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Quantifying determinants of cash crop expansion and their relative effects using logistic regression modeling and variance partitioning

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ABSTRACT

Cash crop expansion has been a major land use change in tropical and subtropical regions worldwide. Quantifying the determinants of cash crop expansion should provide deeper spatial insights into the dynamics and ecological consequences of cash crop expansion. This paper investigated the process of cash crop expansion in Hangzhou region (China) from 1985 to 2009 using remotely sensed data. The corresponding determinants (neighborhood, physical, and proximity) and their relative effects during three periods (1985–1994, 1994–2003, and 2003–2009) were quantified by logistic regression modeling and variance partitioning. Results showed that the total area of cash crops increased from 58,874.1 ha in 1985 to 90,375.1 ha in 2009, with a net growth of 53.5%. Cash crops were more likely to grow in loam soils. Steep areas with higher elevation would experience less likelihood of cash crop expansion. A consistently higher probability of cash crop expansion was found on places with abundant farmland and forest cover in the three periods. Besides, distance to river and lake, distance to county center, and distance to provincial road were decisive determinants for farmers' choice of cash crop plantation. Different categories of determinants and their combinations exerted different influences on cash crop expansion. The joint effects of neighborhood and proximity determinants were the strongest, and the unique effect of physical determinants decreased with time. Our study contributed to understanding of the proximate drivers of cash crop expansion in subtropical regions.

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Introduction

Cash crop development by the market-oriented agriculture, such as the expansion of hazelnut, rubber, fruit, and tea, has been a major land use change worldwide, particularly in developing tropical and subtropical countries (Fox and Vogler, 2005; Ziegler et al., 2009; Castiblanco et al., 2013; Zhang et al., 2014). Given that most cash crop plantations are established by clearing productive paddy and native forest (Miyamoto, 2006; Godone et al., 2014; Su et al., 2014a), ecological consequences of cash crop expansion should be significant. It impairs ecosystem services, influences grain production, alters landscape patterns, and threats biodiversity (Miyamoto, 2006; Yi et al., 2014; Godone et al., 2014). Although attempt to document the process of cash crop expansion is continuous (Li and Fox, 2012; Dong et al., 2013; Su et al., 2014a), understanding of the proximate drivers is still vague. Under such circumstances, quantifying the determinants of cash crop expansion should provide deeper spatial insights into the dynamics and ecological consequences of cash crop development.

The case of China allows for the examination of the complex dynamics of land systems under the influence of a set of broad-scale changes (Su et al., 2011). The transition from planned-based to market-oriented economy was accompanied by agricultural commercialization (van den Berg et al., 2007). The comparative advantage of traditional grain product was drastically decreased by the market forces. Land ownership was privatized and land use was individualized by land reforms (Krusekopf, 2002), which considerably changed the operation mode and plantation structure (Qin et al., 2007; Gibreel et al., 2014). Growing domestic demand and upscaling transportation networks increased the market incentives (Li et al., 2008; Su et al., 2014a). All these factors led to rapid and widespread cash crop expansion in tropical and subtropical China. For example, total area of tea plantations amounted to 35.78 million ha in 2012 and expanded by 1200% during the past six decades. Some cases have reported the continuous cash crop expansion in China (Li and Fox, 2012; Dong et al., 2013; Yi et al., 2014), but no study has quantified the determinants of cash crop expansion.

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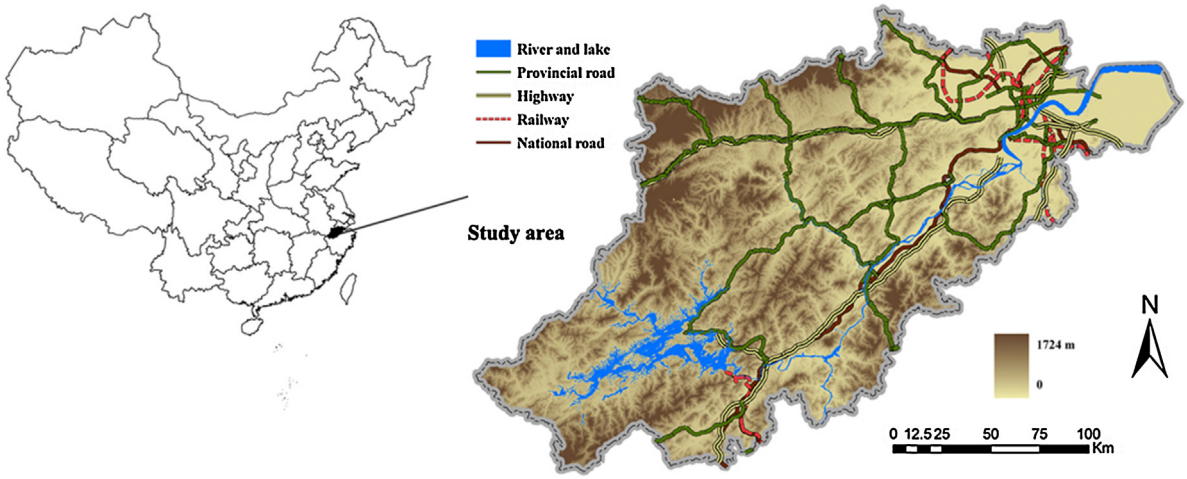

