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Telecoupling urbanization and mountain areas deforestation between 2000 and 2020: Evidence from Zhejiang Province, China

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Abstract

Forest transition theory posits that socioeconomic development in a country or region may cause its forestland to shift from net loss to net gain. However, forest transition may also occur under various policies, resulting in forest gains in some regions but deforestation in other regions. We used the telecoupling framework to address this crucially important issue that has rarely been examined. Using time series satellite images and statistical yearbook data from 2000 to 2020, this study seeks to understand land use change patterns, the corresponding regional spillover effects, and the driving forces behind such patterns in Zhejiang Province, China. The results show that large-scale continuous deforestation has taken place since 2000, causing a total loss of forestland by 22,823 ha. In parallel with this forest loss and a slight decrease in arable land, urban construction land has soared by 169.45%. We found that more developed municipalities such as Hangzhou witnessed increases in urban land at the expense of large-scale deforestation in less developed municipalities such as Lishui. This cross-region land use change pattern may arise from the balance of arable land system (BALS) policy that seeks to achieve a goal of no net loss of arable land. Land use policy—such as the BALS policy—must strike a good balance among competitive land uses that have different objectives such as residents' living, ecology, and production. In addition to enriching the forest transition theory, this study provides a solid basis for future land use decisions in developing regions or countries.

KEYWORDS
deforestation, land use policy, telecoupling, urbanization, Zhejiang Province

1 | INTRODUCTION

Anthropogenic activities have altered the Earth's land surface, causing substantial degradation and loss of vital ecosystems and the corresponding services they support (Elhacham et al., 2020). Land use and cover change under human modification has greatly transformed the Earth's energy balance and biogeochemical cycles, which contribute to climate change and biodiversity degradation and, in turn, affect the nature of the land surface and the provision of ecosystem services (Foley et al., 2005; Turner II et al., 2007). Humans depend on land for food, energy, living space, and socioeconomic development (X. P. Song et al., 2018). With a rapidly growing population, the demand for natural resources has increased drastically worldwide (Foley et al., 2011), resulting in widespread degradation and reduction of ecosystem services (Pandit et al., 2019). To effectively cope with these global challenges, the United Nations has crafted 17 Sustainable Development Goals (SDGs), among which Goal 15 of halting and reversing land degradation mostly pertains to future land planning.

However, taking the SDG agenda seriously and implementing it on the ground will be far from easy (J. Liu et al., 2018). With large-scale biodiversity loss and degradation due to unsustainable land development, deforestation, and infrastructure expansion, a set of undesirable consequences—such as the COVID-19 pandemics—may arise and beset mankind (Dobson et al., 2020; Tollefson, 2020).

The land use transition theory has been proposed to illustrate land change trajectories in the process of socioeconomic development, which can be used to explain the global pattern related to forest net gain (E. F. Lambin & Meyfroidt, 2011). This theory explains changes in land use morphology, including dominant morphology and secondary morphology, of a certain region over a certain period by socioeconomic reform and innovation, which usually corresponds to the transition of socioeconomic development stage (Long, 2020; Long et al., 2020). Topologies of land use transition include forest loss (DeFries et al., 2010), rural housing land transition (T. Li et al., 2015; Long et al., 2007), arable land transformation (Long & Li, 2012; W. Song & Deng, 2015), urban land expansion (Gao et al., 2016), and so on. The land use transition theory offers theoretical and technical support for the rational use of natural resources and land (E. F. Lambin & Meyfroidt, 2010; Long & Qu, 2018). With rural-to-urban migration over large scales accompanying urbanization, sustainable use of land becomes a central concern of policy makers and other stakeholders (Long et al., 2018). The accelerated urbanizing process has triggered a dramatic shift in land use in China, which has been a hot topic of research for many years (Long, 2014).

Rapid urbanization will encroach arable land around municipalities, leading to large-scale loss of arable land (X. Liu et al., 2020). Since the turn of the 21st century, China has stepped into a critical era of rural–urban transition. Widespread and accelerated urbanization has made land resources increasingly scarce, representing a serious challenge to a country like China with a huge population base (Jiang et al., 2012; J. Liu et al., 2007). During the process of urbanization, built-up land is tremendously expanding (E. F. Lambin et al., 2001), seriously affecting food production and consumption systems (Godfray et al., 2010). The cascading effects of such changes may pose an even greater challenge to arable land conservation and thus food security (Davis et al., 2016), leading to deforestation at larger scales, overuse of fertilizer, and other environmental problems (Costello et al., 2020; E. F. Lambin et al., 2001; Long et al., 2011; Lu et al., 2020; Tan et al., 2005).

Maintaining an adequate amount of arable land is a prerequisite for securing food production (Chaplin-Kramer et al., 2015; Foley et al., 2011). Arable land has multifunction, ranging from food production to social security, and to ecological services (Long, 2020). To ensure food security, China's Central Government has executed a series of policies to hold arable land from loss, including the Balance of Arable Land System (BALS) policy, the Basic Cropland Protection System Program, and the policy to couple the increase of urban construction land with reducing rural construction land (Long et al., 2012; Shen et al., 2017; W. Song & Pijanowski, 2014). A common goal of these policies is to maintain the amount of arable land by relocating arable land from adjacent urban areas to remote rural places (Xin & Li, 2018), which may destroy or downgrade the environment in the latter (Y. Liu et al., 2016). However, the effectiveness of these policies and their impacts on social-ecological systems in related areas have not been fully explored. Previous studies have shown widespread deforestation in Zhejiang Province (Xiong et al., 2020) even after the proposed national strategy of ecological protection and ecological civilization. Therefore, more work is needed to understand how these policies caused widespread land degradation.

Institution is a key driver of land change (Stuhlmacher et al., 2020). Land use change is influenced by both policy and socioeconomic development in China (Wang et al., 2018) and elsewhere (Halbac-Cotoara-Zamfir et al., 2019). Under China's accelerated urbanization, land use transformation is mainly represented by the shrinkage of arable land and the expansion of construction land at rural–urban fringe areas (Y. S. Liu et al., 2010; Su et al., 2016). Exploring the institutional dimension of land use change may not only contribute to finding solutions for sustainable land use, but also help reform ineffective land use policies (Long et al., 2018). In this study, we analyze the land use dynamic in Zhejiang Province from 2000 to 2020 using Hansen et al. global forest change (GFC) dataset (Hansen et al., 2013) and the GlobeLand30 land cover product (J. Chen, Ban, & Li, 2014) in conjunction with data from statistical yearbooks and other sources. We aimed to reveal the following: (a) the deforestation process and its linkage to other types of land use change in Zhejiang Province; (b) policy factors that have driven deforestation; (c) the relationships between deforestation and urbanization; and (d) the mechanism in relation to how urbanization in one region has resulted in deforestation in other distant places. This study attempts to contribute to understanding land use change patterns in Zhejiang Province in the context of urbanization, their regional spillover effects, and the corresponding driving forces. In recognition of the challenges related to the 'no net loss' policy at large, we aim to promote effective approaches toward the goal of sustainable use of land.

2 | METHOD AND MATERIALS

2.1 | Study area

Zhejiang Province, one of the most socioeconomically developed provinces in China, is chosen to be our study area for the following reasons. Located at the southeastern coast of China, Zhejiang is located at the southern fringe of the Yangtze River Delta (Figure 1). Lying between $27^\circ 12'$–$31^\circ 30'$N and $119^\circ 42'$–$122^\circ 06'$E, it has a subtropical monsoon climate with abundant rainfall (1100–2000 mm on average annually). With a land area of 10,550,600 ha, Zhejiang is a mountainous province characterized mostly by mountains ($\sim$70%), agricultural land ($\sim$20%), and waterbodies ($\sim$10%), with flat areas mainly in the northeast and mountainous areas in the southwest (Figure 1). As of the end of 2019, the total population was 58.5 million, of which 70% lived in cities, where the forest coverage was 61.15% of the total land area (citation from *Zhejiang Statistical Yearbook*). Zhejiang Province, with a GDP of US$ 954 billion and GDP per capita of US$ 16,474 in 2019, ranks fourth and fifth among China's 31 provinces, respectively. The geographical diversity and rapid

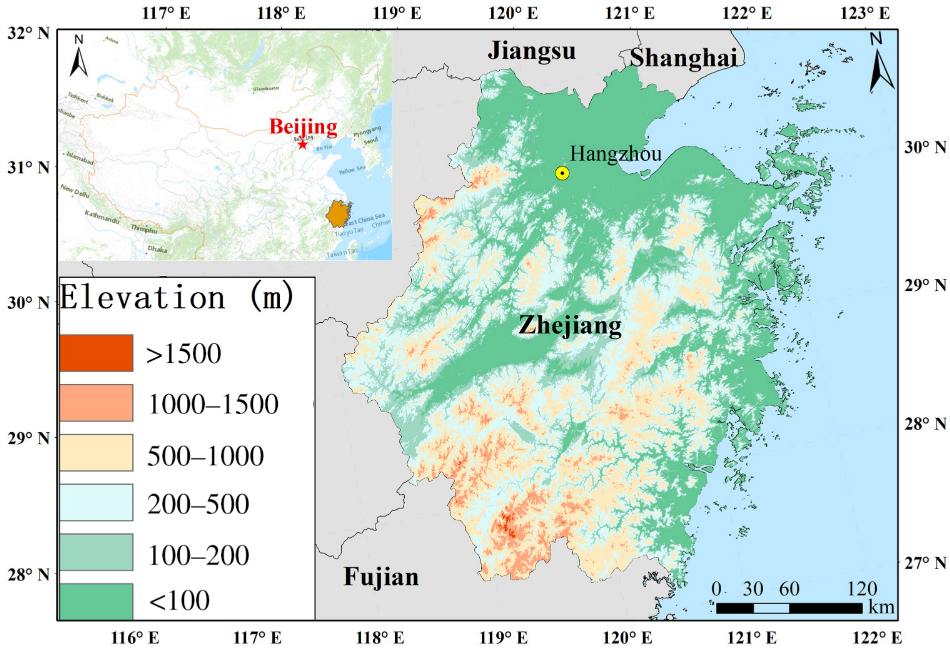


FIGURE 1 Location and elevation of Zhejiang Province, China [Colour figure can be viewed at wileyonlinelibrary.com]

economic development have led to fundamental changes in land cover and land use. Recently, deforestation associated with urbanization has become a serious problem, which renders Zhejiang Province an ideal case for conducting research on policy-related deforestation.

