Published online June 6, 2019

Development of a Plant Geospatial Model for Identifying Chestnut Yield-Limiting Factors

Yu Zhang,* Chun Dong, Jiping Liu, and Shenghua Xu

ABSTRACT

The Chinese chestnut (*Castanea mollissima* Blume) is an essential and highly nutritious nut crop, and income from selling chestnuts is important for small producers. Despite chestnuts being widely planted, chestnut yields are decreasing in northern China. The hypothesis of this paper is that yield reduction is the result of complex topographic conditions, insufficient soil nutrients, unscientific fertilization, and limited availability of productive land. The objective was to create a plant social geospatial model–geographical detector for analyzing the strength of the association between chestnut yields and their potential determinants. In this model system, we used measured data from chestnut to highlight how a geospatial model can be used to identify complex relationships among soil, plants, and geospatial location. Four geographical detectors (i.e., risk, factor, ecological, and interaction) were proposed on the basis of spatial variation analysis. The model was then applied to Qianxi County of Hebei Province in China. Soil parent material, soil texture, and total power of farm machinery were found to be the key factors. The interactive effect of any two factors increased chestnut yield, and the interaction between parent material and total power of farm machinery resulted in the highest yield. The study's approach and findings make it possible to introduce effective and practical measures to increase chestnut yield. Strategies to increase chestnut yield need to be designed with spatial variables being considered.

Core Ideas

- Identifying chestnut yield limiting factors is essential to precision chestnut tree management.
- Four geographical detectors were applied to explore the key factors and interactive effects of geographical and socio-economic factors on chestnut yield using the power of the determinant concept.
- Soil parent material is a major factor in the spatial variation in chestnut yield, whereas aspect was not found to cause any obvious differences in chestnut yield. Among the eight parent materials, the gneiss soil results in the highest chestnut yield within the study area.
- The interaction between soil type and total power of farm machinery resulted in the highest chestnut yield.
- Our approach is a useful target for further research on increasing other crop yield or exploring the effect of factors on other crop yield.

Published in Agron. J. 111:1–10 (2019)
doi:10.2134/agronj2018.04.0241

The Chinese chestnut is an economically and ecologically important species distributed in across Asia, Europe, Africa, and parts of the Americas. China is responsible for approximately 38% of the cultivated land and 75% of the world yield of this species (Gounga et al., 2008; Cheng et al., 2011). However, poor planting environments (Gómez-del-Campo, 2013; Mota et al., 2016), a low level of management (Martins et al., 2010), diseases (Gouveia et al., 2005) and unscientific fertilizing (Tang et al., 2010) have decreased the chestnut yield. As part of ongoing efforts to increase yields, the potential factors limiting yields must be identified.

Previous research has focused on the nutrient status and biological properties of the soil (Arrobas et al., 2018; Mota et al., 2018). Arrobas et al. (2018) showed that yields were limited by soil properties, available nutrients, and leaf nutrient concentration, whereas Mota et al. (2018) reported that yields were limited by the availability of high quality water. Other researchers studied the effects of the understory vegetation on greenhouse gas emissions (Zhang et al., 2014), net N mineralization, and net nitrification rates (Matsushima and Chang, 2007), thinning treatments (Shen et al., 2018), and vegetation removal on the soil's physical and chemical properties (Zhao et al., 2011). Matsushima and Chang (2007) found that N fertilization affects soil nitrogen cycling in chestnut plantations and net N mineralization rates. Soil water content, N, and soil organic C did not differ between the wet and dry seasons (Zhao et al., 2011). However, Shen et al. (2018) noticed that soil N, P, and K contents decreased with increasing soil depth between low-intensity and high-intensity thinning treatments. This suppression may be caused by a reduction in soil nutrients such as N, P, and Ca returning to the soil through leaf litter through the thinning process. The responses of CO_2 and N_2O emissions in Chinese chestnut plantations to various fertilization treatments have also been studied (Zhang et al., 2013). Moreover, the effects of climatic stress, geographic location, elevation, and terrain on Chinese chestnut have been reported (Vázquez et al., 2001; Burke, 2011; Álvarez-Lafuente et al., 2018).

However, most previous studies on chestnut have not evaluated the interactions between multiple factors (Pereira et al., 2011; Mota et al., 2018). Previous studies have found that the biological properties of soil are important for chestnut yield (Wu

Research Center of Government Geographic Information System, Chinese Academy of Surveying and Mapping, Beijing 100830, China. Received 9 Apr. 2018. Accepted 22 Feb. 2019. *Corresponding author (zhangyu6242@163.com).

Abbreviations: DEM, digital elevation model; *PD*, power of the determinant; TN, total N.

et al., 2010; Xu et al., 2010; Arevalo et al., 2011), but few studies have estimated the influences of soil texture (e.g., loam, sandy loam, sand, and light loam) on chestnut yield. Chestnuts primarily grow near water (Liu, 1999; Martins et al., 2010) but the effect of the distance from water on chestnut yield is unknown. Therefore, research is needed to investigate how interactions among climate, soils, and management affect chestnut growth and development (Afif-Khouri et al., 2011). Although numerous studies have quantified the effects of factors such as genome, age, gender, disease status, and pruning on the Chinese chestnut, few have considered the effects of geographical conditions, such as altitude, slope, and distance to a water source. It is also unknown whether chestnut yield varies with the total farm machinery power in an area. Moreover, to the best of our knowledge, few studies have been conducted on chestnut yield even in the main growing region of the Chinese chestnut, where the chestnut plantation history extends over more than 2000 yr.

Pearson's correlation coefficients (Mu et al., 2018), multiple linear regression (Olaya-Abril et al., 2017), logistic regression (Abbaszadeh Afshar et al., 2018), spatial regression (Rodrigues et al., 2014), spatial panel models (Zhou and Wang, 2018), the analytic hierarchy process (Azizkhani et al., 2017), principal component analysis, and fuzzy membership functions (Li et al., 2008) have been proposed as techniques to evaluate the complex relationships between cultural and environmental factors. Usually, classic regression methods have been applied, such as logistic regression and spatial panel models, to measure potential factors (Armenian et al., 1997; Wang and Haining, 2017; Olaleye and Beke, 2017; Wang et al., 2010). Haining (2003) proposed the use of the spatial linear regression and conditional logistic regression methods to identify the potential factors through use of the *t*-values of the regression coefficients. Li et al. (2008) examined the uncertainties of the variables in terms of probabilities using fuzzy membership functions. However, these methods involve many assumptions (i.e., homoscedasticity and normality) and violations of such assumptions can have a major impact on a model's validity. When too many categorical variables exist, the classic models become impractical for analyzing the potential factors. Moreover, interactions between variables are difficult to interpret; if a study is not specifically designed to assess interactions, their inclusion can make it difficult to estimate other effects. Therefore, we need to develop a more suitable and effective model that reveals potential factors better and identifies their influence on chestnut yield.