Fig. 1. Location of Hangzhou region (China) and transportation routes, river and lake within it.

Remotely sensed imageries are critical data source to record the dynamic process of land use change (van Lier et al., 2011; Pandey et al., 2013; Haas and Ban, 2014). Recent literature has seen hard efforts to map cash crop using remotely sensed imageries (Dong et al., 2013; Godone et al., 2014; Su et al., 2014a; Yi et al., 2014). Geographical information system (GIS) provides robust tools to describe the land use pattern changes across time (Zhang et al., 2013). Regression modeling has been widely employed to examine the determinants of land use change using a set of spatially explicit data (Cheng and Masser, 2003; Nainggolan et al., 2012; Arsanjani et al., 2013; Nandy et al., 2014). However, few studies have compared the determinants of land use change and their relative effects over time. In particular, the temporally dynamic effects of different determinants on cash crop expansion remained poorly understood.

This study attempts to quantify the determinants of cash crop expansion and their relative effects over time. Analysis was carried out within the Hangzhou region in subtropical China, using remote sensing, GIS, and regressing modeling. More specifically, our objectives are to: (1) investigate the process of cash crop expansion from 1985 to 2009; (2) examine the determinants of cash crop expansion during different intervals (1985–1994, 1994–2003, and 2003–2009); and (3) compare the relative effects of different determinants over time.

Materials and methods

Study area

Covering about 16,880 km^2, the Hangzhou region is located on the east coast of China, at the confluence of longitude 120.2 east and latitude 30.3 north (Fig. 1). This region is the fourth largest national metropolitan area, with population exceeding 1.7 million. It has a humid subtropical climate, with dry, cloudy, and chilly winters and hot, long, humid summers. Annual mean temperature is 16.48 °C, and rainfall averages 57.1 in. This region receives average annual sunshine of 1757 h. This region has predominant resource endowments, with fertile and productive soils and abundant forest and farmland. Since the implication of 'Household Responsibility' policy in 1980s (Krusekopf, 2002), local farmers became fancy of clearing their farmland and forest to establish cash crop plantations (tea, fruit and hickory). The Hangzhou region is exemplary to investigate the determinants of cash crop expansion.

Extraction of cash crop information

Cash crop information was visually interpreted from Landsat images (1985, 1994, 2003, and 2009). All the images were geometrically corrected and false color composited. We did not divide cash crops into certain species (tea, fruit, and hickory), considering that the Landsat images were of coarse resolution and cash crop species present similar canopy spectral characteristics. The working window for on-screen digitization was fixed at 1:50,000 scale, and skilled experts drew polygons directly along the boundaries of cash crop patches. The 2009 cash crop information was first interpreted and then used as basis to retrospect cash crops for the other years. We assessed its accuracy in reference to 80 points collected in field survey and 40 points from high resolution images. The accuracy reached 90.5%. Accuracy for the other years was evaluated by 120 points from high resolution images, which was 91.2% in 2003, 91.5% in 1994, and 92.7% in 1985. Patterns of cash crops were displayed in Fig. 2.

Selection of explanatory variables

Land use change is resulted from the complex interactions among a set of structural and behavioral factors (Su and Xiao, 2013; Tayyebi and Pijanowski, 2014). Literature has reported a large body of determinants for land use change. These determinants, in most land use change models, are categorized into four types: neighborhood, physical, proximity and socioeconomic (Polimeni, 2005; Zhang et al., 2013; Tayyebi and Pijanowski, 2014; Wehner et al., 2014). Several studies have evidenced the efficiency of this framework to guide the selection of explanatory variables for land use change (Polimeni, 2005; Su and Xiao, 2013; Arsanjani et al., 2013; Müller et al., 2013). Selection of explanatory variables for cash crop expansion in this study was guided by the framework and also was subjected to data availability.