2.2 | Data sources and processing

We utilized primarily GlobeLand30 to detect and analyze land use changes in Zhejiang Province from 2000 to 2020. GlobeLand30 is the first open-source, fine-scale global land cover database based on remote sensing models (J. Chen et al., 2015). This dataset is the only product worldwide on land cover with a 30 m resolution for the years 2000, 2010, and 2020. The GlobeLand30 dataset is derived from over 20,000 LANDSAT and HJ-1 (China Environment and Disaster Reduction Satellite) imageries using machine learning models in combination with pixel-level and object-based processing procedures. In particular, the dataset of 2020 also incorporates the 16-metre resolution GF-1 (China High-Resolution Satellite) multispectral images. The principle of image selection in the dataset is to select multispectral images of the vegetation growing season within ±2 years of the baseline year in which the data were generated and updated, provided that the images are cloud-free or with the least cloud. In areas that are difficult to acquire data, the timing of image acquisition was adjusted to ensure the integrity of the overall coverage. The classification scheme includes 10 land cover types, which are arable land, forest land, grassland, shrubland, wetland, water body, tundra, artificial surface, bare land, and perennial snow and ice, with no mosaic pixels (J. Chen et al., 2015). In this study, artificial surface is defined as built-up land to explore the urban area expanding.

Based on a third-party evaluation, the overall accuracy of classification based on GlobeLand30 (for 2010) is 83.50% and the kappa coefficient is 0.78. This result is from validation effort based on over 150,000 points in 80 tiles of 853 in total. On-the-other-hand, the overall accuracy of classification based on GlobeLand30 (for 2020) is 85.72%, and the kappa coefficient is 0.82 according to our validation results based on over 230,000 points from the whole datasets using a landscape index sampling model (J. Chen, Ban, & Li, 2014; F. Chen et al., 2016; Liang et al., 2015). At the same time, other scholars have used GlobeLand30 dataset to verify the accuracy of the areas, including Zhejiang Province, and found that the data verification results are good (Y. Chen et al., 2021; Ren, 2020). Based on previous verification results and combined with fieldwork, this dataset can meet our research needs.

To better analyze the results of land use change in Zhejiang Province, we also used data from *Zhejiang Land Statistics Yearbook*. Specifically, we analyzed official statistics on land use change in Zhejiang Province since 2000. To capture forest loss in Zhejiang Province more comprehensively, we also selected the European Space Agency (ESA) – Climate Change Initiative (CCI) as another data source. With a medium-resolution (300 m) satellite imagery, the dataset has a global coverage from 2000 to 2018, which classified pixels (using a machine learning algorithm) into over 22 land cover categories (for instance, mosaic natural vegetation of tree, shrub, herbaceous vegetation) (Bontemps et al., 2013). The accuracy of the map is reported to be 71.5% (Defourny et al., 2017). In our study, we reclassified the products according to the IPCC classification criteria and extracted the forest class for further analysis. To align with our land classification typology, all ESA-CCI land cover types with trees and mosaic trees and shrubs were reclassified as forest land.

To further assess the annual change regarding forest loss, we used the latest version (Version 1.7 Update) of the Hansen et al. GFC dataset, which is available online on the Google Earth engine (GEE) website and the Global Forest Watch website. The most updated dataset contains the layers of 2000 tree canopy cover and 2001–2019 forest loss, providing the information regarding the year of forest loss. The product has a 30 m spatial resolution and is synthesized by processing 654,178 LANDSAT-7 ETM+ images in high quality (Hansen et al., 2013). The dataset defines trees as 'all vegetation above 5 m in height' and forest loss as 'the mortality or removal of all tree covers in a 30 m by 30 m pixel' (Hansen et al., 2013). The previous update of forest gain in the Hansen et al GFC dataset was in 2012 and thus may be biased from forest growth in reality. The overall accuracy, assessed by the Food and Agriculture Organization (FAO) statistics using both LiDAR surveys and other satellite data, has been shown to be over 99% (Hansen et al., 2013). To minimize any data error and improve classification accuracy, we have combined remote sensing datasets with field surveys. We define net forest loss to be areas with only forest loss and no gain during the study period. We randomly selected 1000 sample points from net forest loss areas. The accuracy for each sample point is assessed by visual interpretation of high-resolution satellite imagery in pre-disturbance (LANDSAT-7 ETM + high-resolution satellite imagery in 1999, cloud-free) to interpret whether there was a forest in the pixel before the 21st century and super-high-resolution satellite imagery after disturbance (around or after 2019, depending on the availability in the Google Earth imagery). Meanwhile, we visited and investigated different deforestation areas to verify the accuracy of the dataset in Zhejiang Province. The validation results turned to be acceptable, with an overall accuracy of 80% based on the Hansen et al. GFC dataset in Zhejiang Province (Xiong et al., 2020). In addition, we believe that the next generation of Hansen products (e.g., version 2.0) may provide more information on actual forest growth and loss (Zeng et al., 2018). In this assessment, by referring to the Global Forest Watch website, we set 30% as the threshold of defining tree canopy cover for all the following analyses of forest loss.

The administrative division data of Zhejiang Province is derived from Global Administrative Areas (GADM). These datasets have their own strengths in showing the spatial and temporal patterns of land change in Zhejiang Province (Table 1), and the combined use of the results of these data analyses is beneficial in exploring the spatial and temporal characteristics of land use transformation.

3 | RESULTS

3.1 | Deforestation in Zhejiang Province

Our estimation based on the dataset of Hansen et al. shows that the total net forest loss in Zhejiang Province from 2001 to 2019 is 279,501 ha (Figure 2a), a 4.7% decline in forest from the 2000 baseline. Annually, the rate of net forest loss is approximately 12,549 ha per year during 2001–2008, representing a sixfold increase from about 4245 ha in 2001 to nearly 26,993 ha in 2008. From 2009 to 2019, the forest loss was accelerated at a high rate of 16,282 ha each year. The cumulative net forest loss monotonically increased during the entire study period.

In addition to the Hansen et al. dataset, other data products including GlobeLand30 and ESA-CCI also show forest loss in Zhejiang Province after 2000 (Figure 2b). The GlobeLand30 dataset shows that forest cover decreased by 22,823 ha in Zhejiang during 2000–2020 and ESA-CCI 186,014 ha during 2000–2018, but *Zhejiang's Statistical Yearbook* data show an increase in forest at the magnitude of 80,400 ha in Zhejiang from 2000 to 2018 (Figure 2b). There is a discrepancy between statistics from the yearbook and those from the satellite. In comparison with satellite-based estimates, those from the yearbook tend to underestimate the area of forest loss.

At the same time, we analyzed the spatial distribution of forest loss and gain in Zhejiang Province using GlobeLand30 high-resolution satellite images (Figure 2c,d). Over the space of Zhejiang Province, forest loss was found to be a prevalent phenomenon in many parts across the whole province. The landscape in terms of forest loss was shown to be scattered and rarely interconnected in general, but forest loss mainly dominated the mountainous regions within the Province (Figure 2c). Overall, forest loss happened mainly in the western and southern parts of Zhejiang, while the lost area was relatively small in the northeastern part. Forest loss exhibited heterogeneous patterns at the municipality level (Figure 2c). Among all the municipalities in Zhejiang Province, the greatest loss in forest cover was observed in Lishui municipality in South Zhejiang, which is followed by Hangzhou municipality in West Zhejiang (the most economically developed city and the capital city of the province). Jiaxing municipality in proximity to Shanghai (the economic center in eastern China) possessed the least loss of forest. Forest loss was mainly due to conversion to arable land, with the largest amount occurring in Lishui.

Forest gain also occurred in almost all areas of Zhejiang Province. But the increase in forestland in most of those regions was less than the loss of forests. Among all the municipalities, Hangzhou has the largest increase and Jiaxing the smallest increase. The main source of forest gain is by converting arable land to forest, which is observed most in Wenzhou, followed by Lishui and Hangzhou (Figure 2d).