In this study, we investigate the relationship between chestnut yield patterns and potential factors by using a novel geographical detector model. As a spatial analysis technique, the geographical detector technique does not require any assumptions or impose any restrictions with respect to explanatory and dependent variables (Wang et al., 2010). This technique has been widely used in the public health fields, especially for analyzing of the effects of potential factors on local disease risk *(*Hu et al., 2011; Huang et al., 2014). The geographical detector includes four detectors, namely the factor detector, the risk detector, the ecological detector, and the interaction detectors. It is used to explore which potential factors are important and how the factors interact with each other. The method has also been applied in mechanism research on built-up land expansion (Ju et al., 2016) and housing prices (Wang et al., 2017). In addition, the detector recognizes the spatial patterns of potential factors and associates them with chestnut yield, which is difficult to model with traditional methods. We first identified and mapped the spatial distribution of chestnut yield at the village level, then we acquired other relevant physical and social factors, such as elevation, soil parent material, and the distance to water source. Finally, we used the geographical detector to analyze the relationship between chestnut yield and these factors, and we discuss the results here.

MATERIAL AND METHODS

Study Area

The study area, Qianxi County (39°57′N–40°27′N, 118°6′E–118°37′E), is located south of the Yanshan Mountains in northeastern Hebei Province of China (Fig. 1). Qianxi County covers approximately 1459.52 km^2, includes 417 villages, and has a population of 354,000 (approximately 242 people per km^2).

The geomorphology is mountainous and hilly with watersheds. The altitude of the area is between 50 and 900 m a.s.l., and its average altitude is 230 m a.s.l. The area has a warm temperate continental monsoon climate and four distinct seasons. The annual mean temperature is 10°C, and the annual mean precipitation is 804.2 mm each year. Agriculture is the primary human activity and chestnuts are the principal cash crop in this area. Qianxi County is the largest chestnut-producing county in China, and it is famously known as the "Town of the Chinese Chestnut". Chestnut yield is the main source of income for the local farmers. However, problems such as insufficient fertilizer use, terrain conditions, and climatic conditions affect chestnut yield and quality. Chestnuts planted in Qianxi County have a good reputation and are called the "Oriental Pearl" in domestic and international markets.

Determinants of Chestnut Yield and Data Collection

The study area has unique environmental and social characteristics that make it more suitable for chestnut yield than other areas. Because the environmental and social characteristics affect the chestnut yield (Afif-Khouri et al., 2011; Pandit et al., 2011; Portela et al., 2011), we considered both of these factors in our study. On the basis of a literature review and available data, 10 potential environmental and socioeconomic factors were selected as proxy variables to run in the geographical detector. One of the most important factors affecting chestnut yield is the local geography (Martins et al., 2011). We chose elevation, slope, and aspect as proxies of the geography. Another important factor that can affect chestnut yield is the soil condition (Portela et al., 2015), including physical and chemical properties such as soil parent material, texture, and chemical composition. Li et al. (2014) and Bauman et al. (2017) considered soil and nutrients as the primary factors affecting Chinese chestnut plantations. The third factor we considered was the climatic conditions, which can influence chestnut tree growth and fruit development (Wilczyński and Podlaski, 2007). The results of fieldwork have indicated that water is considered one of the primary factors affecting chestnut yield (Deb et al., 2012; Mota et al., 2016). Consequently, in this small region, we assumed that studying the distance to water was more meaningful than studying precipitation and relative humidity. After a literature review, we found that solar radiation was an important factor affecting chestnut yield; thus solar radiation was

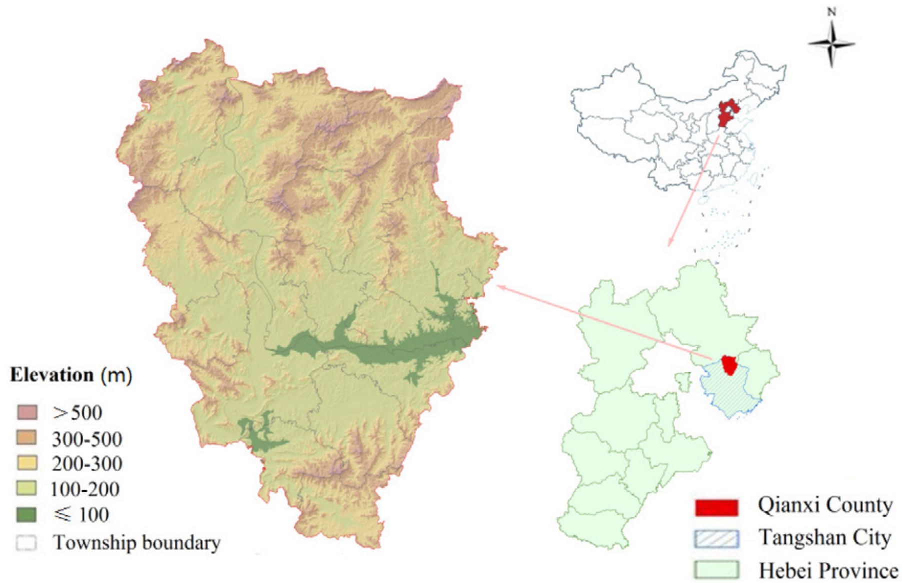

Fig. 1. Map of the study area.

selected as a proxy variable for climatic conditions. The last factor we considered was the productivity condition (Martins et al., 2011), which also has a significant influence on chestnut yield. To express productivity quantitatively and spatially, the labor force and total power of agricultural machinery were selected as proxies. The proxy variables associations of potential factors affecting the chestnut yield are shown in Fig. 2.

Based on these selection factors, the data used in the study included a digital elevation model (DEM), waters, soil parent material and soil texture, chemical composition, total power of agricultural machinery, and labor force.

A DEM from the 1:10,000 topographic database and vector data on the main rivers and administrative boundaries for 2016 were collected from the database of the national geographic condition monitoring of China. The national geographic conditions monitoring of China is a key national project, spearheaded by the National Administration of Surveying, Mapping, and Geoinformation of China. The DEM data are in raster format, with a 1-m resolution.

The elevation, slope, aspect, and solar radiation were extracted from the DEM. Elevation was directly extracted from the DEM as the value of points extracted with ArcGIS software version 10.3 (Environmental Systems Research Institute, Inc., Redlands, CA) Slope was defined by a plane tangent to a topographic surface, as modeled by the DEM at a given point. Slope is defined as the percentage of change in vertical elevation (height) over a certain horizontal distance and can be calculated in degrees. Aspect refers to the orientation of the sloping surface. Aspect affects chestnut growth, which can affect chestnut yield. The solar radiation was calculated via the solar radiation analysis method. This approach incorporates slope, hill shade, and peak aspect reduction and produces an accurate solar radiation map, allowing modifications of the coefficient of atmospheric transmissivity.

A spatial buffer method was used to create polygons around the main water sources that extended for a specified distance. Five hundred meters was specified as the interval distance in our study area, and buffers were drawn around the main water sources with ArcGIS version 10.3 software (Environmental Systems Research Institute, Inc.) to calculate the water buffer region factor.

The soil data were obtained from the Bureau of Agriculture and Animal Husbandry in China's Hebei Province. In this study, the soil is defined by the soil parent material, texture, and chemical composition. The soil parent materials primarily include flood alluvial, loess substance eluvial brown soil, limestone, conglomerate, gneiss, talus leached drab, and other types. Soil texture is divided into four classes: sandy loam, loam, light loam, and sand.

