners’ willingness to plant bioenergy crops under a naïve model ignoring spatial dependence and a spatial model that incorporates spatial dependence; and (c) identifying economic hotspots (i.e., locations where RP is low and potential supply is high) for bioenergy producer investment including landowners’ willingness to supply bioenergy crops through estimates of potential production derived from a partial equilibrium model simulating agricultural land use in the United States.

This analysis is executed in three stages (see Figure S1 in the Appendix for a summary of work flow). First, we create a novel dataset linking spatial information with microsurvey data of landowners in Ohio, Pennsylvania, and New York. Second, we elucidate the effect of spatial dependence on RP for bioenergy crops in the northeastern United States. Spatial dependence is defined by Legendre, & Legendre (2012) as “the property of random variables taking values, at pairs of locations a certain distance apart, that are more similar (positive autocorrelation) or less similar (negative autocorrelation) than expected for randomly associated pairs of observations.” In other words, nearby decision-making landowners may exhibit interdependent decision-making processes that affect their resource allocation behavior and economic performance. Third, we apply Bayesian spatial probit models coupled with results from the Policy Analysis System (POLYSYS) model to identify one economic hotspot for each energy crop, which might be potential sites for establishing bioenergy plants.

Spatial dependence is important in the context of biomass economic accessibility for several reasons (Skevas et al., 2018). First, marginal lands for bioenergy crops could be spatially associated with land that has impediments to productive crop farming, which may cause the spatial clustering of biomass production (Mooney et al., 2015). Another reason is the learning and reciprocity that might develop around a new crop as distinctive as bioenergy crop from conventional farming. Because cellulosic bioenergy crops are not expansively produced, landowners are generally unfamiliar with these crops’ production operations. Thus, they potentially tend to learn technical information from neighboring early adopters. Our results indicate that the spatial RP decreases significantly compared to nonspatial RP, implying that energy crops’ spillover effects will influence landowner’s willingness to supply these bioenergy feedstocks.

2 | STUDY AREA, DATA SOURCES, AND SURVEY DESIGN

2.1 | Study site

Our study site includes three areas: (a) Biomass Crop Assistance Program (BCAP) area, BCAP5, which includes three counties in Pennsylvania (PA) and four counties in Ohio (OH) and currently supports the production of the perennial grasses switchgrass (P. virgatum) and (Miscanthus x giganteus); (b) BCAP10, which includes four counties in New York (NY) and currently supports the production of shrub willow (Salix sp.); and (c) one area in southern NY, which includes three counties with several switchgrass production plots (Figure 1). This region is attractive for perennial-based bioenergy crops for three reasons: (a) there are three local bioenergy crop companies and nine other pellet plants (see Figure 1) that have planted bioenergy crops on over 3,600 ha across OH, PA, and NY; (b) the BCAP program provides financial support to landowners to plant bioenergy crops (Becker, Larson, & Lowell, 2009; Jiang et al., 2019); and (c) this region is also geographically suitable for bioenergy crop growth. For more information about our study sites, see Jiang, Zipp, et al. (2018).

2.2 | Data

We constructed a novel spatial microsurvey dataset, which linked biophysical land information to socioeconomic information for each landowner. We selected landowners with at least 4 ha of suitable and continuous land by overlaying the 30 m resolution National Land Cover Dataset (NLCD) with the Digital Elevation Models (DEM), National Hydrography Dataset (NHD), and the county tax assessment layer to identify

1 The BCAP program was created by the 2008 Farm Bill and renewed by the 2014 Farm Bill to improve domestic energy security by reducing reliance on foreign oil and also to reduce carbon pollution and provide rural development opportunities (Capehart, 2016, Mcminimy, 2015).

2 Ernst Conservation Seeds (switchgrass grower and pellet maker), Aloaterra (miscanthus grower and processor), and Celtic Energy (shrub willow grower) (Harlow & Ernst, 2016).

3 A type of mill or machine press used to create pellets from powdered biomass.
ownership of the candidate plots. We selected pasture, shrub/scrub, grassland, and cropland land cover types (Homer et al., 2015), and removed parcels that contained wetlands or water bodies and that had a slope greater than 8% (Castellano, Volk, and Herrington, 2009). This yielded 60,000 qualified landowners over 530,000 ha of suitable land from which we drew a random sample of 3,000 landowners (Jiang, Zipp, et al., 2018).