Neighborhood determinants reflect the proportion of different land use types (e.g., farmland, forest, water, and urban) within the neighborhood of a given pixel. Previous studies reported that farmland and forest were the most vulnerable land use types to be replaced by cash crops (Miyamoto, 2006; Godone et al., 2014; Su et al., 2014a). We therefore summed the percentage of farmland and forest within 12 × 12 window neighborhood for each pixel. The 12 × 12 window was selected because it could capture the details of land use patterns and presented low noise. Land use information of

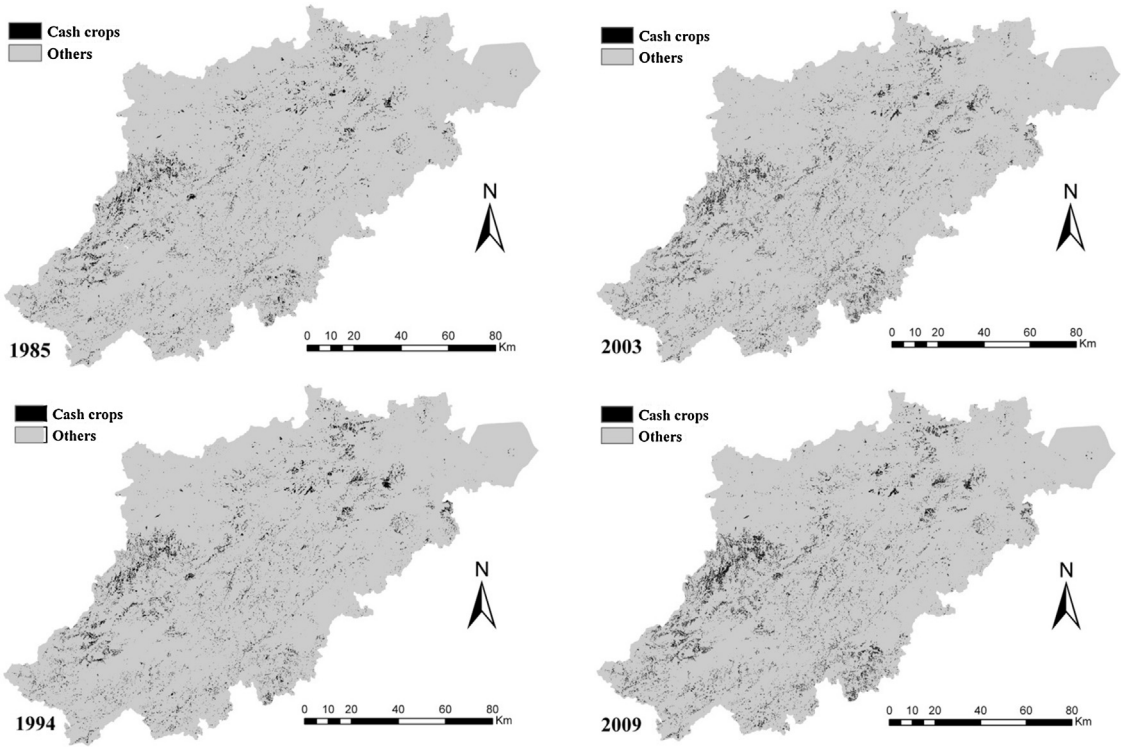

Fig. 2. Cash crop patterns from 1985 to 2009 across Hangzhou region, China.

farmland and forest was extracted based on Su et al. (2014b), which combined visual interpretation and machine-based classifiers.

Physical determinants are fundamental for the direction and extent of land use change. Resource supply and land provisions are restricted by soil texture and topographic factors (Polimeni, 2005; Su and Xiao, 2013; Wehner et al., 2014). We therefore selected two topographic parameters (slope and elevation) and four soil texture variables (loam, clay, sand, and silt) as potential physical determinants.

Proximity determinants refer to the distance to transportation routes, socioeconomic centers, and rivers and lakes. High proximity to transportation routes can reduce costs for human living and production activities. Different types of transportation routes exert varying influences on land use change (Su et al., 2014c). We therefore selected four variables to indicate proximity to transportation routes: distance to national road, distance to provincial road, distance to highway, and distance to railway. The Qiantang River and Qiandao Lake play critical role in agricultural production and urban development for Hangzhou region. Distance to river and lake was thus picked up. Greater proximity to socioeconomic centers suggests higher probability of human activities intensity. We further chose two variables: distance to city center and distance to county center. It should be mentioned that transportation routes were changing during the study period. We did not consider those under construction for each period.