There are nine composition types: Zn, Pb, K, Mn, P, Cu, Fe, organic matter, and total N (TN). Common interpolation methods are the regression inverse distance weighting method, polynomial interpolation, Kriging, and the spline interpolation

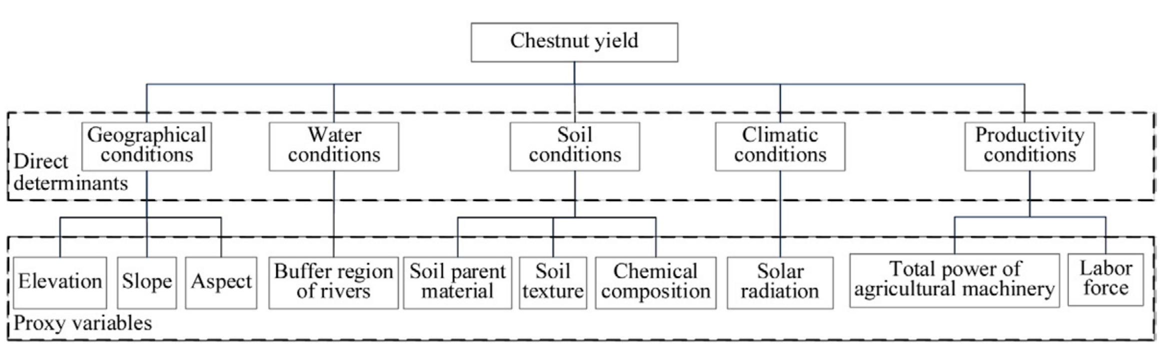

Fig. 2. Relationship between the determinants of chestnut yield and their proxies.

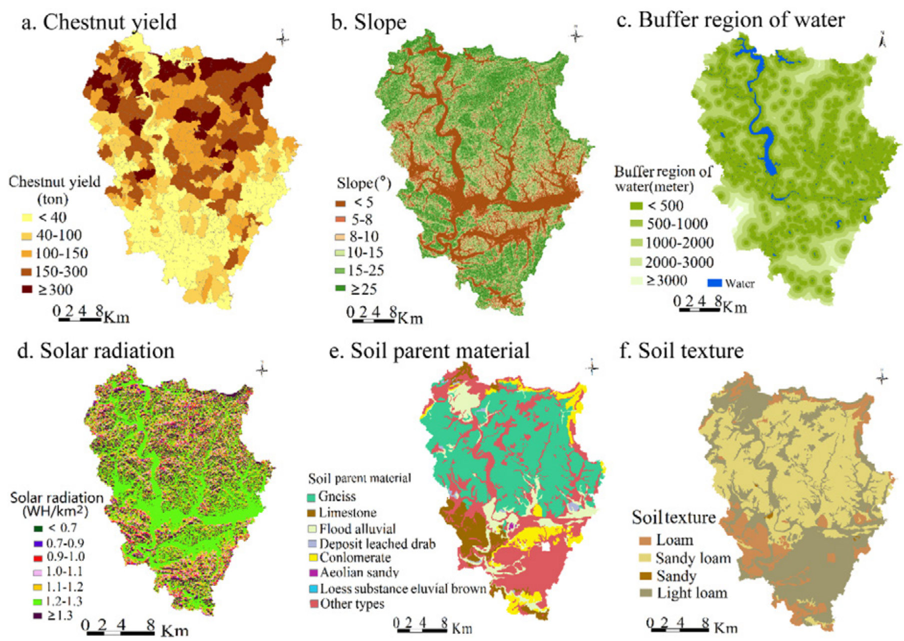

Fig. 3. Maps of chestnut yield and geographical factors. (a) Chestnut yield; (b) slope; (c) water buffer region; (d) solar radiation; (e) soil parent material; (f) soil texture.

method (Wang 1999). These methods were used for discretizing chemical elements and estimating soil chemical composition spatially in our study. Cross-validation can used to determine which model provides the best assessment (Goovaerts 1997). To ensure accuracy, the quintiles and probability depend on the interpolated SEs as much as the predictions. Of these methods, the regression inverse distance weighting method was selected to estimate soil chemical composition. With this method, the mean SEs were 2.31 and were close to the root mean squared prediction error, which was 1.52. In addition, the root mean squared standardized error was 1.18, which is close to 1. Moreover, this model provides unbiased optimal estimates for regionalized variables in a limited area (Blanda et al., 2018; Lu and Wong, 2008).

Socioeconomic data from 417 villages of Qianxi County in 2016 were collected, including the labor force and the total power of agricultural machinery. The data were collected from tables of the national economy of Qianxi by village and sourced from the Bureau of Statistics of Qianxi. (Bureau of Statistics of Qianxi, 2016). The labor force and the total power of agricultural machinery in each village for the 417 villages were provided in table format. On the basis of fields having the village name in common as an attribute, the table data were linked to the administrative boundaries of the village in vector form.

The selected factors needed to be reclassified into several classes after they had been collected, extracted, and calculated. For a specified number of classes, different methods generally define the cutting values differently. In this study, instead of other methods such as equal intervals, quantiles, the and *K*-means algorithm, the natural breaks method was used. This method determines the cutting values by minimizing within-class variance and maximizing between-class variance over an iterative series of calculations (Brewer and Pickle 2002). The selected factors were reclassified according to the natural breaks method and their maps are shown in Fig. 3.

Several steps were followed to achieve the purpose of the study (Fig. 4). According to the input requirements of the geographical detector model, all of the data were projected or reprojected to the Albers conical equal area projection (Krasovsky spheroid) and resampled to a grid size of 500 by 500 m, resulting in 5829 grids in Qianxi County in the database. Next, the grids were overlaid with layers of the selected limiting factors to obtain the chestnut yield values and the attribute information of the limiting factor layers in each grid. The chestnut yield data and the related factor data in the grids were then used as input to the factor detector and the ecological detector model, respectively. After that, the model output in the previous step was used as an input for the interactive detector and the risk detector. Based on the results of these steps, the key factors that significantly affected chestnut yield, the auxiliary factors that were affected by other factors, and the appropriate types and ranges of the limiting factors were selected.

Geographical Detector

The data analysis was performed by following a geographical detector approach (Wang et al., 2010). Basically, a geographical detector measures the correspondence of the spatial distribution of the dependent variables to that of the explanatory variables. This approach can handle both quantitative and nominal data without any assumptions or restrictions with respect to the variables. Here, we refer to the geographical detector (Wang et al., 2010) and assume that if chestnut yield is influenced by a particular potential factor, then the spatial distribution of the factor and chestnut yield will be similar within a geographical space. This assumption has two implications: (i) the potential factor might positively affect chestnut yield, or (ii) the spatial distribution of the factor might have a negative relationship with chestnut yield.