3.2 | Urban expansion in Zhejiang Province

According to *China Statistical Yearbooks* (2001–2018) (Figure 3a), the proportion of urban area in Zhejiang Province increased steadily between 2001 and 2018. During the same period, the proportions of

TABLE 1 Data sources in the study

Data	Period	Spatial resolution	Temporal resolution	Data sources
GlobeLand30	2000/2010/2020	30 m	Decade	http://www.globeland30.org/
Hansen v1.7	2001–2019	30 m	Year	http://earthenginepartners.appspot.com/science-2013-global-forest
ESA-CCI	2000–2018	300 m	Year	http://www.esa-landcover-cci.org/
Statistical yearbook	2000–2018	/	Year	https://data.cnki.net/
GADM	Up to date	/	/	https://gadm.org/download_country_v3.html

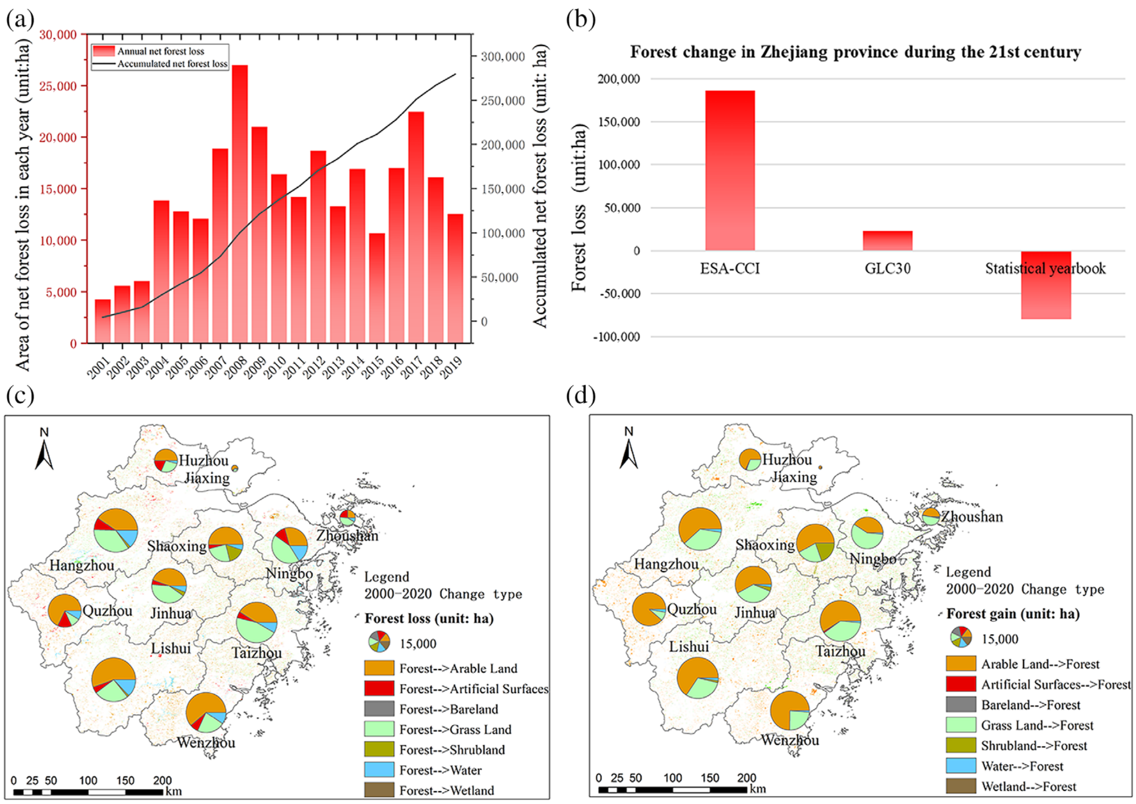


FIGURE 2 Temporal changes and spatial patterns of deforestation in Zhejiang Province from 2000 to 2020. (a) Cumulative net forest loss (line) and annual net forest loss (bar) from 2001 to 2019 were based on GFC annual forest loss. (b) Scale of forest change. The bar charts are estimates based on satellite-based land-cover change products and statistical yearbook data (GlobeLand30, 2000–2020; ESA-CCI, 2000–2018; statistical yearbook, 2000–2018). (c) Spatial distribution of net forest loss converted to other land classifications from 2000 to 2020 was based on GlobeLand30. (d) Spatial distribution of net forest gain derives from other land classifications from 2000 to 2020 also from GlobeLand30 [Colour figure can be viewed at wileyonlinelibrary.com]

urban land area and forest land area increased by 70.29% and 1.45%, respectively, while the arable land area decreased by 5.26%. The rest of the land types had a gradual decrease (Figure 3a). Using the GlobeLand30 data, we found that during 2000–2020, the area of urban land use increased by 169.45%, while the area of forest and arable land decreased by 0.40% and 19.20%, respectively (Figure 3b).

Meanwhile, we used GlobeLand30 to analyze the spatial distribution of urban land changes in Zhejiang Province (Figure 3c,d). Spatially, urban area loss and gain occurred in almost all the Province, but the lost patches were dispersed and much smaller compared with the gained areas, although the amount of net loss is only approximately 6% of the net gain. Of these, Ningbo and Hangzhou had the largest urban area gains, while Lishui and Zhoushan had the smallest gains (Figure 3c,d).

According to the GlobeLand30 dataset, the largest land use changes from 2000 to 2020 took place in the form of land use conversions among urban construction land, arable land, and forest in Zhejiang Province (Figure 4). The conversion from arable land to urban area is the largest (562,399 ha), followed by conversions from arable land to forest land (260,322 ha) and from forest land to arable land (210,474 ha). The changes in other land uses are relatively small. We observe that urban land expansion primarily comes from losses of arable land, while arable land increases as a result of deforestation.

3.3 | Telecoupling illustration: Land use change in Hangzhou and Lishui

According to the GlobeLand30 dataset, we compared land use change patterns of Hangzhou and Lishui between 2000 and 2020. As a result, we found that the largest conversion from arable land to urban area in Hangzhou was 77,288 ha, followed by 37,036 ha from arable land to forest land and 26,551 ha from forest land to arable land. In Lishui, land use conversion was characterized by 37,198 ha of arable land to forest land, 36,787 ha of forest land to arable land, and only 16,910 ha of arable land to urban area. These results show that the biggest land change in Hangzhou is from arable land to urban land. The change in Lishui municipality is mainly due to conversion between arable land and forest land, and its area of forestland loss is larger than that of Hangzhou Municipality (Figure 5).

4 | DISCUSSION

4.1 | Causes of deforestation in Zhejiang Province

Zhejiang Province has experienced massive deforestation since 2000, representing a significant land use change in the region. During the