Socioeconomic and proximity determinants always present fluid boundaries, since distance to transportation routes and distance to urban centers were used as spatial indicators of socioeconomic conditions (Miyamoto, 2006; Zhang et al., 2013; Su et al., 2014a). Census-based variables (e.g., population density, gross domestic product, and income) were not incorporated into analysis in this study, considering that resolution of statistical data was coarse and accorded with that of the other variables in logistic regression. General descriptions and calculation of the selected determinants were shown in Table 1.

Spatial autocorrelation and sampling

We calculated Moran's *I* statistics for the patterns of cash crop expansion, in order to detect the potential existence of spatial autocorrelation that would violate the independence assumption. Results suggested that spatial autocorrelation should be carefully treated (Moran's $I = 0.48$). A combined strategy of systematic sampling and random sampling was employed to minimize the autocorrelation (Cheng and Masser, 2003). Threshold for the systematic sampling was determined by detecting spatial lag autocorrelation (Nainggolan et al., 2012). It was found that autocorrelation was significantly reduced when the distance threshold reached 270 m (Moran's $I = 0.06$). We therefore sampled the original data along the *X* and *Y* directions at every nine pixels. We further applied random sampling, and the sampled pixels were from the most dominant category. Such operation was to guarantee that the proportion of points where cash crop expansion occurred (coded as 1) approximately equaled to that of unchanged points (coded as 0). The number of sampled points amounted to 360 for period of 1985–1994, 708 for period of 1994–2003, and 440 for period of 2003–2009.

Logistic regression and variance partitioning

Logistic regression, which was expressed as Eq. (1), was employed to identify the determinants of cash crop expansion. We established one regression for each period, using the selected potential determinants as explanatory variables and binary samples coded as 1 (expanded) or 0 (unchanged) as dependent variable. All the explanatory variables were subjected to standardization and normalization before regression.

$$\log it(y) - \log\left(\frac{y}{1-y}\right) = \gamma + \sum_{i=1}^{n} \alpha_i x_i + e \quad (1)$$

Table 1
Selected explanatory variables for cash crop expansion.

Category	Variables	Data source	Calculation
Physical	Elevation (m)	Digital elevation model with 30 m resolution	
	Slope (°)	Digital elevation model with 30 m resolution	Surface analysis module in ArcGIS 9.3
	Soil texture-clay	Digital soil map at 1:50,000 scale	
	Soil texture-loam	Digital soil map at 1:50,000 scale	
	Soil texture-sand	Digital soil map at 1:50,000 scale	
	Soil texture-silt	Digital soil map at 1:50,000 scale	
Neighborhood	Percentage of farmland (%)	Interpreted land use map	Neighborhood Statistics module in ArcGIS 9.3
	Percentage of forest (%)	Interpreted land use map	Neighborhood Statistics module in ArcGIS 9.3
Proximity	Distance to national road (m)	Digital infrastructure map at 1:50,000 scale	Distance analysis module in ArcGIS 9.3
	Distance to provincial road (m)	Digital infrastructure map at 1:50,000 scale	Distance analysis module in ArcGIS 9.3
	Distance to highway (m)	Digital infrastructure map at 1:50,000 scale	Distance analysis module in ArcGIS 9.3
	Distance to railway (m)	Digital infrastructure map at 1:50,000 scale	Distance analysis module in ArcGIS 9.3
	Distance to river and lake (m)	Digital river map at 1:50,000 scale	Distance analysis module in ArcGIS 9.3
	Distance to city center (m)	Digital infrastructure map at 1:50,000 scale	Distance analysis module in ArcGIS 9.3
	Distance to county center (m)	Digital infrastructure map at 1:50,000 scale	Distance analysis module in ArcGIS 9.3

where y is the probability of cash crop expansion; x is potential determinants; α is estimated parameters; γ is intercept and e is error.

Performance of logistic regression was evaluated by four indicators, including the percentage of correct predictions (PCP, Eq. (2)), area under the receiver operating characteristic curve (AUC ROC), adjusted R^2, and Moran's I for model residuals' autocorrelation. Higher AUC ROC values denote that pixels experiencing cash crop expansion are assigned higher probability values than the other ones. Lower Moran's I values imply that the problem of spatial autocorrelation is treated.

$$\mathrm{PCP} = \frac{N_c}{N_t} \tag{2}$$

where PCP is the percentage of correct predictions; N_c is the number of correctly predicted samples; N_t is the total number of samples.