As shown in Fig. 5, in our study region, the entire geographical space was denoted as Q and the spatial distribution of the chestnut yield was denoted C. The entire geographical space was divided by a regular grid system (G) consisting of g_i units (1, 2… n) divided into n_G units that covered all of Q; the chestnut yield in each grid unit was denoted C_i ($1 \le i \le n_G$). A potential factor

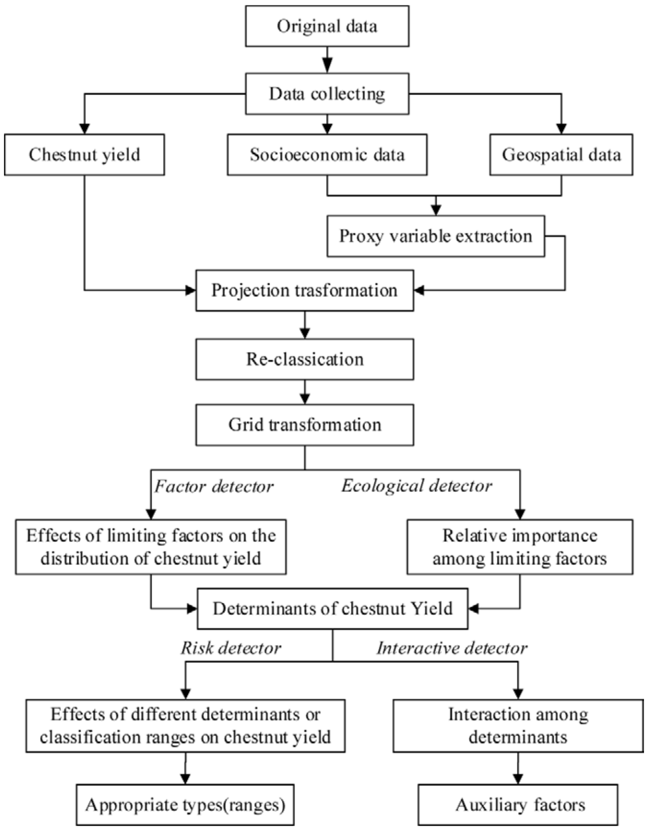

Fig. 4. Technique flowchart.

that impacted chestnut yield was denoted F in the space and this factor was divided into n_F subzones. After intersecting C and F, there were n_F subzones in Q. Every subzone had $n_{F,m}$ ($1 \le m \le n_F$) grids and $n_G = \sum_{m=1}^{n_F} n_{F,m}$. The chestnut yield in every grid in the subzone was defined as $C_{m,i}$ ($1 \le m \le n_F$, $1 \le i \le n_{F,m}$). The average chestnut yield in Q was easily calculated as $\overline{C_G}$ and the dispersion variance in chestnut yield in Q was σ_G^2. A similar calculation over the subzones (F_i) was performed to obtain the average value ($\overline{C_{m,i}}$) and the dispersion variance ($\sigma_{C_{m,i}}^2$) of C. These are calculated as follows:

$$\overline{C_G} = \frac{1}{n_G}\sum_{i=1}^{n_G} C_i \text{, } \overline{C_m} = \frac{1}{n_{F,m}}\sum_{i=1}^{n_{F,m}} C_{m,i} ; \qquad [1]$$

$$\sigma_G^2 = \frac{1}{n_G}\sum_{i=1}^{n_G}(C_i - \overline{C_G})^2 , \ \sigma_{C_{m,i}}^2 = \frac{1}{n_{F,m}}\sum_{i=1}^{n_{F,m}}(C_i - \overline{C_{m,i}})^2 . \qquad [2]$$

Factor Detector

The relationship of the effect of each potential factor on chestnut yield was measured with a factor detector that used the power of the determinant (PD) quantified here. The whole geographical space Q was divided into several subzones by F and the overall resulting variance was calculated as σ_{GF}^2. The PD wasw computed as follows:

$$\sigma_{GF}^2 = \frac{1}{n_{G,F}}\sum_{m=1}^{n_F}\sum_{i=1}^{n_{F,m}}(C_{m,i} - \overline{C_m})^2 ; \qquad [3]$$

$$PD = 1 - \frac{\sigma_{GF}^2}{\sigma_G^2} , \qquad [4]$$

where $n_{G,F} = \sum_{m=1}^{n_F} n_{F,m}$. In general, the PD value lies between 0 and 1. The influence of each factor on chestnut yield is directly proportional to the value of PD: if chestnut yield is completely influenced by the factor, then would PD equal 1; if the factor is irrelevant to chestnut yield, then $PD = 0$.

Risk Detector

When $\overline{C_{m_i}}$ and $\overline{C_{m_j}}$ differ between subzones, then the chestnut yield in these two subzones may differ. We tested the significance of differences between $\overline{C_{m_i}}$ and $\overline{C_{m_j}}$ with t-tests (Press et al., 1992); the degree of freedom is shown as df. The formulas are as follows:

$$t_{\overline{C_{m_i}} - \overline{C_{m_j}}} = \frac{\overline{C_{m_i}} - \overline{C_{m_j}}}{[\sigma_{m_i}^2 / n_{F,m_i} + \sigma_{m_j}^2 / n_{F,m_j}]^{1/2}} ; \qquad [5]$$

$$df = \frac{\sigma_{F_i}^2 / n_{F,m_i} - \sigma_{F_j}^2 / n_{F,m_j}}{\frac{1}{n_{F,m_i} - 1}(\sigma_{F_i}^2 / n_{F,m_i})^2 + \frac{1}{n_{F,m_j} - 1}(\sigma_{F_j}^2 / n_{F,m_j})^2} . \qquad [6]$$

To test the null hypothesis that $\overline{C_{m_i}} = \overline{C_{m_j}}$, the confidence level α (generally 5%) can be used. The null hypothesiscan then be rejected when $|t_{\overline{C_{m_i}} - \overline{C_{m_j}}}| > t\alpha \div 2$, thus showing that the chestnut yield in these two subzones is significantly different; otherwise, the observed difference may be caused by an error.

Ecological Detector

Assuming that the two factors are F_i and F_j, the overall variance of these two potential factors is $\sigma_{GF_i}^2$ and $\sigma_{GF_j}^2$, respectively. The F-test was used to compare the differences between $\sigma_{GF_i}^2$ and $\sigma_{GF_j}^2$ as follows:

$$F = \frac{n_{G,F_i}(n_{G,F_i} - 1)\sigma_{GF_i}^2}{n_{G,F_j}(n_{G,F_j} - 1)\sigma_{GF_j}^2} . \qquad [7]$$

The distribution of this statistic is $F(n_{G,F_i} - 1, n_{G,F_j} - 1)$ and its degree of freedom was n_{G,F_i}, n_{G,F_j}. To test the null hypothesis $\sigma_{GF_i}^2 = \sigma_{GF_j}^2$, we used a significance level of α = 5% and calculated the confidence level. When H_0 is rejected at this confidence level α, then these two factors have a significant impact on chestnut yield and the factor F_i (or F_j) is a more significant determinant than F_j (or F_i).

Interactive Detector

An interactive detector quantifies the interactive effect of two or more potential factors on chestnut yield. Two potential factors, F_i and F_j, may be independent or have a combined effect on chestnut yield, and the combined effect may weaken or strengthen each factor. The geographical layers F_i and F_j are overlaid to create a new layer. The PDs of F_i, F_j, and L are calculated via Eq. [4], then the power of the determinants was used as input into Eq. [7] for evaluation. The expressions are as follows:

Enhance: $PD(F_i \cap F_j) > PD(F_i)$ or $PD(F_j)$;

Enhance, bivariate: $PD(F_i \cap F_j) > PD(F_i)$ and $PD(F_j)$;