2.3 Survey design

We used a mixed mail and Internet questionnaire to collect our survey data. The survey questions were grouped into four parts: (a) landowners’ land management and land uses; (b) statements related to landowners’ concerns over and general attitude toward bioenergy (Skevas, Hayden, Swinton, & Lupi, 2016); (c) landowners’ willingness to supply energy crops at hypothetical prices of $44, $77, $110, and $165 per dry metric ton; and (d) demographic information on age, education, gender, and income (see Jiang, Zipp, et al. (2018) for further survey details). The survey response rate was acceptable at 32.5% (Alexander et al., 2014).

3 ECONOMETRIC MODEL AND ECONOMIC HOTSPOT ANALYSIS

3.1 Econometric model

Following Jiang, Jacobson, and Langholtz (2018) and Jiang, Zipp, et al. (2018), landowners are assumed to maximize utility or well-being. Respondent n will agree to grow bioenergy crops if this decision makes them better off. Allowing for spatial dependence, utility can be written as follows:

\[ y^* = \rho \bar{y}^* + X\beta + \epsilon, \quad \epsilon \sim N(0, \sigma^2 I_n) \]  

\[ y^* = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} \epsilon \]  

\[ y_n = \begin{cases} 1 & \text{if } y^*_n \geq 0 \\ 0 & \text{if } y^*_n < 0 \end{cases} \]

We do not observe landowner utility, \( y^* = (y^*_1, \ldots, y^*_n)' \), but we observe whether or not the landowner agrees to grow bioenergy crops, \( y_n = 1 \), only if they are better off doing so and we estimate the probability that landowners agree to grow bioenergy crops as a function of dependent variables, \( \Pr\{y_n = 1\} = \Pr\{y^*_n \geq 0\} \). The independent variables include a matrix of covariates \( X (n \times k) \) associated with the parameter vector \( \beta (k \times 1) \) (see Table S1 in the Appendix for variable description) and a spatial weight matrix, \( W (n \times n) \), that captures the dependence structure between neighboring observations. We apply an inverse-distance weights matrix with nonzero elements \( w_{ij} < 1/d_{ij}^2 \) if \( d_{ij} < 100 \) miles. Therefore, we have nonzero elements in the spatial weight matrix for all neighbors within 100 miles of each other. We believe 100 miles\(^4\) represents a reasonable distance for the neighbor relationship within our study area. \( \rho \) is the spatial autoregressive parameter. \( \sigma^2 \) is assumed to be 1. The \( k + 1 \) model parameters to be estimated are the vector \( \beta \) and the scalar \( \rho \).

\(^4\)We tried distances of 25, 50, 75, 125, and 150 miles, and the results were robust to this specification.
We chose the Bayesian methodology to estimate our spatial probit model, which has been proven to be an effective estimation method (LeSage, Kelley Pace, & Pace, 2009). The basic idea in Bayesian estimation is to sample from a posterior distribution of the model parameters \( p(\mathbf{y}^*, \mathbf{\beta}, \rho | \mathbf{y}) \) given the data \( \mathbf{y} \) and some prior expected densities of the data and parameters, \( p(\mathbf{y}^*) \cdot p(\mathbf{\beta}) \) and \( p(\rho) \). This sampling for the posterior distribution \( p(\mathbf{y}^*, \mathbf{\beta}, \rho | \mathbf{y}) \) can be realized by a Markov Chain Monte Carlo and Gibbs sampling scheme, where we sample from the following three conditional densities \( p(\mathbf{y}^* | \mathbf{\beta}, \rho, \mathbf{y}), p(\mathbf{\beta} | \mathbf{y}^*, \rho), \) and \( p(\rho | \mathbf{y}^*, \mathbf{y}) \).