The relative effects of different determinants was qualified by the variance partitioning (VP) method, which decompose the total explained variances (adjusted R^2) into several fractions (Anderson and Gribble, 1998; Heikkinen et al., 2005). We calculated three categories of fractions: (1) unique shares of individual category of determinants (physical, proximity and neighborhood); (2) joint shares of two categories of determinants; and (3) joint shares of three categories of determinants.

Results

Dynamic process of cash crop expansion

Table 2 showed that cash crops experienced substantial expansion during the study period. The total area increased from 58,874.1 ha in 1985 to 90,375.1 ha in 2009, with a net growth of 53.5%. Expansion rate reached 28.7% in period of 1994–2003, which was three times higher than that in the other two periods. Besides, annual expansion rate from 1994 to 2003 was highest among the three intervals. All these results denoted that expansion of cash crops was more intense during the period of 1994–2003.

Table 2
Areal changes of cash crops from 1985 to 2009 across Hangzhou region, China.

Year	Area (ha)	Percentage (%)	Period	Expansion rate (%)	Annual expansion (ha/yr)
1985	58,874.1	3.4			
1994	65,124.2	3.9	1985–1994	10.6	1.2
2003	83,795.9	5.0	1994–2003	28. 7	3.2
2009	90,375.1	5.5	2003–2009	7.9	1.3

Determinants of cash crop expansion

The determinants of cash crop expansion identified by logistic regression were displayed in Table 3. For the three intervals, PCP exceeded 0.8, AUC ROC reached 0.85, and adjusted R^2 were greater than 0.5. Moran's I for model residuals approached zero, signifying that the problem of spatial autocorrelation was treated. All these statistics suggested that the established logistic regression was powerful in explaining the dynamics of cash crop expansion. Influences of slope, percentage of farmland, percentage of forest, distance to provincial road, distance to river and lake, and distance to county center were pronounced, since the six variables remained as significant determinants during the three periods. Soil texture (loam) was also predictor for cash crop expansion in periods 1980–1994 and 1994–2003. During the first period, elevation and distance to highway acted as influential factor but exerted insignificant impact within the last two periods.

Fig. 3 exhibited the contributions of different categories of determinants and their combinations to the total variations. The unique influence of neighborhood determinants was greater than that of the other categories of determinants. It implied that neighborhood determinants played more important role in cash crop expansion. The unique influence of physical determinants decreased with time,

Table 3
Outputs of logistic regression models.

Variables	1985–1994	1994–2003	2003–2009
Constant	2.131**	4.412**	3.041**
Elevation (m)	−0.001**	ns	ns
Slope (°)	−0.002**	−0.001**	−0.001**
Soil texture-clay	ns	ns	ns
Soil texture-loam	0.001**	0.001**	ns
Soil texture-sand	ns	ns	ns
Soil texture-silt	ns	ns	ns
Percentage of farmland (%)	0.513**	0.422**	0.305**
Percentage of forest (%)	3.544**	4.374**	3.418**
Distance to national road (km)	ns	ns	ns
Distance to provincial road (km)	−0.064**	−0.058**	−0.052**
Distance to highway (km)	−0.012**	ns	ns
Distance to railway (km)	ns	ns	ns
Distance to river and lake (km)	−0.005**	−0.012**	−0.003**
Distance to city center (km)	ns	ns	ns
Distance to county center (km)	−0.389**	−0.258**	−0.237**
n	360	708	440
PCP (%)	81.3	80.6	82.5
AUC ROC	0.88	0.84	0.87
Adjusted R^2	0.55	0.51	0.58
Moran's I for model residuals	0.000	0.001	0.001

ns: insignificant relationships. Abbreviation: percentage of correct predictions (PCP); area under the receiver operating characteristic curve (AUC ROC).
** $p < 0.01$.