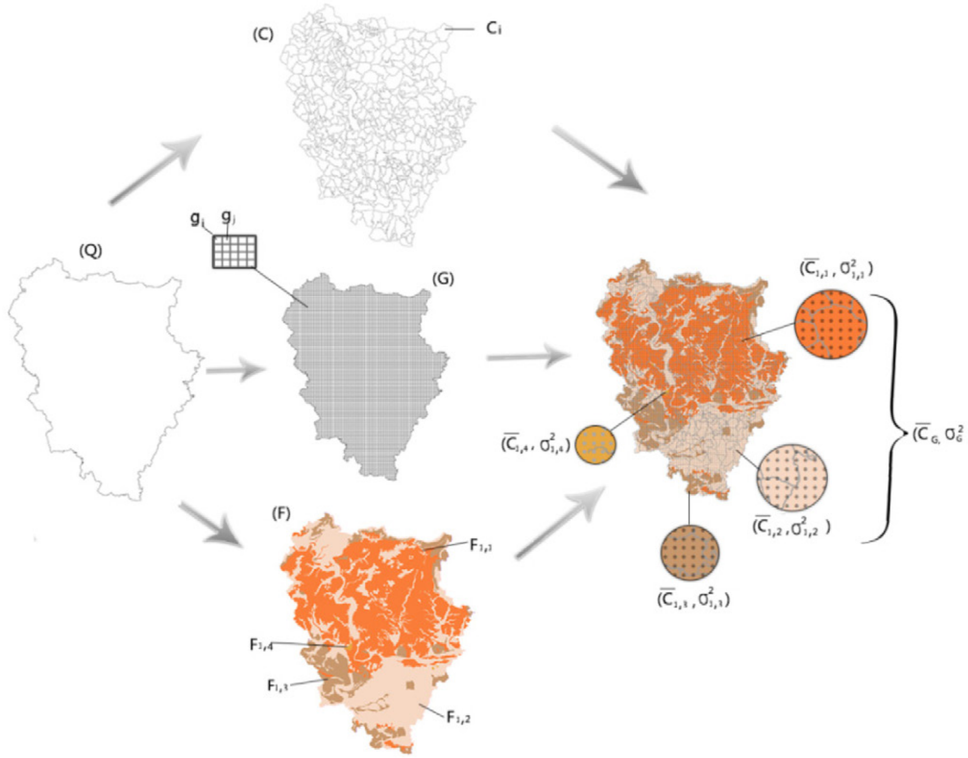

Fig. 5. Division of the study area (*Q*), the regular grid (*G*), the geographical zones of a potential factor (*F*), and the *N*, *G*, and *F* features overlaid onto the statistical parameters.

Enhance, nonlinear: $PD\ (F_i \cap F_j) > PD\ (F_i) + PD\ (F_j)$;

Weaken: $PD\ (F_i \cap F_j) < PD\ (F_i) + PD\ (F_j)$;

Weaken, univariate: $PD\ (F_i \cap F_j) < PD\ (F_i)$ or $PD\ (F_j)$;

Weaken, nonlinear: $PD\ (F_i \cap F_j) < PD\ (F_i)$ and $PD\ (F_j)$; and

Independent: $PD\ (F_i \cap F_j) = PD\ (F_i) + PD\ (F_j)$.

RESULTS

Given that multiple independent variables were included in the model, multicollinearity among the potential factors was examined via the variance inflation factor. According to the standard values suggested by the statistician Gujarati (1995), if the variance inflation factor is less than 5, then the model can be considered to exhibit multicollinearity, which can cause the instability of the estimated values of the coefficients and the inaccuracy of the results of the analysis. In this study, the variance inflation factor values for the aspect, Zn, Pb, K, P, Cu and organic matter were greater than 13, and the variance inflation factor values among the other variables were less than 5.7. Therefore, we chose elevation, slope, water buffer region of water, solar radiation, soil parent material, soil texture, labor force quantity, total power of farm machinery, and chemical compositions (Fe, Mn, and TN) as the explanatory variables.

The results of the aforementioned geographical detectors are listed below. The factor detector was used to evaluate which determinants were responsible for chestnut yield. These results were ranked by *PD* value as follows: soil parent material (0.28) > soil texture (0.25) > total power of farm machinery (0.23) > Fe (0.19) > water buffer region (0.17) > labor force quantity (0.14) > Mn (0.12) > TN (0.11) > elevation (0.10) > slope (0.04) > solar radiation (0.03). The ranking results showed that the first three factors (with *PD* > 0.20) can be considered as the primary potential factors that explain the spatial variability of chestnut yield.

The risk detector was used to calculate the geographical domain area and to analyze the effect of several soil parent material variables on chestnut yield. The order of the corresponding average values was as follows: gneiss (44.58 Mg) > flood alluvial (27.56 Mg) > other types (24.58 Mg) > conglomerate (22.39 Mg) > deposit leached drab (22.07 Mg) > limestone (15.49 Mg) > loess substance eluvial brown (12.32 Mg) > aeolian sandy (9.70 Mg). The results of the significance tests between chestnut yield and soil parent material that are significant at a confidence of 95% are listed in Table 1. The results indicate that the gneiss soil parent material significantly affected chestnut yield at a magnitude approximately five times greater than that of the aeolian sandy type.

The significant differences among all four soil textures are shown in Table 2. The order of the corresponding mean values is as follows: sandy loam (39.90 Mg) > light loam (28.29 Mg) > loam (18.80 Mg) > sand (11.17 Mg). These results suggest that the sandy loam category significantly affected chestnut yield, at a level more than threefold that of sand. There was no significant difference between loam and sand.

The total power of farm machinery also strongly affected chestnut yield. As the total power of farm machinery increased, chestnut yield increased when the total power was less than

Table 1. Average chestnut yield, according to soil parent material.†

Zone	DLD	FA	L	G	Con	AS	LSEB	OT
DLD	–	–	–	–	–	–	–	–
FA	N	–	–	–	–	–	–	–
L	N	Y	–	–	–	–	–	–
G	Y	Y	Y	–	–	–	–	–
C	N	Y	Y	Y	–	–	–	–
AS	Y	Y	N	Y	Y	–	–	–
LSEB	N	Y	N	Y	Y	N	–	–
OT	N	N	Y	Y	N	Y	Y	–

† DLD, deposit leached drab; FA, flood alluvial; L, limestone; G, gneiss; Con, conglomerate; AS, aeolian sandy; LSEB, loess substance eluvial brown; OT, other types; Y, the difference between the two factors is significant at a confidence level of 95%; N, nonsignificant difference.

approximately 3000 kW. When the total power exceeded ~3000 kW, chestnut yield decreased. The geographical detector showed that higher chestnut yield was not always associated with increased value. The following order was found as the total power of farm machinery increased: Level 1 (9.30 Mg) < Level 5 (11.64 Mg) < Level 2 (17.34 Mg) < Level 3 (27.39 Mg) < Level 4 (38.54 Mg). Chestnut yield first increased and then decreased after reaching an inflection point of approximately 3000 kW. A similar analysis can be conducted to analyze the correlations among other potential factors and chestnut yield with the risk detector.

As Table 3 shows, the ecological detector revealed that the variations in *PD* values between slope, Mn, Fe, and TN were not statistically significant; however, the differences among soil parent material, labor force quantity, the total power of farm machinery, water buffer region, and elevation were more significant than the other five potential factors. None of the remaining factors was statistically significant.

The interactive detector was used to analyze whether the potential factors operated independently or were interconnected and to examine the combined impact of two or more potential factors on chestnut yield with the interactive *PD* value. From Table 4, the interactive *PD* value of soil parent material × total power of farm machinery was greater ($PD = 0.37$) than that of the soil parent material alone ($PD = 0.28$). Most interactive *PD* values of multiple potential factors were higher than the *PD* value of any single potential factor. Combinations of the above-mentioned potential factors can effectively explain the spatial variability of the chestnut yield in the study area. Although few interconnected effects reduced the *PD* value, the slope × TN interaction ($PD = 0.05$) reduced the effect of TN alone.