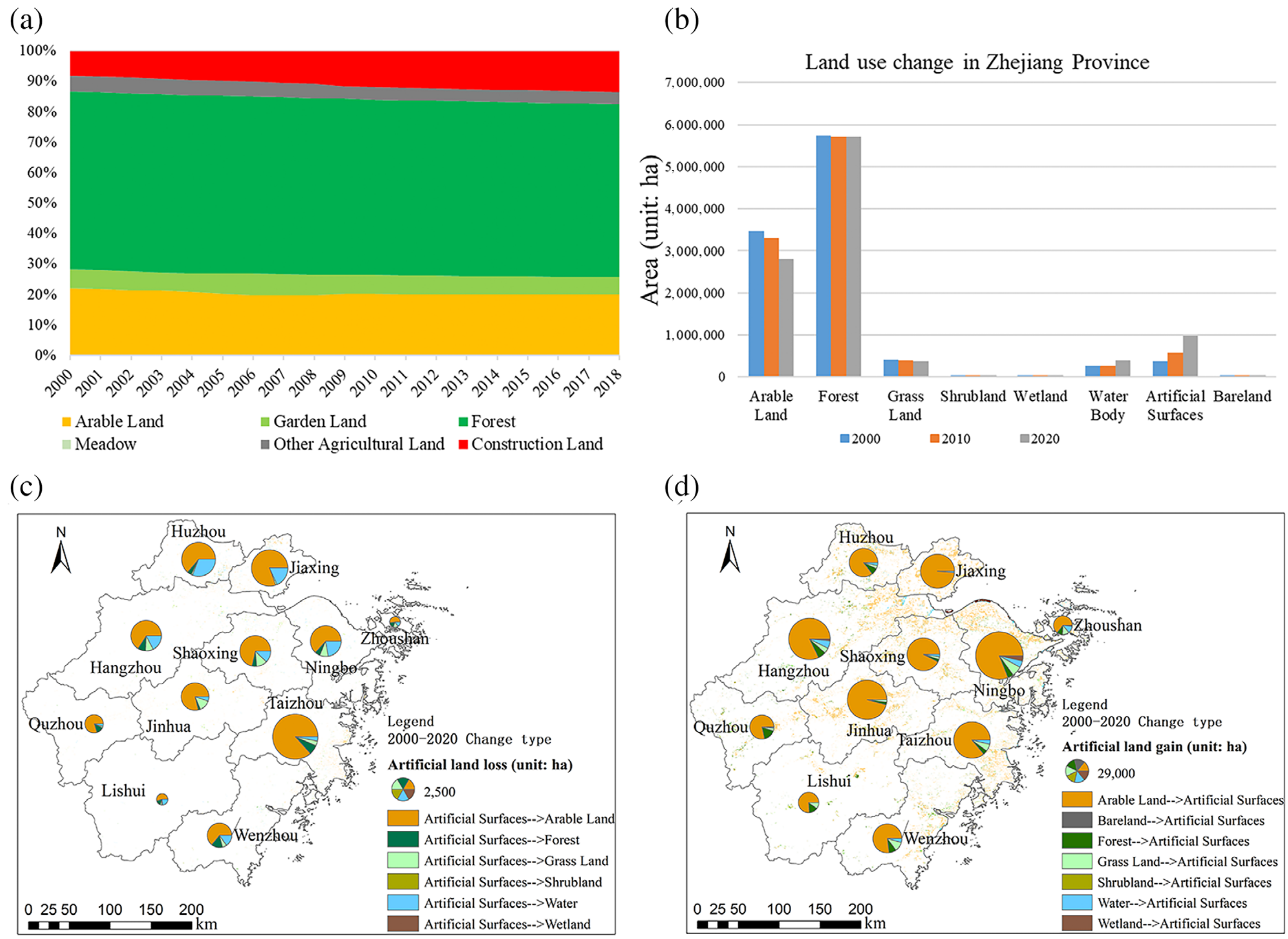


FIGURE 3 Temporal changes and spatial patterns of urban land in Zhejiang Province. Data of temporal change of land use are from (a) statistical yearbook between 2000 and 2018 and (b) GlobeLand30 between 2000 and 2020. (c) Spatial distribution of built-up land loss converted to other land classifications from 2000 to 2020. (d) Spatial distribution of built-up land gain derives from other land classifications over the same time span [Colour figure can be viewed at wileyonlinelibrary.com]

study period, remote sensing data showed a decrease in forest area in Zhejiang Province between 2000 and 2020.

According to satellite-based land use and land cover products, we detected a substantial decrease in forest area in the early 2000s (Figure 2b). While data on forest decline are not uniform, inconsistent definitions of forest may be a plausible reason for explaining the different rates of forest loss among various land cover products (H. Chen et al., 2020; Zeng et al., 2018). The Hansen's forest dataset shows that extensive deforestation occurred in Zhejiang Province in the early 2000s (Xiong et al., 2020). However, while the forest dataset by Hansen et al. can reflect annual net forest loss, it cannot reflect actual net changes in forest cover. Therefore, we used GlobeLand30 and ESA-CCI datasets to analyze net forest cover change. We also found that the higher-resolution GlobeLand30 (30 m) dataset showed less forest loss than the ESA-CCI (300 m) dataset. The GlobeLand30 dataset was produced with a globally trained machine learning algorithm. This algorithm, less suitable for detecting irregularly shaped mountain crop fields, may account for its underestimation of forest loss (Zeng et al., 2018). The resolution of the ESA-CCI (300 m) product requires a classification scheme to use mosaic classes, which might result in mixing arable land with other land cover types (Ozdogan & Woodcock, 2006). Yet, despite the inconsistent changes in forest loss area, remotely sensed land data that do not rely on government statistics tend to be more likely to show objective patterns with relatively high reliability (Zeng et al., 2018).

Forest transition theory assumes that forest in a country or a region will shift from a net loss to a net gain along with socioeconomic development (Meyfroidt et al., 2010). However, it has also been shown that if a country or region is engaged in cross-region trade flows (e.g., South America soybean), then deforestation may positively correlate with the growth of urban population and agricultural exports (DeFries et al., 2010). Some studies also show that forestland tends to be lost as China's GDP per capita rises (Vina et al., 2016). The accelerated urbanization in Zhejiang Province from 2000 to 2020 has resulted in conversion from agricultural land to urban land (Figure 4). Besides, we also observed a large amount of forest loss (i.e., land converted to arable land) (Figure 4) and continued forest fragmentation in Zhejiang Province, which might arise from the reclamation of

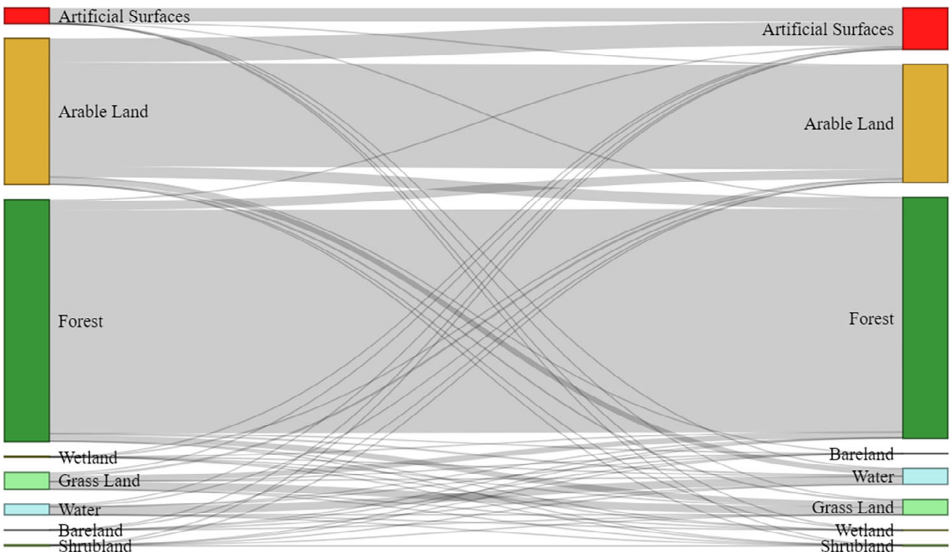


FIGURE 4 Sankey map of land use transformation in Zhejiang Province from 2000 to 2020 [Colour figure can be viewed at wileyonlinelibrary.com]

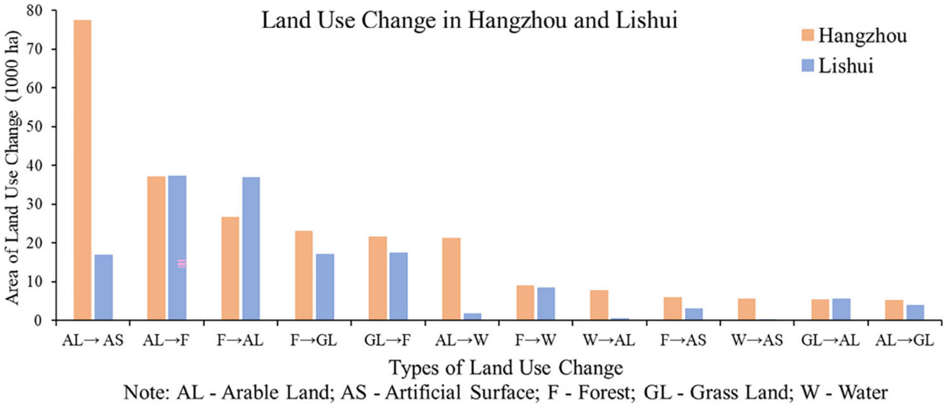


FIGURE 5 Land use change in Hangzhou and Lishui from 2000 to 2020 [Colour figure can be viewed at wileyonlinelibrary.com]

agricultural land (Xiong et al., 2020). Such large-scale and rapid deforestation should be of concern to governments and the scientific community.

4.2 | Policy evolution on the BALS

The implementation of the BALS policy, established to play a dual role of guaranteeing economic development and protecting the environment, might have achieved this goal (Long et al., 2012; Xin & Li, 2018). However, this policy also attracted great debate and was changed several times.

China's BALS policy can be divided into three stages (Figure 6). The initial stage was for systematic policy construction. China first proposed the arable land acquisition and compensation system in 1997. The BALS policy was formally written into the new Land Management Law in 1998. To protect arable land, China amended the Land Management Law to maintain the amount of arable land with a new arable land replenishment mechanism, giving rise to the 'occupy one ha and replenish one ha' policy in 1999. In 2001, all provinces (including autonomous regions) basically achieved a balance in the amount of arable land, ensuring that the total area of arable land was not in decline. The focus of land consolidation during this period was to increase the amount of arable land, provide space for urbanization and industrialization, ensure food security, and increase farmers' income (W. Song & Pijanowski, 2014).