Marginal impacts of an explanatory variable, \( x_r \), on the expected dependent variable, \( \mathbb{E}[y_n|x_r] \) in a spatial probit model are:

\[
\frac{\partial \mathbb{E}[y_n|x_r]}{\partial x_r} = \varphi (S^{-1}I_n \hat{\mathbf{x}}_r \mathbf{\beta}_r) OS^{-1}I_n \mathbf{\beta}_r \tag{4}
\]

where \( S = I_n - \rho \mathbf{W} \), \( \hat{x}_r \) is the \( r \)th explanatory variable, \( \mathbb{E}(\cdot) \) is its mean, \( \mathbf{\beta}_r \) is the probit estimate, and \( \varphi(\cdot) \) is the standard normal density. Estimates for three effects can be derived from the marginal impact equation: (a) direct, (b) indirect, and (c) total effects. The direct effect of changing an explanatory variable for a particular landowner on the dependent variable for that landowner is represented by the main diagonal elements of Equation 4. A total effect of how a change in an explanatory variable impacts the probability of all landowners in the sample to supply bioenergy crops is the average of the row sums of Equation 4 (Loomis & Mueller, 2013). The indirect effect measures the impact of changing a particular element of an explanatory variable on the dependent variable of all other landowners (Elhorst, 2014), which is the difference between total impact and the direct impacts.

The RP can be calculated from the spatial probit model for all the explanatory variables as

\[
RP = - \left( (T_1 * \hat{X}_1) \ (T_2 * \hat{X}_2) + \cdots + (T_{k-1} * \hat{X}_{k-1}) \right) \ / \mathbf{\beta}_{\text{bid}} \tag{5}
\]

where \( T_k \) is the total impact calculated from Equation 4 and \( \mathbf{\beta}_{\text{bid}} \) is the estimated coefficient on the prices offered to landowners for each bioenergy crop (Loomis & Mueller, 2013). The RP equation implies that a change in the value of an explanatory variable for one landowner will have an impact on that landowner and their neighbors. In addition, the change in the value of the neighbors will have a feedback effect on the landowner. This is because the total impacts are a function of the spatial weight matrix and the estimated spatial autoregressive parameter. We consider these feedback or spatial spillover effects from the spatial probit in our RP estimates by using total impacts to obtain RP. All these statistical analyses were performed in R software mainly with spatial probit packages (Wilhelm & de Matos, 2013).

### 3.2 Economic hotspot analysis

We define economic hotspots as areas where RPs are low and potential supply is high. To explore the presence of economic hotspots, we first estimate the Getis–Ord \( G^*_i \) statistic (Getis & Ord, 1992; Ord & Getis, 1995). The statistic is calculated as:

\[
G^*_i = \frac{\sum_{j=1}^n w_{ij} c_j - \bar{C} \sum_{j=1}^n w_{ij}}{S \sqrt{\frac{N}{N-1} \sum_{j=1}^n (w_{ij})^2}} \tag{6}
\]

Within Equation 6, \( c_j \) is the attribute value for observation \( j \), \( w_{ij} \) is the spatial weight between observation \( i \) and \( j \), \( N \) is the total number of sample size, and

\[
\bar{C} = \frac{\sum_{j=1}^n c_j}{N} \tag{7}
\]

\[
S = \sqrt{\frac{N}{N-1} \sum_{j=1}^n (c_j)^2} - \left( \bar{C} \right)^2 \tag{8}
\]

Equation 6 compares, proportionally, the local sum of an attribute value (e.g., a RP estimate) for a spatially located observation (e.g., landowners) and its neighbors to the sum of all attribute values in the data. That is, it identifies clusters of observations whose values are atypically high or low compared to the entire sample. The resulting \( G^*_i \) score is \( z \) distribution (standard normal), with a high positive or negative value, implying that the local attribute sum is very different from the expected value of local sum, based on all the feature values in the data. The hypothesis test identifies high (low) value observations surrounded by other high (low) value observations, where the difference between values observed for these identified clusters and those for the surrounding observations is too great to be the result of random chance, with a specific statistical significance level (e.g., \( \rho < 0.05 \)). These are defined as statistically significant hot (cold) spots (Getis & Ord, 1992).