Table 2. Difference in average chestnut yield among four soil texture categories.†

Difference	Loam	Sandy loam	Sand	Light loam
Loam	–	–	–	–
Sandy loam	Y	–	–	–
Sand	N	Y	–	–
Light loam	Y	Y	Y	–

† Y, the difference between the two factors is significant at a confidence level of 95%; N, nonsignificant difference.

DISCUSSION

The identification of the factors that play the greatest role in chestnut productivity is important. With the four detectors, we found that soil parent material, soil texture, and total power of farm machinery were primarily responsible for chestnut yield, where gneiss soil and a high total power of farm machinery exhibited the highest yield. Additionally, the interactive effects of soil parent material × soil texture, soil parent material × total power of farm machinery and soil texture × total power of farm machinery are even stronger than are their separate effects. Nevertheless, although slope, solar radiation, and chemical composition have weak effects on chestnut yield, they contributed significantly to productivity when interacting with soil parent material, soil texture, or total power of farm machinery, indicating the importance of these three factors.

Chestnut yield can be only partially explained by geographic, climatic, nutritional, or other single factors. The results often indicated the combined effect of the mixtures and interactions of multiple factors. One finding was that chestnut yield did not always increase with the total power of farm machinery. This finding was demonstrated by a higher amount of chestnut yield at Level 4 (1775–3191 kW), which gradually decreased at Level 5 (>3191 kW). As a result, Level 4 was associated with the highest concentration of chestnut yield, which indicates that below the inflection point of 3191 kW, the total power of farm machinery plays a more important role than the labor force, but above the inflection point, the labor force ratio is a decisive factor (a higher value indicates higher potential chestnut yield). This observation indicates that merely increasing the total power of farm machinery would be insufficient to increase chestnut yield significantly in practice.

Our study has some limitations. The first limitation is the discretization of quantitative data. The geographical detector is useful for analyzing qualitative data, such as soil parent material and aspect, wherea quantitative data, such as labor force and solar

Table 3. Statistically significant differences among the factors according to the ecological detector.†

Difference	LFQ	TPOFM	WBR	E	SL	SR	SPM	STT	Mn	Fe	TN
LFQ	–	–	–	–	–	–	–	–	–	–	–
TPOFM	N	–	–	–	–	–	–	–	–	–	–
WBR	N	N	–	–	–	–	–	–	–	–	–
E	N	N	Y	–	–	–	–	–	–	–	–
SL	N	N	N	N	–	–	–	–	–	–	–
SR	N	N	Y	N	N	–	–	–	–	–	–
SPM	Y	Y	Y	Y	N	Y	–	–	–	–	–
STT	Y	N	Y	Y	N	Y	N	–	–	–	–
Mn	N	N	N	N	N	N	N	N	–	–	–
Fe	N	N	N	N	N	N	N	N	N	–	–
TN	N	N	N	N	N	N	N	N	N	N	–

† LFQ, labor force quantity; TPOFM, total power of farm machinery; E, elevation; SL, slope; WBR, water buffer region; SR, solar radiation; SPM, soil parent material; STT, soil texture; TN, total N; Y, the difference between the two factors is significant at a confidence level of 95%; N, nonsignificant difference.

Table 4. Power of the determinant values for interactions between pairs of factors on the chestnut yield.†

Difference	LFQ	TPOFM	WBR	E	SL	SR	SPM	STT	Mn	Fe	TN
LFQ	–	–	–	–	–	–	–	–	–	–	–
TPOFM	0.27	–	–	–	–	–	–	–	–	–	–
WBR	0.24	0.28	–	–	–	–	–	–	–	–	–
E	0.17	0.31	0.22	–	–	–	–	–	–	–	–
SL	0.06	0.12	0.19	0.17	–	–	–	–	–	–	–
SR	0.08	0.27	0.14	0.19	0.08	–	–	–	–	–	–
SPM	0.35	0.37	0.34	0.24	0.18	0.21	–	–	–	–	–
STT	0.33	0.33	0.32	0.21	0.21	0.15	0.36	–	–	–	–
Mn	0.16	0.25	0.20	0.07	0.12	0.12	0.28	0.24	–	–	–
Fe	0.12	0.21	0.22	0.11	0.13	0.07	0.14	0.17	0.16	–	–
TN	0.13	0.17	0.24	0.09	0.05	0.10	0.09	0.13	0.15	0.09	–

† LFQ, labor force quantity; TPOFM, total power of farm machinery; E, elevation; SL, slope; WBR, water buffer region; SR, solar radiation; SPM, soil parent material; STT, soil texture; TN, total N.

radiation, must first be discretized and classified into different zones. Our study compared the natural break, quantile break, equal interval break, and K-means methods and revealed no significant difference among them. Therefore, we chose the natural break method to discretize the quantitative data. The issue of discretizing quantitative data effectively must be solved in the future. The second limitation was that not all potential factors were present in our research. In our study area (a small region), no significant variations occurred in temperature, which could affect chestnut yield, although chestnut was influenced by meteorological and climatic parameters. Thus some limiting factors for chestnut planting on a small scale, such as the mean temperature, rainfall, and relative humidity, were not included in our model for lack of data. We analyzed the interactive influences of two factors only on chestnut yield. Therefore, we intend to study the combined effects of multiple factors on chestnut yield in future work.

CONCLUSIONS

In this study, four geographical detectors were applied to explore the key factors and interactive effects of geographical, water, soil, climatic, and productivity conditions on chestnut yield via the *PD* concept. To the best of our knowledge, this study is the first to examine the effect of potential factors on chestnut yield in the largest chestnut-growing area of China. We also used the geographical detector technique to analyze the effects of the selected potential factors on chestnut yield and obtained some interesting results. Our study shows that the soil parent material is a major factor in the spatial variation of chestnut yield, whereas aspect was not found to cause any obvious differences in chestnut yield. Among the eight parent materials, the gneiss soil resulted in the highest chestnut yield within the study area. The findings are consistent with an evaluation of chestnut planting suitability (Li et al., 2014; Zhang et al., 2015), who also showed that soil parent material and texture were the key factors limiting chestnut yield and that among the soil parent materials, the gneiss type resulted in the highest chestnut yield. We also found that the total power of farm machinery played a greater role in chestnut yield than the labor force. Although the *PD* value of the water buffer region was small, the combination of this factor with chemical composition significantly enhanced chestnut yield.

Our results are useful for providing information that can be used to increase yield. To improve yield and expand the local chestnut economy, effective and flexible approaches to increase chestnut yield are provided in our study, such as adjusting the soil parent material and soil texture, by rationally developing gneiss regions, cultivating sandy loam soil, and increasing the total power of farm machinery on the basis of sufficient irrigation or being close to water sources, as well as the knowledge that yields flourish in gneiss and sandy loam soil under good water conditions.

CONFLICT OF INTEREST DISCLOSURE

The authors declare that there is no conflict of interest.

ACKNOWLEDGMENTS

This project was funded by a grant from the National Natural Science Foundation of China (No.71773117) and was funded by Key Laboratory of Earth Observation and Geospatial Information Science(No.AR191901). The authors express sincere appreciation to Dr. Jinfeng Wang and JiXia Huang for their suggestions in identifying the spatial determinants of chestnut yield.