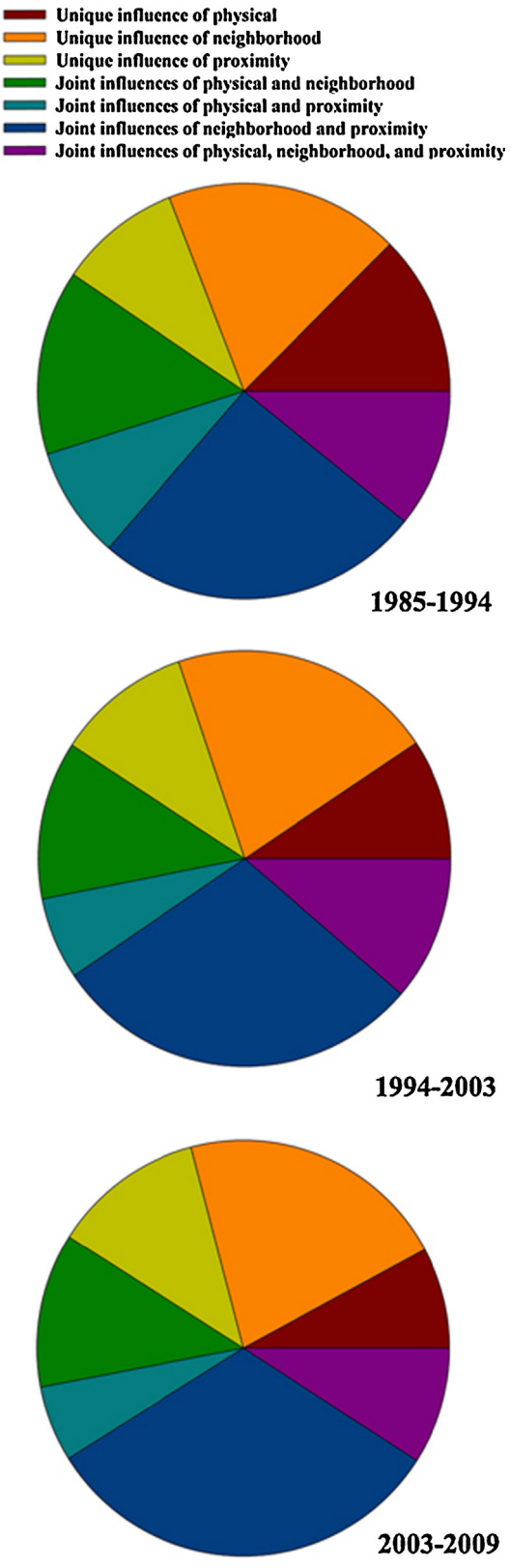

Fig. 3. Contributions of different categories of determinants and their combinations to the total variances.

suggesting that the cash crop expansion received fewer restrictions from topology. The joint influences of neighborhood and proximity were the strongest during the three periods, and became stronger through time. Such results suggested that cash crop expansion was more subjected to the combined effects from neighborhood and proximity factors.

Discussion and conclusions

This study employed logistic regression modeling to quantify the determinants of cash crop expansion. This approach was found to be capable of capturing the relationships between cash crop expansion probability and proximate determinants namely physical, neighborhood and proximity factors.

Slope and elevation were negative explanatory variables, suggesting that steep areas with higher elevation would experience smaller probability of cash crop expansion. These results accorded with previous discoveries that cash crop cultivation were mainly observed in flat and nonmarginal sites (Reis and Yomralioglu, 2006; Marull et al., 2010; Godone et al., 2014). The negative influence of topology should be attributed to it that these places are of relatively higher accessibility and less restrictions for cultivation (Su et al., 2014a). Soil was also an important factor in shaping land use patterns (Nagashima et al., 2002; Castiblanco et al., 2013). Our results demonstrated that cash crops were more likely to grow in loam soils. For many reasons, loam is a healthy and nutritious mixture, from which diverse vegetations and plants benefit a lot to thrive (Kaufmann and Cleveland, 2008). Such biophysical template exhibited promising suitability for cropping and thus favored cash crop expansion.

A consistently higher probability of cash crop expansion was found on places with abundant farmland and forest cover in the three periods, considering the positive influence of percentage of farmland and forest within the 360 m neighborhood. This result coincided with the findings in Colombia (Castiblanco et al., 2013), Indonesia (Miyamoto, 2006), Italy (Godone et al., 2014), Turkey (Reis and Yomralioglu, 2006), and China (Yi et al., 2014; Su et al., 2014a). Cash crop plantation is more profitable than agriculture and forestry. Driven by competitive profitability, cash crop would sprawl at the expense of farmland and forest. All these contributed to the significant impact of neighborhood variables on the likelihood of cash crop expansion.

Proximity variables had different effects on cash crop expansion. Provincial road exerted more significant impact on cash crop expansion, compared to the other transportation types. It makes sense since human movement and activities within the city are largely relied on provincial road. The negative influence of proximity determinants (provincial road, and river and lake) should be attributed to it that shorter distance would reduce cropping costs and increase profitability. For example, reclamations are more likely to occur in places closer to villages and rivers. Besides, higher proximity to socioeconomic centers (county center) offers more accessibility to resources and market. Consequently, distance to river and lake, distance to county center, and distance to provincial road became decisive determinants for farmers' choice of cash crop plantations.