In addition, we also examine the potential supply for each county for each bioenergy crop. “Potential supply” in this context means the supply potentially available under the technical (e.g., land limitations) and economic (e.g., costs of production, prices, and competing demands) constraints as specified in the 2016 Billion-Ton Report (Langholtz, Stokes, & Eaton, 2016). We use POLYSYS, a policy simulation model of the US agricultural sector (De La Torre Ugarte & Ray, 2000), to get the potential supply for each bioenergy crop. The POLYSYS modeling framework is a linear program that can simulate changes in agricultural markets and production systems and estimates the
impacts to the US agricultural sector from these changes. POLYSYS is used to estimate how growers may respond to market signals, such as new demand for biomass, while simultaneously considering the impact on other non-energy crops. POLYSYS was used to quantify potential biomass resources in the 2016 Billion-Ton Report and has been used in other agricultural and biofuels analyses (De La Torre Ugarte & Ray, 2000; Hellwinckel, Clark, Langholtz, & Eaton, 2016; Langholtz, Eaton, Turhollow, & Hilliard, 2014; Langholtz et al., 2012).

POLYSYS solves for the most profitable mix of land-use alternatives on agricultural lands from the growers’ perspective. POLYSYS calculates the net present value (NPV) of agricultural alternatives over a 20 year planning horizon and selects the most profitable mix of production alternatives. For this study, POLYSYS was run from 2017 to 2040, solving crop areas and supply at the county level. The bioenergy crops were modeled for the mean RP in a county.

4 | RESULTS AND DISCUSSION

4.1 | Model estimation result

A description of the variables used in assessing the landowners’ willingness to supply bioenergy crops can be found in Table S1 in the Appendix. The estimation results are presented in Table 1. We found that spatial effects are statistically significant for switchgrass at the 10%

|                | Switchgrass | Miscanthus | Willow |
|----------------|-------------|------------|--------|
| (Intercept)    | -1.7280***  | -1.8300*** | -1.0558*** |
|                | (0.2112)a   | (0.2210)   | (0.2331) |
| Age            | -0.0056*    | -0.0032    | -0.0194*** |
|                | (0.0025)    | (0.0029)   | (0.0031) |
| Land size (ha) | 0.0001      | 0.0000     | -0.0003† |
|                | (0.0001)    | (0.0001)   | (0.0001) |
| Agricultural income | -0.0030    | -0.0026    | -0.0051* |
|                | (0.0017)    | (0.0020)   | (0.0026) |
| Marginal land percentage | 0.0080*** | 0.0062**  | 0.0082** |
|                | (0.0022)    | (0.0022)   | (0.0025) |
| Bid price      | 0.0138***   | 0.0112***  | 0.0115*** |
|                | (0.0007)    | (0.0008)   | (0.0009) |
| Distance to pellet facility | -0.0092*** | -0.0095*** | -0.0057* |
|                | (0.0024)    | (0.0028)   | (0.0028) |
| Education: high school | -0.2527**  | -0.339***  | -0.4712*** |
|                | (0.089)     | (0.0962)   | (0.1106) |
| Education: postgraduate | 0.1868†     | 0.3900*** | 0.3215** |
|                | (0.1003)    | (0.1050)   | (0.1073) |
| Education: less high school | -0.3843*    | -0.4060*  | -0.7440*** |
|                | (0.1593)    | (0.1930)   | (0.2170) |
| Education: vocational school | -0.1980*    | -0.2130*  | -0.3480** |
|                | (0.0898)    | (0.0965)   | (0.1110) |
| Knowledge about crop | 0.1481***  | 0.1220*    | 0.1420*  |
|                | (0.0417)    | (0.0524)   | (0.0558) |
| ρ              | 0.1242†     | -0.0227    | 0.0070 |
|                | (0.0699)    | (0.0679)   | (0.0633) |
| Mean RP ($/dt) | 120.06      | 176.75     | 118.55 |
| Confidence interval–lower | 113.42     | 158.49     | 114.02 |
| Confidence interval–upper | 126.70     | 195.03     | 119.70 |

Abbreviation: RP, reservation price.
***p < 0.001; **p < 0.01; *p < 0.05; †p < 0.1.

aStandard deviation in the bracket.