REFERENCES

Afif-Khouri, E., P. Álvarez-Álvarez, M.J. Fernández-López, J.A. Oliveira-Prendes, and A. Cámara-Obregón. 2011. Influence of climate, edaphic factors and tree nutrition on site index of chestnut coppice stands in north-west Spain. Forestry 84:385–396. doi:10.1093/forestry/cpr025

Abbaszadeh Afshar, F.A., S. Ayoubi, and A. Jafari. 2018. The extrapolation of soil great groups using multinomial logistic regression at regional scale in arid regions of Iran. Geoderma 315:36–48. doi:10.1016/j.geoderma.2017.11.030

Álvarez-Lafuente, A., L.F. Benito-Matías, J.L. Peñuelas-Rubira, and L.M. Suz. 2018. Multi-cropping edible truffles and sweet chestnuts: Production of high-quality *Castanea sativa* seedlings inoculated with *Tuber aestivum*, its ecotype *T. uncinatum*, *T. brumale*, and *T. macrosporum*. Mycorrhiza 28:29–38. doi:10.1007/s00572-017-0805-9

Arevalo, C.B.M., J.S. Bhatti, S.X. Chang, and D. Sidders. 2011. Land use change effects on ecosystem carbon balance: From agricultural to hybrid poplar plantation. Agric. Ecosyst. Environ. 141:342–349. doi:10.1016/j.agee.2011.03.013

Armenian, H.K., A. Melkonian, E.K. Noji, and A.P. Hovanesian. 1997. Deaths and injuries due to the earthquake in Armenia: A cohort approach. Int. J. Epidemiol. 26:806–813. doi:10.1093/ije/26.4.806

Arrobas, M., S. Afonso, and M.Â. Rodrigues. 2018. Diagnosing the nutritional condition of chestnut groves by soil and leaf analyses. Sci. Hortic. (Amsterdam) 228:113–121. doi:10.1016/j.scienta.2017.10.027

Azizkhani, M., A. Vakili, Y. Noorollahi, and F. Naseri. 2017. Potential survey of photovoltaic power plants using Analytical Hierarchy Process (AHP) method in Iran. Renew. Sust. Energ. Rev. 75:1198–1206. doi:10.1016/j.rser.2016.11.103

Bauman, J.M., J. Adamson, R. Brisbin, E.T. Cline, and C.H. Keiffer. 2017. Soil metals and ectomycorrhizal fungi associated with American chestnut hybrids as reclamation trees on formerly coal mined land. Int. J. Agron. 2017:1–12. doi:10.1155/2017/9731212

Blanda, V., M. Blanda, F. La Russa, R. Scimeca, S. Scimeca, R.D. Agostino, et al. 2018. Geo-statistical analysis of *Culicoides* spp. distribution and abundance in Sicily, Italy. Parasit. Vectors 11:78. doi:10.1186/s13071-018-2658-2

Brewer, C.A., and L. Pickle. 2002. Evaluation of methods for classifying epidemiological data on choropleth maps in series. Ann. Ass. Am. Geogr. 92:662–681. doi:10.1111/1467-8306.00310

Burke, K.L. 2011. The effects of logging and disease on American chestnut. For. Ecol. Manage. 261:1027–1033. doi:10.1016/j.foreco.2010.12.023

Bureau of Statistics of Qianxi. 2016. Tabulation on the 2016 national economic statistics of Qianxi. Qianxi Statistics. Rural Economic Investigation Team of Qianxi County, Tangshi City, Hebei, China. p. 86–145.

Cheng, Z.P., Q. Wu, J.B. Huang, C.G. Hu, and Z.L. Wang. 2011. Primary identification of chestnut blight resistant Chinese chestnut cultivars and superior lines. (In Chinese, with English abstract.) S. Cn. Fruits 40:40–43.

Deb, S.K., M.K. Shukla, and J.G. Mexal. 2012. Estimating midday leaf and stem water potentials of mature pecan trees from soil water content and climatic parameters. HortScience 47:907–916. doi:10.21273/HORTSCI.47.7.907

Gómez-del-Campo, M. 2013. Summer deficit irrigation in a hedgerow olive orchard cv. Arbequina: Relationship between soil and tree water status, and growth and yield components. Span. J. Agric. Res. 11:547–555. doi:10.5424/sjar/2013112-3360

Goovaerts, P. 1997. Geostatistics for natural resources evaluation. Oxford Univ. Press, New York.

Gounga, M.E., S.Y. Xu, and Z. Wang. 2008. Nutritional and microbiological evaluations of chocolate-coated Chinese chestnut (*Castanea mollissima*) fruit for commercial use. J. Zhejiang Univ. Sci. B 9:675–683. doi:10.1631/jzus.B0820138

Gouveia, M.E., A. Choupina, V. Coelho, E. Monte, R. Hermosa, and C.G. Abreu. 2005. Diagnosis of ink disease of chestnut by molecular identification of associated *Phytophthora* species. Acta Hortic. 639:585–590. doi:10.17660/ActaHortic.2005.693.77

Gujarati, D.N. (1995) Econometrics. 3rd ed. McGraw-Hill, Inc., New York.

Haining, R. 2003. Spatial data analysis: Theory and practice. Cambridge Univ. Press, Cambridge, UK.

Hu, Y., J.F. Wang, X. Li, D. Ren, and J. Zhu. 2011. Geographical detector-based risk assessment of the under-five mortality in the 2008 Wenchuan earthquake, China. PLoS One 6:e21427. doi:10.1371/journal.pone.0021427

Huang, J.X., J.F. Wang, Y.C. Bo, C.D. Xu, M.G. Hu, and D.C. Huang. 2014. Identification of health risks of hand, foot and mouth disease in China using the geographical detector technique. Int. J. Environ. Res. Public Health 11:3407–3423. doi:10.3390/ijerph110303407

Ju, H.R., Z.X. Zhang, L.J. Zuo, J.F. Wang, S.R. Zhang, X. Wang, et al. 2016. Driving forces and their interactions of built-up land expansion based on the geographical detector: A case study of Beijing, China. Int. J. Geogr. Inf. Sci. 30(11):2188–2207. doi:10.1080/13658816.2016.1165228

Li, H.L., G.H. Huang, and Y. Zou. 2008. An integrated fuzzy-stochastic modeling approach for assessing health-impact risk from air pollution. Stochastic Environ. Res. Risk Assess. 22:789–803. doi:10.1007/s00477-007-0187-1

Li, Y., J. Zhang, S.X. Chang, P. Jiang, G. Zhou, Z. Shen, et al. 2014. Converting native shrub forests to Chinese chestnut plantations and subsequent intensive management affected soil C and N pools. For. Ecol. Manage. 312:161–169. doi:10.1016/j.foreco.2013.10.008

Liu, L. 1999. The world chestnut industry and consideration on the development of Chinese chestnut in the 21st century. Hebei J. For. Orchard Res. 14:89–93.