Land use pattern changes are resulted from multiple drivers as well as their interactions and combinations. This study demonstrated that different categories of determinants and their combinations exerted different influence on cash crop expansion. Neighborhood factors reflected the resource endowments for cash crop expansion and proximity represented the opportunities of cultivation. Consequently, the joint effects of neighborhood and proximity determinants were the strongest. The unique effect of physical determinants decreased with time. Increasing domestic demand for cash crops accelerated the establishment of cash crop plantations. Technology advancement lowered the costs for land reclamation in locations with high elevation. Consequently, previously forested areas that were less suitable for cropping were converted to cash crop plantations (e.g., hickory).

The demonstrated methodology (remote sensing, spatial analysis, data sampling, regression modeling) can be applicable to other regions experiencing rapid cash crop expansion. It can be referred from the modeling results that areas more vulnerable to cash crop expansion in the future would be those covered by forest and farmland with high proximity to provincial road, river and lake, and county center. Our study highlighted the need to adequately quantify determinants of cash crop expansion and their relative effects. On one hand, more potential determinants, socioeconomic variables in particular, must be considered. On the other hand, more sophisticated sampling and regression techniques should be employed to characterize the changing influence from different categories of determinants.

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References

Anderson, M., Gribble, N., 1998. Partitioning the variation among spatial, temporal and environmental components in a multivariate data set. Aust. J. Ecol. 23, 158–167.

Arsanjani, J.J., Helbich, M., Kainz, W., Boloorani, A.D., 2013. Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. Int. J. Appl. Earth Obs. Geoinform. 21, 265–275.

Castiblanco, C., Etter, A., Aide, T.M., 2013. Oil palm plantations in Colombia: a model of future expansion. Environ. Sci. Policy 27, 172–183.

Cheng, H.Q., Masser, I., 2003. Urban growth pattern modeling: a case study of Wuhan city, PR China. Landsc. Urban Plan. 62, 199–217.

Dong, J., Xiao, X., Chen, B., Torbick, N., Jin, C., Zhang, G., Biradar, C., 2013. Mapping deciduous rubber plantations through integration of PALSAR and multi-temporal Landsat imagery. Remote Sens. Environ. 134, 392–402.

Fox, J., Vogler, J., 2005. Land-use and land-cover change in Montane Mainland Southeast Asia. Environ. Manag. 36, 394–403.

Gibreel, T.M., Herrmann, S., Berkhoff, K., Nuppenau, E., Rinn, A., 2014. Farm types as an interface between an agroeconomical model and vCLUE-Naban land change model: application for scenario modeling. Ecol. Indic. 36, 766–778.

Godone, D., Garbarino, M., Sibona, E., Garnero, G., Godone, F., 2014. Progressive fragmentation of a traditional Mediterranean landscape by hazelnut plantations: the impact of CAP over time in the Langheregion (NW Italy). Land Use Policy 36, 259–266.

Haas, J., Ban, Y., 2014. Urban growth and environmental impacts in Jing-Jin-Ji, the Yangtze River Delta and the Pearl River Delta. Int. J. Appl. Earth Obs. Geoinform. 30, 42–55.

Heikkinen, R., Luoto, M., Kuussaari, M., Pöyry, J., 2005. New insights into butterfly-environment relationships using partitioning methods. Proc. R. Soc. B 272, 2203–2210.

Kaufmann, R.K., Cleveland, C.J., 2008. Environmental Science. McGraw-Hill, pp. 318–319.

Krusekopf, C.C., 2002. Diversity in land-tenure arrangements under the household responsibility system in China. China Econ. Rev. 13, 297–312.

Li, H., Ma, Y., Aide, T.M., Liu, W., 2008. Past, present and future land-use in Xishuangbanna, China and the implications for carbon dynamics. For. Ecol. Manag. 255, 16–24.

Li, Z., Fox, J.M., 2012. Mapping rubber tree growth in mainland Southeast Asia using time-series MODIS 250 m NDVI and statistical data. Appl. Geogr. 32, 420–432.

Marull, J., Pinob, J., Tello, E., Cordobilla, M.J., 2010. Social metabolism, landscape change and land-use planning in the Barcelona Metropolitan Region. Land Use Policy 27, 497–510.

Miyamoto, M., 2006. Forest conversion to rubber around Sumatran villages in Indonesia: comparing the impacts of road construction, transmigration projects and population. For. Policy Econ. 9, 1–12.

Müller, D., Leitão, P.J., Sikor, T., 2013. Comparing the determinants of cropland abandonment in Albania and Romania using boosted regression trees. Agric. Syst. 117, 66–77.