TABLE 1 Statistical analysis of determinants of landowners’ willingness to supply bioenergy crops
significance level (as measured by the parameter $\rho$) but not for Miscanthus and willow. A possible explanation for the insignificant spatial effects for Miscanthus and willow is that these crops are relatively new to landowners (Jiang, Zipp, et al., 2018). Even by watching neighboring early adopters and innovators, risk-averse landowners may still hesitate to grow Miscanthus and willow. The marginal land percentage has a positive influence on landowners’ decisions, implying that landowners who own marginal lands are more likely to grow bioenergy crops (Jiang, Zipp, et al., 2018). This also implies that land productivity influences landowners’ decision on bioenergy crop supply. Price has a positive effect on landowners’ willingness to supply, which is consistent with economic theory of supply (Altman, Bergtold, Sanders, & Johnson, 2015). The awareness or prior knowledge of the crop’s potential also improves landowners’ willingness to supply bioenergy crops. Age and education have a statistically significant effect on landowners’ willingness to supply, but not for all three bioenergy crops. Age does not significantly influence the Miscanthus supply decision but does negatively influence switchgrass and willow supply decisions, which is consistent with the result of Joshi and Mehmood (2011), implying that older farmers may have less time to learn (and reap) the benefits of a new crop; hence, they may also be less willing to adopt a new crop (Tyndall, Berg, & Colletti, 2011). Education has a strong impact on the landowners’ willingness—people who have a college degree are more likely to supply compared to landowners who have a high school degree or less, which is consistent with the literature on the adoption of new agricultural technology (Fu & Liu, 2017; Fu et al., 2018; Jensen et al., 2007; Mooney et al., 2015). We also noticed that an increase in the distance to the nearest pellet facility negatively influences landowners’ decisions to grow bioenergy crops. This is because long transportation distance may increase the marginal delivered cost of bioenergy crops and thereby influence landowner’s willingness to grow these crops (Volk et al., 2006). The reason for including the distance to pellet plants instead of other plants (such as an ethanol plant or a cellulosic biofuel plant) is that pellet plants have been widely established in the study area.

### 4.2 Reservation price results and implication

The reservation prices vary among the three bioenergy crops. Miscanthus has the highest average RP, $176 per dry metric ton (dt), and switchgrass and willow have almost the same RPs, $113/dt and $114/dt (Table 1). Compared to the RP without the spatial consideration (switchgrass $168/dt, Miscanthus $190/dt, and willow $229/dt (Jiang, Zipp, et al., 2018), the mean RP decreases $54/dt for switchgrass, $14/dt for Miscanthus, and $116/dt for willow. This finding is consistent with Loomis and Mueller (2013) who find a 50% difference between RP estimated from a standard probit versus a spatial probit model. The decreased RP values are probably driven by impact of the established pellet market on the willingness to supply these specific crops. Currently, several pellet plants have been established in the study areas (Figure 1). These plants have a strong demand for more than 500 thousand tons for grass pellets and hardwood pellets every year (NREL, 2018). This huge and stable demand makes landowners recognize the potential market for bioenergy crops and may lower their reservation prices. The largest reduction in RP is for willow. This possibly attributes to the woody biomass being widely used by pellet plants. Currently, over 90% of established pellet plants use hardwood/softwood (NREL, 2018). As a fast-growing hardwood (3 year rotation), willow is responsive to market demand.

Although the pellet plants have been located in the study areas for several years, there are no cellulosic biofuel plants using bioenergy crops in our study region. A couple of reasons may explain the absence. First, there is a price gap currently existing between the cellulosic biofuel producer and feedstock growers. Several studies reported that biofuel producers are only willing to pay $27–$55/ton to feedstock producers because, at this price range, cellulosic ethanol generated from these crops is competitive with petroleum-based gasoline when oil prices are near $55–$70 per barrel (Volk et al., 2006). Given the current volatile oil price of around $70/barrel (EIA, 2018), biofuel producers’ willingness to pay price will be around $55/ton, which is far lower than the RPs for feedstock growers. Second, compared to pellet facilities, biofuel plants require a larger investment both in capital and in labor and time. This is because converting bioenergy crops to cellulosic ethanol usually requires at least two basic steps: pretreatment and fermentation (Li & Henkelman, 2017; Mohapatra, Mishra, Behera, & Thatai, 2017). This two-step process increases the complexity of, and processing time required for, converting the cellulosic biomass into ethanol. Therefore, it will cause the cost of generation cellulosic biofuel to be much larger compared to pellets. Therefore, profit-oriented producers may find it difficult to make a financial investment in a new practice when there is a price gap and unstable supply. But, in terms of feedstock costs, bioenergy crop-based cellulosic ethanol is competitive with corn-based ethanol after accounting for the spatial effect. If we assume that 1 ton of cellulosic feedstock yields about 66 gallons of ethanol (National Research Council, 2008), then the feedstock cost for using Miscanthus ($176/dt) to produce ethanol is $2.66/gallon and using switchgrass ($113/dt) and willow ($114/dt) is $1.71/gallon. For comparison, corn-based ethanol costs around $1.30/gallon, given the corn price of $3.66/bushel and the conversion rate of 2.8 gallon/bushel (National Research Council, 2008). This finding implies that for feedstock growers to grow bioenergy crops, they require a price competitive...
with conventional food crops, as they need to compete with corn for the limited resources such as land, water, and labor. In addition, this finding reveals the land cover may also be another factor influencing landowners’ willingness to supply these energy crops.