The second stage featured systematic policy improvement. From 2004 onwards, the Chinese Government has been focusing on the quality of newly created arable land, issuing a series of policies. In 2004, the government introduced measures to control the quality of land during land conversions, assuring that the quantity and quality of newly created arable land should meet national standards. The year 2005 saw a shift of focus to administrative accountability, starting to implement an accountability target assessment and chief executive responsibility system. In 2006, several specific institutional assessment mechanisms were introduced, which issued several pilot projects demanding that decreases in rural construction land be linked to increases in urban construction land (Long & Li, 2012). In 2008, China proposed to designate permanent basic arable land to ensure that the quantity of arable land would not be reduced, and its quality would be improved. In 2009, arable land was required to be fully replenished before the land occupation, and subsequent operational rules were

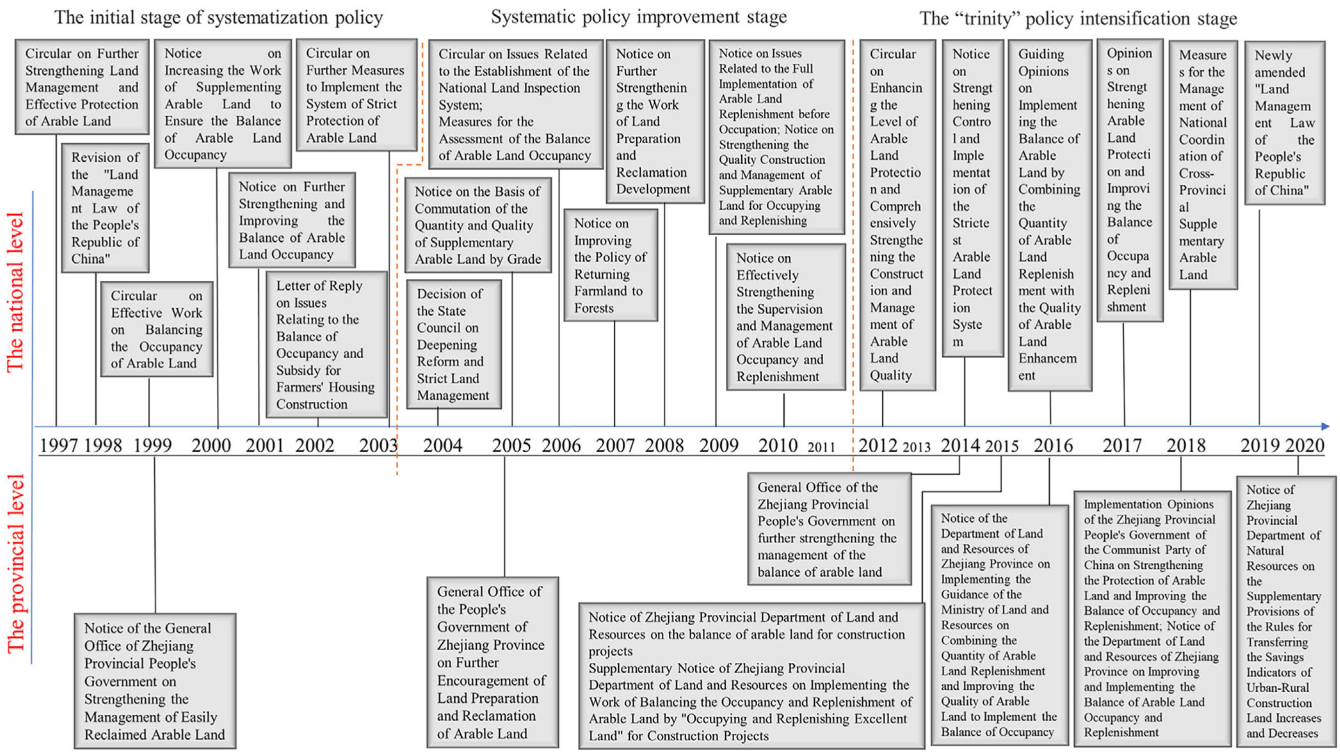


FIGURE 6 The Balance of Arable Land System (BALS) policy evolution [Colour figure can be viewed at wileyonlinelibrary.com]

issued to strengthen the quality and management of replenished arable land. At this stage, the quantity and quality of arable land were protected, and the productivity of arable land was relatively ensured (Long, 2020).

The third stage was characterized by a 'Trinity' of quantitative, qualitative, and ecological policy. The Chinese Government authorities have further improved their management approach by emphasizing a policy of balancing land occupation and compensation between provinces. To ensure the quality of replenished arable land, a decree was issued in 2012 to strengthen the management of arable land and maintain land quality. In 2014, the Chinese Government proposed that the occupation of high-quality land and paddy land should be compensated; in 2016, a combination of quality improvement and remediation was proposed. In 2018, China formed the Ministry of Natural Resources to strengthen the unified integration and management of natural resources. In 2018, the Ministry of Natural Resources issued a national coordinated management decree to establish the inter-provincial replenishment of arable land along with a management scheme for construction land transfer between rural and urban areas in different provinces. This provides a clear direction for the unified management of arable land resources, focusing more on the ecological functions of land use (Long, 2020; Long et al., 2018).

The expansion of arable land, although able to satisfy market demands and conform with policies, may lead to ecological problems such as deforestation (Henders et al., 2018). Our study shows that the largest source of urban construction land in Zhejiang Province is arable land, and the largest source of arable land is through converting forest land (Figure 4). In the context of the BALS policy, the total amount of arable land quantity needs to be guaranteed, which inevitably leads to converting forest land to arable land in Zhejiang Province. In China, large municipalities like Hangzhou are often blamed for the massive loss of high-quality arable land (Hu et al., 2020). Hangzhou's GDP continued to increase from 138.26 to 1537.31 billion yuan during 2000–2019, representing an 11-fold increase. The resident population of Hangzhou municipality increased by 48% from 7.02 to 10.36 million, while the registered population increased by 28% from 6.22 to 7.95 million. Lishui's GDP, on-the-other-hand, only increased from 13.676 to 147.661 billion yuan (1 Yuan = 0.12~0.16 US$ for 2000–2019) during 2000–2019 with a slow resident population growth from 2.16 to 2.21 million and a slow registered population increase from 2.49 to 2.71 million. Lishui has a more registered population than resident population, while Hangzhou has less registered population than resident population. This means that the population in Lishui was outflowing, while the population in Hangzhou was growing due to inflows from other areas (Figure 7). The largest land change in Hangzhou is the conversion from arable land to urban land, while in Lishui, the major changes feature mutual conversions between arable land and forest land, with the area of forest land loss larger than that in Hangzhou (Figure 5). The less-urbanized Lishui municipality also has the most deforested area in Zhejiang Province (Xiong et al., 2020). A stable or depopulated landscape may face a higher deforestation pressure largely because distant urbanization processes would demand increases in arable land in surrounding places. In contrast, the BALS policy allows for the deployment of land resources within the province. In this context, Lishui Municipality becomes the place that supplies land resources for other cities and towns because of its lower

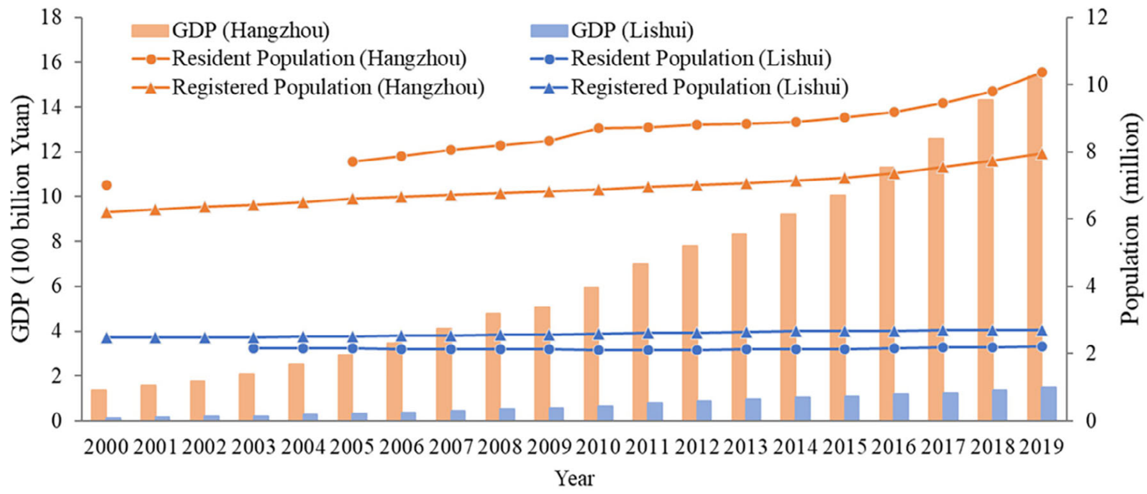
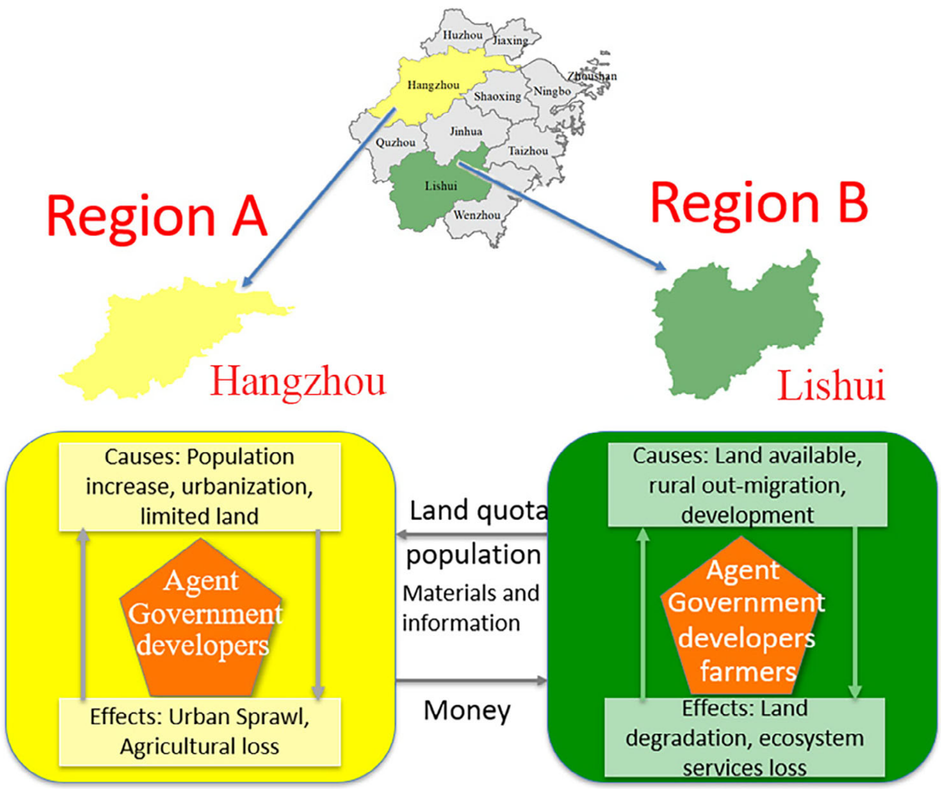


FIGURE 7 Socioeconomic change in Hangzhou and Lishui Municipalities of Zhejiang Province from 2000 to 2019 [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 8 Telecoupling of deforestation and urbanization in Hangzhou and Lishui [Colour figure can be viewed at wileyonlinelibrary.com]



level of urbanization. As a result, Lishui will likely continue experiencing land degradation and ecosystem loss.