Nagashima, K., Sands, R., Whyte, A.G.D., Bilek, E.M., Nakagoshi, N., 2002. Regional landscape change as a consequence of plantation forestry expansion: an example in the Nelson region, New Zealand. For. Ecol. Manag. 163, 245–261.

Nainggolan, D., de Vent, J., Boix-Fayos, C., Termansen, M., Hubacek, K., Reed, M.S., 2012. Afforestation, agricultural abandonment and intensification: competing trajectories in semi-arid Mediterranean agro-ecosystems. Agric. Ecosyst. Environ. 159, 90–104.

Nandy, R.K.S., Agarwal, R., Kushwaha, S.P.S., 2014. Forest cover dynamics analysis and prediction modeling using logistic regression model. Ecol. Indic. 45, 444–455.

Pandey, B., Joshi, P.K., Seto, K.C., 2013. Monitoring urbanization dynamics in India using DMSP/OLS night time lights and SPOT-VGT data. Int. J. Appl. Earth Obs. Geoinform. 23, 49–61.

Polimeni, J.M., 2005. Simulating agricultural conversion to residential use in the Hudson River Valley: Scenario analyses and case studies. Agric. Hum. Values 22, 377–393.

Qin, J., Kong, X.B., Zhang, F.R., Miao, Y.X., Liu, L.W., 2007. Change of soil organic matter as affected by household land use based on 3S technology in urban fringes of north China. N. Z. J. Agric. Res. 50, 1093–1102.

Reis, S., Yomralioglu, T., 2006. Detection of current and potential hazelnut plantationareas in Trabzon, North East Turkey using GIS and RS. J. Environ. Biol. 27, 653–659.

Su, S., Zhang, Q., Zhang, Z., Zhi, J., Wu, J., 2011. Rural settlement expansion and paddy soil loss across an ex-urbanizing watershed in eastern coastal China during market transition. Reg. Environ. Change 11, 651–662.

Su, S., Yang, C., Hu, Y., Luo, F., Wang, Y., 2014a. Progressive landscape fragmentation in relation to cash crop cultivation. Appl. Geogr. 53, 20–31.

Su, S., Ma, X., Xiao, R., 2014b. Agricultural landscape pattern changes in response to urbanization at ecoregional scale. Ecol. Indic. 40, 10–18.

Su, S., Xiao, R., Li, D., Hu, Y., 2014c. Impacts of transportation routes on landscape diversity: a comparison of different route types and their combined effects. Environ. Manag. 53, 636–647.

Su, S., Xiao, R., 2013. Spatially varying determinants of farmland conversion across Qiantang watershed, China. Environ. Manag. 52, 907–916.

Tayyebi, A., Pijanowski, B.C., 2014. Modeling multiple land use changes using ANN, CART and MARS: comparing tradeoffs in goodness of fit and explanatory power of data mining tools. Int. J. Appl. Earth Obs. Geoinform. 28, 102–116.

van den Berg, M.M., Hengsdijk, H., Wolf, J., van Ittersum, M.K., Wang, G.H., Roetter, R.P., 2007. The impact of increasing farm size and mechanization on rural income and rice production in Zhejiang province, China. Agric. Syst. 94, 841–850.

van Lier, O.R., Luther, J.E., Leckie, D.G., Bowers, W.W., 2011. Development of large-area land cover and forest change indicators using multi-sensor Landsat imagery: application to the Humber River Basin, Canada. Int. J. Appl. Earth Obs. Geoinform. 13, 819–829.

Wehner, S., Herrmann, S., Berkhoff, K., 2014. CLUENaban—a land use change model combining social factors with physical landscape factors for a mountainous area in Southwest China. Ecol. Indic. 36, 757–765.

Yi, Z., Cannon, C.H., Chen, J., Ye, C., Swetnam, R.D., 2014. Developing indicators of economic value and biodiversity loss for rubber plantations in Xishuangbanna, southwest China: a case study from Menglun township. Ecol. Indic. 36, 788–797.

Zhang, L., Kono, Y., Kobayashi, S., 2014. The process of expansion in commercial banana cropping in tropical China: a case study at a Dai village, Mengla County. Agric. Syst. 124, 32–38.

Zhang, Z., Su, S., Xiao, R., Jiang, D., Wu, J., 2013. Identifying determinants of urban growth from a multi-scale perspective: a case study of the urban agglomeration around Hangzhou Bay, China. Appl. Geogr. 45, 193–202.

Ziegler, A.D., Fox, J.M., Xu, J., 2009. The rubber juggernaut. Science 324, 1024–1025.