The direct effects (Figure 2) reflect how changes in explanatory variables affect landowners’ own decisions to supply land for bioenergy crops, while the indirect effects (Figure 3) show how changes in explanatory variables affect other landowner’s decisions to supply land for bioenergy crops. The cumulative effect of these two impacts is the total effect (Figure 4), which reflects the effect on all landowners in the sample. The positive values in these figures indicate a positive effect on willingness to supply,
while negative values imply a negative effect on willingness to supply. Variables with confidence intervals containing zeros do not statistically significantly influence landowner’s decision. For direct effect (Figure 2) and total effect (Figure 4), the significance of the marginal effects is consistent with the significance estimated in the model (Table 1). For indirect effect (Figure 3), most variables are not statistically significant except education’s effect for switchgrass. We found that education (vocational school, less than high school, and high school) negatively influences other landowners’ willingness to supply switchgrass. This suggests that landowners might be sharing knowledge and learning about switchgrass with their neighbors, which has the potential to increase adoption of this crops.

4.3 | Identifying possible economic hotspots

To test for the possibility of economic hotspots, the Getis–Ord $G^*_i$ statistic is applied to individual-specific RP for each bioenergy crop, with sampled landowners as the spatial units of observation. For ease of interpretation, the maps (Figure 5a–c) illustrate the statistical significance (10%, 5%, and 1%) of a $z$ score for each spatial unit. The default is a $|Z| < 1.65$, a statistically insignificant result. The red and blue dots (Figure 5a–c) are: (a) those for which $1.65 < Z < 1.96$, $1.96 < Z < 2.58$, and $Z > 2.58$, indicating a hotspot at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively, and (b) those with parallel negative $z$ scores, indicating a cold spot at identical levels of significance. Hotspots represent clusters of atypically high RP estimates; cold spots represent clusters of atypically low RP estimates. The cold spots layers were overlaid onto supply layers constructed from the POLYSYS model to identify regions with both strong socioeconomic willingness to supply and strong supply potential, which were identified as economic hotspots.

The most extensive spatial clustering of RPs estimates is found for switchgrass. A large economic hotspot is identified in eastern BCAP5 area (the blue circle in Figure 5a). In this region, there is a low RP from landowners but a strong supply potential, especially for Mercer and Crawford counties in PA. The average production capacity reaches to over 5,625 dry tons per year from year 2019 to 2029 in this region under the $120/dt price scenario (Langholtz et al., 2016). These findings indicate that eastern BCAP5 region has the potential to be the next bioenergy production site. This potential site may directly link to the pellet plant located in Meadville, PA. This plant currently uses switchgrass as a raw material to generate pellets, with an annual capacity of 22,679 dry tons (NREL, 2018). This existing pellet plant implies that the outlet of switchgrass has been established, which therefore lowers landowners’ RPs. Also, at the $120/dt price scenario, growing switchgrass is competitive with other field crops, and that is why POLYSYS highlights this region with strong supply potential.