Zhejiang Province, the first province that has implemented the BALS policy in China, needs to evaluate its consequences and effectiveness. It is easy to focus on assessing the quantitative balance and difficult to assess the qualitative and ecological balance (Lin et al., 2017). As arable land varies greatly over spatial and temporal dimensions, the policy needs to be further adjusted in the future to effectively protect high-quality arable land resources and support national food security and ecological safety. In Zhejiang, for example, the conversion of forestland to agricultural land has occurred in parallel with the BALS policy implementation, inevitably leading to loss of forestland (Xiong et al., 2020).

4.3 | Telecoupling and the no net loss of cropland policy

The telecoupling framework can explain the long-range land change mechanisms (J. Liu, 2017; Sun et al., 2020), which may apply to this

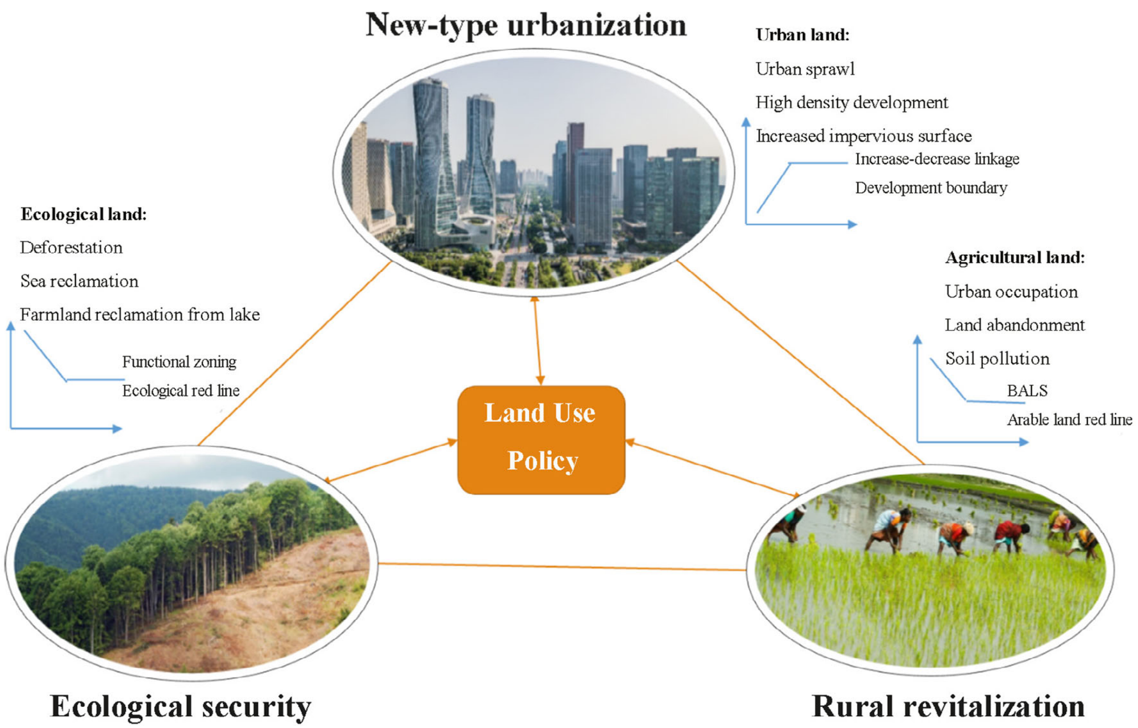


FIGURE 9 Mutual relationships among productive, living, and ecological land [Colour figure can be viewed at wileyonlinelibrary.com]

particular deforestation phenomenon in Zhejiang Province. The representative land use change patterns in Hangzhou and Lishui municipalities may stand as an ideal case for demonstrating the telecoupling concept (J. Liu, 2017; Sun et al., 2020). In Zhejiang Province, Hangzhou is the most urbanized municipality, while Lishui is comparatively less urbanized. As Hangzhou's urban population increased, its limited land resources could no longer meet the needs of the region's urbanization. Therefore, urban expansion inevitably took arable land resources from surrounding areas, leading to a reduction in arable land area. The governments could enact policies to find replacement of land resources through the role of an intermediate agent (such as a higher-level government). The municipality of Lishui, however, has sufficient reserved land resources due to its lower level of economic development, massive out-migration of rural population, and slower urban development. Through the role of an agent, a local government can supply its reserved land resources to meet the need of other areas in need of land supply. Land and money may flow between two such regions to get what each needs. For instance, Hangzhou may buy reserved land resources from Lishui for urbanization, whereas Lishui could receive a corresponding compensation. Meanwhile, Lishui may also suffer from land degradation and loss of ecosystems in the region as a result (Figure 8).

The simultaneous demand of land for urban development, ecological conservation, and rural revitalization is a challenge for China's policy and planning for land and other related resources (R. Chen, Ye, et al., 2014). A rational land planning and management system needs to reconcile the balance among productive land, living land, and ecological land (Figure 9). However, many land use policies implemented in China for more than 20 years are irrational in some aspects as they do not coordinate well with each other. These policies have either failed to ensure the productivity of arable land or resulted in ecological land degradation, which clearly contradicts China's strategy for sustainable development (Bryan et al., 2018). Moreover, appropriate land use policies must be in line with socioeconomic development (Xin & Li, 2018). With urbanization, the continuing migration of rural population to cities will inevitably lead to the emergence of hollow villages and the abandonment of large amounts of arable land in rural areas (Zhang et al., 2018), which will further challenge the effectiveness and efficiency of BALS (S. Li et al., 2018).

5 | CONCLUSIONS

The present study draws on datasets from multiple sources to investigate land use change with an emphasis on forest change in Zhejiang Province during 2000–2020 under the implementation of the BALS policy. Our investigation found that there was a large decrease in forest area during the study period, which is accompanied by the expansion of urban land and shrinkage of arable land. At the sub-provincial scale, such land use conversions among different types induced by BALS occurred not in adjacent areas but in distant places.

By relying on the telecoupling framework, we are able to better explain land use and land cover change patterns and mechanisms. Using the Hangzhou (west) and Lishui (south) municipalities as an illustration, the encroachment of arable land by urban development in Hangzhou has been 'compensated' through agricultural expansion at the sacrifice of deforestation in Lishui, according to the principle of balancing arable land in BALS. This finding empirically supports the telecoupling theory. Under this framework, BALS has evolved from focusing on quantity protection to focusing on the 'trinity' of quantity, quality, and ecological protection. Policy makers should be mindful of forest losses and mechanisms behind such losses while designing and implementing land-based policies, especially those involving societal and economic development and agricultural protection. By fully considering the patterns of multiple land types (e.g., urban, arable land, ecological land) and their relationships (e.g., the telecoupled interconnections), a more comprehensive land use policy can be sophistically designed and appropriately executed to reach the harmony among promoting development, securing food production, and preventing land degradation. At broader scales, this study further enriches the theory of forest transition, providing a basis for future land use policies or decisions.

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DATA AVAILABILITY STATEMENT

The GlobeLand30 datasets are available at http://www.globeland30.org/; Satellite-observed high-resolution forest cover change in the twenty-first century (Hansen v1.7) is available at: http://earthenginepartners.appspot.com/science-2013-global-forest. The ESA-CCI land-cover products are available at http://www.esa-landcover-cci.org/. Statistical yearbook datasets are available at: https://data.cnki.net/. All datasets are also available on request from the corresponding author.

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REFERENCES

Bontemps, S., Defourny, P., Radoux, J., Van Bogaert, E., Lamarche, C., Achard, F., Mayaux, P., Boettcher, M., Brockmann, C., Kirches, G., Zulkhe, M., Kalogirou, V., Seifert, F. M. & Arino, O. (2013). Consistent global land cover maps for climate modelling communities: Current achievements of the ESA's land cover CCI. Paper presented at the Proceedings of the ESA Living Planet Symposium, Edinborough.