Lu, G.Y., and D.W. Wong. 2008. An adaptive inverse-distance weighting spatial interpolation technique. Comput. Geosci. 34:1044–1055. doi:10.1016/j.cageo.2007.07.010

Martins, A., F. Raimundo, O. Borges, I. Linhares, V. Sousa, J.P. Coutinho, et al. 2010. Effects of soil management practices and irrigation on plant water relations and productivity of chestnut stands under Mediterranean conditions. Plant Soil 327:57–70. doi:10.1007/s11104-009-0031-0

Martins, A., G. Marques, O. Borges, E. Portela, J. Lousada, F. Raimundo, et al. 2011. Management of chestnut plantations for a multifunctional land use under Mediterranean conditions: Effects on productivity and sustainability. Agrofor. Syst. 81:175–189. doi:10.1007/s10457-010-9355-2

Matsushima, M., and S.X. Chang. 2007. Effects of understory removal, N fertilization, and litter layer removal on soil N cycling in a 13-year-old white spruce plantation infested with Canada bluejoint grass. Plant Soil 292:243–258.

Mota, M., T. Pinto, and T. Marques. 2016. Study on yield values of two irrigation systems in adult chestnut trees and comparison with non-irrigated chestnut orchard. Rev. Cienc. Agrar. (Belem) 41(1):236–248.

Mota, M., T. Marques, T. Pinto, F. Raimundo, A. Borges, J. Caço, et al. 2018. Relating plant and soil water content to encourage smart watering in chestnut trees. Agric. Water Manage. 203:30–36. doi:10.1016/j.agwat.2018.02.002

Mu, Y.H., X.D. Liu, and L.D. Wang. 2018. A Pearson's correlation coefficient based decision tree and its parallel implementation. Inf. Sci. 435:40–58. doi:10.1016/j.ins.2017.12.059

Olaleye, A.O., and A.K. Beke. 2017. Predictors of drug sensitive tuberculosis treatment outcomes among hospitalized patients in South Africa: A multinomial logit model. Infect Dis (Lond.) 49:478–481. doi:10.1080/23744235.2017.1280618

Olaya-Abril, A., P.A. Luis, L.G. Beatriz, and O.R. Rafael. 2017. Soil organic carbon distribution in Mediterranean areas under a climate change scenario via multiple linear regression analysis. Sci. Total Environ. 592:134–143. doi:10.1016/j.scitotenv.2017.03.021

Pandit, A.H., M.A. Mir, A. Kour, and K.M. Bhat. 2011. Selection of chestnuts (*Castanea sativa*) in Srinagar district of the Kashmir valley, India. Int. J. Fruit Sci. 11:111–118. doi:10.1080/15538362.2011.578511

Press, W., A. Teukolsky, W. Vetterling, and B. Flannery. 1992. Numerical recipes in C. 2nd ed. Cambridge Univ. Press, New York.

Pereira, M.G., L. Caramelo, C. Gouveia, J. Gomes Laranjo, and M. Magalhães. 2011. Assessment of weather-related risk on chestnut productivity. Nat. Hazards Earth Syst. Sci. 11:2729–2739. doi:10.5194/nhess-11-2729-2011

Portela, E., J. Ferreira-Cardoso, and J. Louzada. 2011. Boron application on a chestnut orchard: Effect on yield and quality of nuts. J. Plant Nutr. 34:1245–1253. doi:10.1080/01904167.2011.580812

Portela, E., J. Ferreira-Cardoso, J. Louzada, and J. Gomes-Laranjo. 2015. Assessment of boron application in chestnuts: Nut yield and quality. J. Plant Nutr. 38:973–987. doi:10.1080/01904167.2014.963116

Rodrigues, M., J. de la Riva, and S. Fotheringham. 2014. Modeling the spatial variation of the explanatory factors of human-caused wildfires in Spain using geographically weighted logistic regression. Appl. Geogr. 48:52–63. doi:10.1016/j.apgeog.2014.01.011

Shen, Y., R. Cheng, W. Xiao, S. Yang, Y. Guo, N. Wang, et al. 2018. Labile organic carbon pools and enzyme activities of *Pinus massoniana* plantation soil as affected by understory vegetation removal and thinning. Sci. Rep. 8:573. doi:10.1038/s41598-017-18812-x [erratum 8:11466]

Tang, Z.H., X. Liu, S.H. Liu, and Z.M. Sun. 2010. Studies on the difference of the chestnut qualities between Yanshan and Taihangshan Areas. Zhongguo Nongxue Tongbao 26:103–107.

Vázquez, G., F. Chenlo, and R. Moreira. 2001. Modelling of desorption isotherms of chestnut: Influence of temperature and evaluation of isosteric heats. Dry. Technol. 19:1189–1199. doi:10.1081/DRT-100104814

Wang, C.Y., and R. Haining. 2017. Testing the new economic geography's wage equation: A case study of Japan using a spatial panel model. Ann. Reg. Sci. 58:417–440. doi:10.1007/s00168-016-0804-3

Wang, J.F., X.H. Li, G. Christakos, Y.L. Liao, T. Zhang, X. Gu, et al. 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. Int. J. Geogr. Inf. Sci. 24:107–127. doi:10.1080/13658810802443457

Wang, Y., S.J. Wang, G.D. Li, H.G. Zhang, L.X. Jin, Y.X. Su, et al. 2017. Identifying the determinants of housing prices in China using spatial regression and the geographical detector technique. Appl. Geogr. 79:26–36. doi:10.1016/j.apgeog.2016.12.003

Wang, Z.Q. 1999. Geostatistics and its application in ecology. Science Pressa, Beijing.

Wilczyński, S., and R. Podlaski. 2007. The effect of climate on radial growth of horse chestnut (*Aesculus hippocastanum* L.) in the Świętokrzyski National Park in central Poland. J. Forest Res. 12:24–33. doi:10.1007/s10310-006-0246-3

Wu, J.S., P.K. Jiang, S.X. Chang, Q.F. Xu, and Y. Lin. 2010. Dissolved soil organic carbon and nitrogen were affected by conversion of native forests to plantations in subtropical China. Can. J. Soil Sci. 90:27–36. doi:10.4141/CJSS09030

Xu, Q.F., J.S. Wu, and P.K. Jiang. 2010. Soil biological properties with weed removal in a Chinese chestnut (*Castanea mollissima*) plantation. J. Zhejiang Forest. Coll. 27:659–663.

Zhang, L.F., L. Wang, Y. Zhang, R. Zhao, and Y. Liang. 2015. Evaluation on suitability of crop growth under support of geographic conditions census data: An example of chestnut in Qianxi County. Remote Sens. Environ. 30:52–59.

Zhang, J., Y. Li, S.X. Chang, P. Jiang, G. Zhou, J. Liu, et al. 2014. Understory vegetation management affected greenhouse gas emissions and labile organic carbon pools in an intensively managed Chinese chestnut plantation. Plant Soil 376:363–375. doi:10.1007/s11104-013-1996-2

Zhang, J.J., Y.F. Li, P.K. Jiang, G.M. Zhou, and J. Liu. 2013. Effect of fertilization on labile carbon pools and emissions of greenhouse gas in soils of Chinese chestnut stands. J. Plant Nutr. Fert. 19:745–752.

Zhao, J., X.L. Wang, Y.H. Shao, G.L. Xu, and S.L. Fu. 2011. Effects of vegetation removal on soil properties and decomposer organisms. Soil Biol. Biochem. 43:954–960. doi:10.1016/j.soilbio.2011.01.010

Zhou, C.S., and S.J. Wang. 2018. Examining the determinants and the spatial nexus of city-level CO_2 emissions in China: A dynamic spatial panel analysis of China's cities. J. Clean. Prod. 171:917–926. doi:10.1016/j.jclepro.2017.10.096