For Miscanthus, the economic hotspot is also in eastern BCAP5, but not in an extensive pattern. Compared to switchgrass, Miscanthus productivity is about twice as high (Heaton, Voigt, & Long, 2006) and we estimate, for the same region, Miscanthus supply is much higher than switchgrass, about 27,000 dt/year. However, landowners’ RP is not clustered intensively compared to switchgrass. Part of the reason...
**FIGURE 5**  (a) Switchgrass economic hotspot analysis. Yellow stars represent pellet plants currently located within or near study sites. Star size varies based on pellet plant annual production capacity. Cold spots (blue dots) represent the clustering of low RP, while hotspots (red dots) mean the clustering of high reservation price (RP). The circle size and color vary based on confidence level. The supply is the result from Policy Analysis System (POLYSYS), which is the mean value from year 2019 to 2029 for switchgrass. The blue circle is the economic hotspot, representing the region with low RP and high supply. (b) Miscanthus economic hotspot analysis. Yellow stars represent pellet plants currently located within or near study sites. Star size varies based on pellet plant annual production capacity. Cold spots (blue dots) represent the clustering of low RP, while hotspots (red dots) mean the clustering of high RP. The circle size and color vary based on confidence level. The supply is the result from POLYSYS, which is the mean value from year 2019 to 2029 Miscanthus. The blue circle is the economic hotspot, representing the region with low RP and high supply. (c) Willow economic hotspot analysis. Yellow stars represent pellet plants currently located within or near study sites. Star size varies based on pellet plant annual production capacity. Cold spots (blue dots) represent the clustering of low RP, while hotspots (red dots) mean the clustering of high RP. The circle size and color vary based on confidence level. The supply is the result from POLYSYS, which is the mean value from year 2019 to 2040 for willow. The blue circle is the economic hotspot, representing the region with low RP and high supply.
is that currently there is no pellet plant that directly uses Miscanthus and landowners may have concern about the demand for Miscanthus. Another reason might attribute to the landowners’ unfamiliarity with this crop. Unlike switchgrass, Miscanthus is not native in the United States and it only became of interest for energy since 2004 (Elbheri, Coyle, Dohlmam, & Kmak, 2008). Therefore, risk-averse landowners may have concern over its production cost and thus require higher RPs. Similar but less extensive patterns are found for willow in the middle of southern NY and the southern area of BCAP10 (Figure 5c), while southern BCAP10 looks more promising due to the high supply potential. The pellet plant located in southern BCAP10 currently uses hardwood to produce pellets, with an annual capacity of 70,000 dry tons. Landowners from this region are also more likely to supply willow.

The identification of economic hotspots is helpful for policymakers and biofuel producers to locate potential sites for a cellulosic biofuel plant or biopower plant that capitalizes on the agglomeration benefits. Choosing a site located within the blue circle can expect a high willingness to supply from landowners and a strong supply potential. POLYSYS results suggest a high potential supply (economic hotspots) of switchgrass and Miscanthus in Mercer and Crawford counties in PA (Figure 5a,b) and willow in Oneida county in NY (Figure 5c).

5 CONCLUSION

This paper examines the spatial dependence effect of landowners to supply three bioenergy crops, switchgrass, Miscanthus, and willow, and identifies economic hotspots for each crop, which might be used to identify potential sites to build up bioenergy supply chains. Our study compiles a novel dataset by linking spatial information with our micro-survey data to assess the pellet location effect on landowners’ willingness to supply bioenergy crops. In addition, we apply spatial probit models to examine the spatial dependence effect for each bioenergy crop. We observe that landowners’ spatial dependence is only significant for switchgrass, but not for Miscanthus and willow. These results indicate that educating a small group of landowners might be also effective in promoting the supply of switchgrass because neighbors can influence landowners’ decisions.

In addition, we find that the spatial RP decreased compared to the nonspatial RP. By allowing for spatial dependence, bioenergy crop-based ethanol becomes competitive with corn-based ethanol in terms of feedstock cost, implying that the existing pellet plant market has a positive effect on landowners’ willingness to grow bioenergy crops. However, we also notice that the reduced RP is still higher compared to biofuel producers’ willingness to pay price and much higher than the break-even price for each crop (Abrahamson, Volk, Smart, & Cameron, 2010; Jacobson & Helsel, 2014).

Finally, we identify an economic hotspot for each crop. These spots were identified with considerations on landowners’ RP and supply potential. Economic hotspots represent areas where RP is expected to be low and potential supply is high, which might be a potential target site for bioenergy development. This information will be useful for policymakers and/or businesses aiming to select a potential site to build up supply chain.

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SUPPORTING INFORMATION
Additional supporting information may be found online in the Supporting Information section at the end of the article.

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