Bryan, B. A., Gao, L., Ye, Y., Sun, X., Connor, J. D., Crossman, N. D., Stafford-Smith, M., Wu, J., He, C., Yu, D., Liu, Z., Li, A., Huang, Q., Ren, H., Deng, X., Zheng, H., Niu, J., Han, G., & Hou, X. (2018). China's response to a national land-system sustainability emergency. *Nature*, *559*(7713), 193–204. https://doi.org/10.1038/s41586-018-0280-2

Chaplin-Kramer, R., Sharp, R. P., Mandle, L., Sim, S., Johnson, J., Butnar, I., Milà i Canals, L., Eichelberger, B. A., Ramler, I., Mueller, C., McLachlan, N., Yousefi, A., King, H., & Kareiva, P. M. (2015). Spatial patterns of agricultural expansion determine impacts on biodiversity and carbon storage. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(24), 7402–7407. https://doi.org/10.1073/pnas.1406485112

Chen, F., Chen, J., Wu, H., Hou, D. Y., Zhang, W. W., Zhang, J., Zhou, X. G., & Chen, L. J. (2016). A landscape shape index-based sampling approach for land cover accuracy assessment. *Science China Earth Sciences*, *59*(12), 2263–2274. https://doi.org/10.1007/s11430-015-5280-5

Chen, H., Zeng, Z., Wu, J., Peng, L., Lakshmi, V., Yang, H., & Liu, J. (2020). Large uncertainty on Forest area change in the early 21st century among widely used global land cover datasets. *Remote Sensing*, *12*(21), 3502. https://doi.org/10.3390/rs12213502

Chen, J., Ban, Y., & Li, S. (2014). Open access to Earth land-cover map. *Nature*, *514*(7523), 434. https://doi.org/10.1038/514434c

Chen, J., Chen, J., Liao, A., Cao, X., Chen, L., Chen, X., He, C., Han, G., Peng, S., Lu, M., Zhang, W., Tong, X., & Mills, J. (2015). Global land cover mapping at 30 m resolution: A POK-based operational approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, *103*, 7–27. https://doi.org/10.1016/j.isprsjprs.2014.09.002

Chen, R., Ye, C., Cai, Y., Xing, X., & Chen, Q. (2014). The impact of rural out-migration on land use transition in China: Past, present and trend. *Land Use Policy*, *40*, 101–110. https://doi.org/10.1016/j.landusepol.2013.10.003

Chen, Y., Shao, H., & Li, Y. (2021). Consistency analysis and accuracy assessment of multi-source land cover products in the Yangtze River Delta. *Transactions of the Chinese Society of Agricultural Engineering*, *37*(06), 142–150. https://doi.org/10.11975/j.issn.1002-6819.2021.06.018

Costello, C., Cao, L., Gelcich, S., Cisneros-Mata, M. A., Free, C. M., Froehlich, H. E., Golden, C. D., Ishimura, G., Maier, J., Macadam-Somer, I., Mangin, T., Melnychuk, M. C., Miyahara, M., de Moor, C. L., Naylor, R., Nøstbakken, L., Ojea, E., O'Reilly, E., Parma, A. M., … Lubchenco, J. (2020). The future of food from the sea. *Nature*, *588*(7836), 95–100. https://doi.org/10.1038/s41586-020-2616-y

Davis, K. F., Gephart, J. A., Emery, K. A., Leach, A. M., Galloway, J. N., & D'Odorico, P. (2016). Meeting future food demand with current agricultural resources. *Global Environmental Change*, *39*, 125–132. https://doi.org/10.1016/j.gloenvcha.2016.05.004

Defourny, P., Kirches, G., Brockmann, C., Boettcher, M., Peters, M., Bontemps, S., Lamarche, C., Schlerf, M. & Santoro, M. (2017). *Land cover CCI. Product user guide version 2.0*. Paris: European Space Agency.

DeFries, R. S., Rudel, T., Uriarte, M., & Hansen, M. (2010). Deforestation driven by urban population growth and agricultural trade in the twenty-first century. *Nature Geoscience*, *3*(3), 178–181. https://doi.org/10.1038/ngeo756

Dobson, A. P., Pimm, S. L., Hannah, L., Kaufman, L., Ahumada, J. A., Ando, A. W., Bernstein, A., Busch, J., Daszak, P., Engelmann, J., Kinnaird, M. F., Li, B. V., Loch-Temzelides, T., Lovejoy, T., Nowak, K., Roehrdanz, P. R., & Vale, M. M. (2020). Ecology and economics for pandemic prevention. *Science*, *369*(6502), 379–381. https://doi.org/10.1126/science.abc3189

Elhacham, E., Ben-Uri, L., Grozovski, J., Bar-On, Y. M., & Milo, R. (2020). Global human-made mass exceeds all living biomass. *Nature*, *588*, 442–444. https://doi.org/10.1038/s41586-020-3010-5

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., … Snyder, P. K. (2005). Global consequences of land use. *Science*, *309*(5734), 570–574. https://doi.org/10.1126/science.1111772

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., Mueller, N. D., O'Connell, C., Ray, D. K., West, P. C., Balzer, C., Bennett, E. M., Carpenter, S. R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., … Zaks, D. P. M. (2011). Solutions for a cultivated planet. *Nature*, *478*(7369), 337–342. https://doi.org/10.1038/nature10452

Gao, B., Huang, Q., He, C., Sun, Z., & Zhang, D. (2016). How does sprawl differ across cities in China? A multi-scale investigation using nighttime light and census data. *Landscape and Urban Planning*, *148*, 89–98. https://doi.org/10.1016/j.landurbplan.2015.12.006

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., & Toulmin, C. (2010). Food security: The challenge of feeding 9 billion people. *Science*, *327*(5967), 812–818. https://doi.org/10.1126/science.1185383

Halbac-Cotoara-Zamfir, R., Keesstra, S., & Kalantari, Z. (2019). The impact of political, socio-economic and cultural factors on implementing environment friendly techniques for sustainable land management and climate change mitigation in Romania. *Science of the Total Environment*, *654*, 418–429. https://doi.org/10.1016/j.scitotenv.2018.11.160

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, *342*(6160), 850–853. https://doi.org/10.1126/science.1244693

Henders, S., Ostwald, M., Verendel, V., & Ibisch, P. (2018). Do national strategies under the UN biodiversity and climate conventions address agricultural commodity consumption as deforestation driver? *Land Use Policy*, *70*, 580–590. https://doi.org/10.1016/j.landusepol.2017.10.043

Hu, G., Li, X., Zhou, B.-B., Ma, Q., Meng, X., Liu, Y., Chen, Y., & Liu, X. (2020). How to minimize the impacts of urban expansion on farmland loss: Developing a few large or many small cities? *Landscape Ecology*, *35*, 2487–2499. https://doi.org/10.1007/s10980-020-01073-x

Jiang, L., Deng, X., & Seto, K. C. (2012). Multi-level modeling of urban expansion and cultivated land conversion for urban hotspot counties in China. *Landscape and Urban Planning*, *108*(2–4), 131–139. https://doi.org/10.1016/j.landurbplan.2012.08.008

Lambin, E. F., & Meyfroidt, P. (2010). Land use transitions: Socio-ecological feedback versus socio-economic change. *Land Use Policy*, *27*(2), 108–118. https://doi.org/10.1016/j.landusepol.2009.09.003

Lambin, E. F., & Meyfroidt, P. (2011). Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(9), 3465–3472. https://doi.org/10.1073/pnas.1100480108

Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., Coomes, O. T., Dirzo, R., Fischer, G., Folke, C., George, P. S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E. F., Mortimore, M., Ramakrishnan, P. S., Richards, J. F., … Xu, J. (2001). The causes of land-use and land-cover change: Moving beyond the myths. *Global Environmental Change*, *11*(4), 261–269. https://doi.org/10.1016/S0959-3780(01)00007-3

Li, S., Li, X., Sun, L., Cao, G., Fischer, G., & Tramberend, S. (2018). An estimation of the extent of cropland abandonment in mountainous regions of China. *Land Degradation & Development*, *29*(5), 1327–1342. https://doi.org/10.1002/ldr.2924

Li, T., Long, H., Liu, Y., & Tu, S. (2015). Multi-scale analysis of rural housing land transition under China's rapid urbanization: The case of Bohai Rim. *Habitat International*, *48*, 227–238. https://doi.org/10.1016/j.habitatint.2015.04.002

Liang, D., Zuo, Y., Huang, L., Zhao, J., Teng, L., & Yang, F. (2015). Evaluation of the consistency of MODIS land cover product (MCD12Q1) based on Chinese 30 m GlobeLand30 datasets: A case study in Anhui Province, China. *ISPRS International Journal of Geo-Information*, *4*(4), 2519–2541. https://doi.org/10.3390/ijgi4042519

Lin, L., Ye, Z., Gan, M., Shahtahmassebi, A., Weston, M., Deng, J., Lu, S., & Wang, K. (2017). Quality perspective on the dynamic balance of cultivated land in Wenzhou, China. *Sustainability*, *9*(1), 95. https://doi.org/10.3390/su9010095

Liu, J. (2017). Integration across a metacoupled world. *Ecology and Society*, *22*(4), 29. https://doi.org/10.5751/es-09830-220429

Liu, J., Dietz, T., Carpenter, S. R., Alberti, M., Folke, C., Moran, E., Pell, A. N., Deadman, P., Kratz, T., Lubchenco, J., Ostrom, E., Ouyang, Z., Provencher, W., Redman, C. L., Schneider, S. H., & Taylor, W. W. (2007). Complexity of coupled human and natural systems. *Science*, *317*(5844), 1513–1516. https://doi.org/10.1126/science.1144004

Liu, J., Hull, V., Godfray, H. C. J., Tilman, D., Gleick, P., Hoff, H., Pahl-Wostl, C., Xu, Z., Chung, M. G., Sun, J., & Li, S. (2018). Nexus approaches to global sustainable development. *Nature Sustainability*, *1*(9), 466–476. https://doi.org/10.1038/s41893-018-0135-8

Liu, X., Huang, Y., Xu, X., Li, X., Li, X., Ciais, P., Lin, P., Gong, K., Ziegler, A. D., Chen, A., Gong, P., Chen, J., Hu, G., Chen, Y., Wang, S., Wu, Q., Huang, K., Estes, L., & Zeng, Z. (2020). High-spatiotemporal-resolution mapping of global urban change from 1985 to 2015. *Nature Sustainability*, *3*, 564–570. https://doi.org/10.1038/s41893-020-0521-x

Liu, Y., Feng, Y., Zhao, Z., Zhang, Q., & Su, S. (2016). Socioeconomic drivers of forest loss and fragmentation: A comparison between different land use planning schemes and policy implications. *Land Use Policy*, *54*, 58–68. https://doi.org/10.1016/j.landusepol.2016.01.016

Liu, Y. S., Wang, J. Y., & Long, H. L. (2010). Analysis of arable land loss and its impact on rural sustainability in southern Jiangsu Province of China. *Journal of Environmental Management*, *91*(3), 646–653. https://doi.org/10.1016/j.jenvman.2009.09.028

Long, H. (2014). Land use policy in China: Introduction. *Land Use Policy*, *40*, 1–5. https://doi.org/10.1016/j.landusepol.2014.03.006

Long, H. (2020). *Land use transitions and rural restructuring in China*. Singapore: Springer Nature.

Long, H., Ge, D., Zhang, Y., Tu, S., Qu, Y., & Ma, L. (2018). Changing man-land interrelations in China's farming area under urbanization and its implications for food security. *Journal of Environmental Management*, *209*, 440–451. https://doi.org/10.1016/j.jenvman.2017.12.047

Long, H., Heilig, G. K., Li, X., & Zhang, M. (2007). Socio-economic development and land-use change: Analysis of rural housing land transition in the transect of the Yangtse River, China. *Land Use Policy*, *24*(1), 141–153. https://doi.org/10.1016/j.landusepol.2005.11.003

Long, H., & Li, T. (2012). The coupling characteristics and mechanism of farmland and rural housing land transition in China. *Journal of Geographical Sciences*, *22*(3), 548–562. https://doi.org/10.1007/s11442-012-0946-x

Long, H., Li, Y., Liu, Y., Woods, M., & Zou, J. (2012). Accelerated restructuring in rural China fueled by 'increasing vs. decreasing balance' land-use policy for dealing with hollowed villages. *Land Use Policy*, *29*(1), 11–22. https://doi.org/10.1016/j.landusepol.2011.04.003

Long, H., & Qu, Y. (2018). Land use transitions and land management: A mutual feedback perspective. *Land Use Policy*, *74*, 111–120. https://doi.org/10.1016/j.landusepol.2017.03.021

Long, H., Qu, Y., Tu, S., Zhang, Y., & Jiang, Y. (2020). Development of land use transitions research in China. *Journal of Geographical Sciences*, *30*(7), 1195–1214. https://doi.org/10.1007/s11442-020-1777-9

Long, H., Zou, J., Pykett, J., & Li, Y. (2011). Analysis of rural transformation development in China since the turn of the new millennium. *Applied Geography*, *31*(3), 1094–1105. https://doi.org/10.1016/j.apgeog.2011.02.006

Lu, D., Xu, J., Yue, W., Mao, W., Yang, D., & Wang, J. (2020). Response of PM2.5 pollution to land use in China. *Journal of Cleaner Production*, *244*, 118741. https://doi.org/10.1016/j.jclepro.2019.118741

Meyfroidt, P., Rudel, T. K., & Lambin, E. F. (2010). Forest transitions, trade, and the global displacement of land use. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(49), 20917–20922. https://doi.org/10.1073/pnas.1014773107

Ozdogan, M., & Woodcock, C. E. (2006). Resolution dependent errors in remote sensing of cultivated areas. *Remote Sensing of Environment*, *103*(2), 203–217. https://doi.org/10.1016/j.rse.2006.04.004

Pandit, R., Parrotta, J. A., Chaudhary, A. K., Karlen, D. L., Vieira, D. L. M., Anker, Y., Chen, R., Morris, J., Harris, J., & Ntshotsho, P. (2019). A framework to evaluate land degradation and restoration responses for improved planning and decision-making. *Ecosystems and People*, *16*(1), 1–18. https://doi.org/10.1080/26395916.2019.1697756

Ren, H. (2020). Research on Sample Size Estimation for Accuracy Assessment of Land Cover Products. (Master's Theses), Beijing University of Civil Engineering and Architecture, Available from CNKI.

Shen, X., Wang, L., Wu, C., Lv, T., Lu, Z., Luo, W., & Li, G. (2017). Local interests or centralized targets? How China's local government implements the farmland policy of requisition-compensation balance. *Land Use Policy*, *67*, 716–724. https://doi.org/10.1016/j.landusepol.2017.06.012

Song, W., & Deng, X. (2015). Effects of urbanization-induced cultivated land loss on ecosystem services in the North China Plain. *Energies*, *8*(6), 5678–5693. https://doi.org/10.3390/en8065678

Song, W., & Pijanowski, B. C. (2014). The effects of China's cultivated land balance program on potential land productivity at a national scale. *Applied Geography*, *46*, 158–170. https://doi.org/10.1016/j.apgeog.2013.11.009

Song, X. P., Hansen, M. C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E. F., & Townshend, J. R. (2018). Global land change from 1982 to 2016. *Nature*, *560*, 639–643. https://doi.org/10.1038/s41586-018-0411-9

Stuhlmacher, M., Turner, B. L., Frazier, A. E., Kim, Y., & Leffel, J. (2020). Institutional shifts and landscape change: The impact of the Período Especial on Cuba's land system architecture. *Journal of Land Use Science*, *15*(5), 690–706. https://doi.org/10.1080/1747423x.2020.1829119

Su, S., Zhou, X., Wan, C., Li, Y., & Kong, W. (2016). Land use changes to cash crop plantations: Crop types, multilevel determinants and policy implications. *Land Use Policy*, *50*, 379–389. https://doi.org/10.1016/j.landusepol.2015.10.003

Sun, J., Liu, J., Yang, X., Zhao, F., Qin, Y., Yao, Y., … Zhang, J. (2020). Sustainability in the Anthropocene: Telecoupling framework and its applications. *Acta Geographica Sinica*, *75*(11), 2408–2416. https://doi.org/10.11821/dlxb202011010

Tan, M., Li, X., Xie, H., & Lu, C. (2005). Urban land expansion and arable land loss in China - a case study of Beijing-Tianjin-Hebei region. *Land Use Policy*, *22*(3), 187–196. https://doi.org/10.1016/j.landusepol.2004.03.003

Tollefson, J. (2020). Why deforestation and extinctions make pandemics more likely. *Nature*, *584*(7820), 175–176. https://doi.org/10.1038/d41586-020-02341-1

Turner, B. L., II, Lambin, E. F., & Reenberg, A. (2007). The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(52), 20666–20671. https://doi.org/10.1073/pnas.0704119104

Vina, A., McConnell, W. J., Yang, H. B., Xu, Z. C., & Liu, J. G. (2016). Effects of conservation policy on China's forest recovery. *Science Advances*, *2*(3), 7. https://doi.org/10.1126/sciadv.1500965

Wang, J., Lin, Y., Glendinning, A., & Xu, Y. (2018). Land-use changes and land policies evolution in China's urbanization processes. *Land Use Policy*, *75*, 375–387. https://doi.org/10.1016/j.landusepol.2018.04.011

Xin, L., & Li, X. (2018). China should not massively reclaim new farmland. *Land Use Policy*, *72*, 12–15. https://doi.org/10.1016/j.landusepol.2017.12.023

Xiong, B., Chen, R., Xia, Z., Ye, C., & Anker, Y. (2020). Large-scale deforestation of mountainous areas during the 21st century in Zhejiang Province. *Land Degradation & Development*, *31*(14), 1761–1774. https://doi.org/10.1002/ldr.3563

Zeng, Z., Estes, L., Ziegler, A. D., Chen, A., Searchinger, T., Hua, F., Guan, K., Jintrawet, A., & F. Wood, E. (2018). Highland cropland expansion and forest loss in Southeast Asia in the twenty-first century. *Nature Geoscience*, *11*(8), 556–562. https://doi.org/10.1038/s41561-018-0166-9

Zhang, Q., Song, C., & Chen, X. (2018). Effects of China's payment for ecosystem services programs on cropland abandonment: A case study in Tiantangzhai township, Anhui, China. *Land Use Policy*, *73*, 239–248. https://doi.org/10.1016/j.landusepol.2018.01.001

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