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Young Scientists Summer Program

Ecological network analysis of urban land resource use within China

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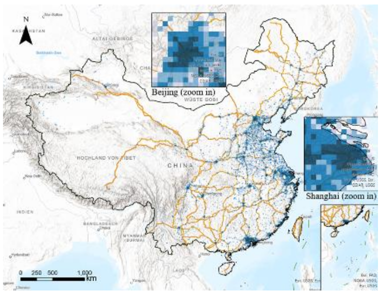

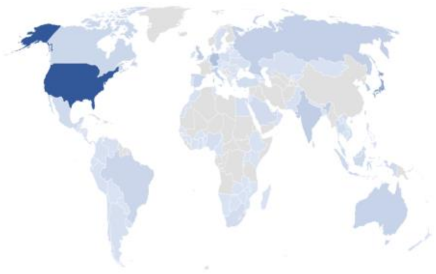

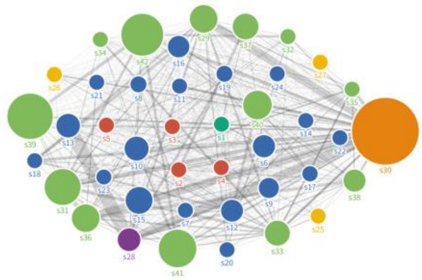

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Abstract

Land is an essential factor for economic and industrial production. Urban land area has been consistently increased all over the world since 1840s as a notable feature of industrial and economic evolution. Urban land expansion not only causes direct environmental consequences such as deforestation, biodiversity loss, and pollution, but also act as a leverage that causes vast amounts of embodied natural resources consumption through global trade and supply chains. China is known as the "world's factory" and most populated country. However, how land resources are used in its industrial and socioeconomic systems is still vague. In this research, we applied a land use estimation model to mapping the urban land footprint of 30 economic sectors in 30 provinces within China. We examined spatial distributions of urban land resource use, final demand drivers, and virtual land flow pathways. The results show that the urban land footprint related to economic activities of China's 30 provinces totalled 3.13 million hectares in the year of 2012. Spatial mismatches are shown between the production-based and consumption-based footprints. Intensive urban land use mainly occurred in the coastal areas of China, with large cities as the center of hot spots, shown significant spatial agglomerations. The North Coast of China (CNC) had the largest consumption-based footprint, followed by Yellow River midstream of China (CYL) and East Coast of China (CEC). The biggest external pulling effect was demonstrated by the Yellow River midstream of China (CYL), which drove 128,465 hectares of external land use. For provinces, Guangdong, Shandong, and Jiangsu remained the three highest provinces of land footprint from both production and consumption side. In terms of the final demand drivers of land flows, the results indicated that 85% of the urban land use in China was driven by domestic consumptions, with 15% due to foreign consumptions. From a global view, North America and Western Europe are the two main importers of China's urban land. America is the top importer of China's urban land, accounting for 103,785 ha, and 21.8% of all the foreign consumptions. From ecological network perspective, the industrially developed regions exhibited more complex network structures, with a higher total system throughflow, more resource flow pathways, a longer path length, and a greater circularity. Our results reveal the association between human socioeconomic activity with direct land demand and virtual land flows.

About the author

Wei XIE is currently a Ph.D. candidate at Fudan University in Environmental Science. He graduated from Shandong University, China, in 2015 with a degree in Ecology. He completed his MS degree in Landscape Ecology at the Chinese Academy of Sciences (2018). His main fields of scientific interest include land management, land resource metabolism, and industrial system analysis. Specifically, he focuses on 1) the land resource use and virtual flows between industrial and socio-economic systems; and 2) the interactions between natural systems and human systems linked to land use. (Contact: xiewei@iiasa.ac.at; wxie18@fudan.edu.cn)

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别酒青门路，归轩白马津。

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1. Introduction

1.1 Thinking land from a systematic perspective

Land plays an essential role in terrestrial ecosystems as well as human systems. Land is central to addressing sustainability issues. How human use, manage and interact with land is the key to achieve the 2030 Agenda and the sustainable development goals (Meyfroidt et al., 2022). On one hand, human production and economic activities are based on land. Land is widely considered to be a non-renewable scarce resource (Haberl et al., 2014; Lambin & Meyfroidt, 2011). This competitiveness and scarcity of land induce trade-offs between multi-purpose uses, such as retaining the original ecosystem or being transformed by human beings, resulting in the conflicts between ecological protection and economic development (Goldstein et al., 2012; Tietenberg & Lewis, 2015). On the other hand, land use change is the major driving force for environmental problems, linking to the causes, consequences, and even solutions to climate change. This can be understood from the feedbacks and interactions between land use and its consequences (Foley et al., 2005a). Here we can briefly summarize in four points. One is that land use changes can cause its original ecosystem services or function loss (e.g., carbon sequestration and purification of water/air), which will subsequently increase the opportunity costs (Betts et al., 2017; Fargione et al., 2008). Secondly, human-altered land surfaces, especially the land intensively used by industry, will bring a large number of embodied natural resource use and greenhouse gas emissions (Eugenia Kalnay & Ming Cai, 2003; van Vliet, 2019; Zhai et al., 2020). Thirdly, land-use change and global climate change often present an interacting positive feedback relationship (Bonan, 2008; Bradford et al., 2016). Global warming and environmental deterioration accompanying with land use changes will backward destroy habitats on the land, accelerating land degradation (Borrelli et al., 2020; Eugenia Kalnay & Ming Cai, 2003). The fourth is the climate solutions or emission reduction pathways also consume land resources, which can aggravate the scarcity of limited land resources in turn, and therefore rise challenges to sustainable development (Brizga, 2020; Field et al., 2020; Zheng et al., 2022). Overall, land systems are complex with multiple interactions between ecological processes and socioeconomic dynamics. This calls the need of systematic thinking of land and future development pathways.

The systematic thinking of land begins with systematic thinking about land concerns and the current situation, with help and broad empirical support from land system science (LSS). Meyfroidt et al. (2021) distilled information from land system science into ten empirical realities organized around four core, higher-level facts and six more specialized ones (*Figure 1)*. From this view, it is necessary to considering land as a multi-purpose resource, concerning its multiple values and meanings (Goldstein et al., 2012; van Riper et al., 2018). And also treating land as a complex system, be aware of the land leverage, that is, large impacts from small footprints, particularly in urban areas (Barnes et al., 2017; See et al., 2022). The systematic thinking about land is followed by a detailed review of the various ways of utilizing land resources. In addition, land is separated from natural resources in recognition of its distinct role in the provision of space and is increasingly be considered as single asset category differencing from soil resources (United Nations, 2021). In addition to aggregated total amounts, the spatial patterns of land use determine how urban land patches interact with broader contexts (Gao & Pesaresi, 2021). This means that the assessment of land resources also has to realize the spatial characteristics, beyond the accounting stage, also illuminate the location of the occurrence of pressure, boundaries and ecological adjacencies with the help of spatialized approaches. This treatment of land permits a clearer articulation of the latent geographical disparities in land value and environmental impacts, and to provide support for biodiversity conservation and regional governance (Creamer et al., 2016; United Nations, 2021). To achieve the sustainable development, the core is to systematic thinking the land issues, the basis is to systematic identification of land resources, and the key is to systematic analysis of land flows. This involves extensive account construction, systematic correlation analysis and spatial assessment.

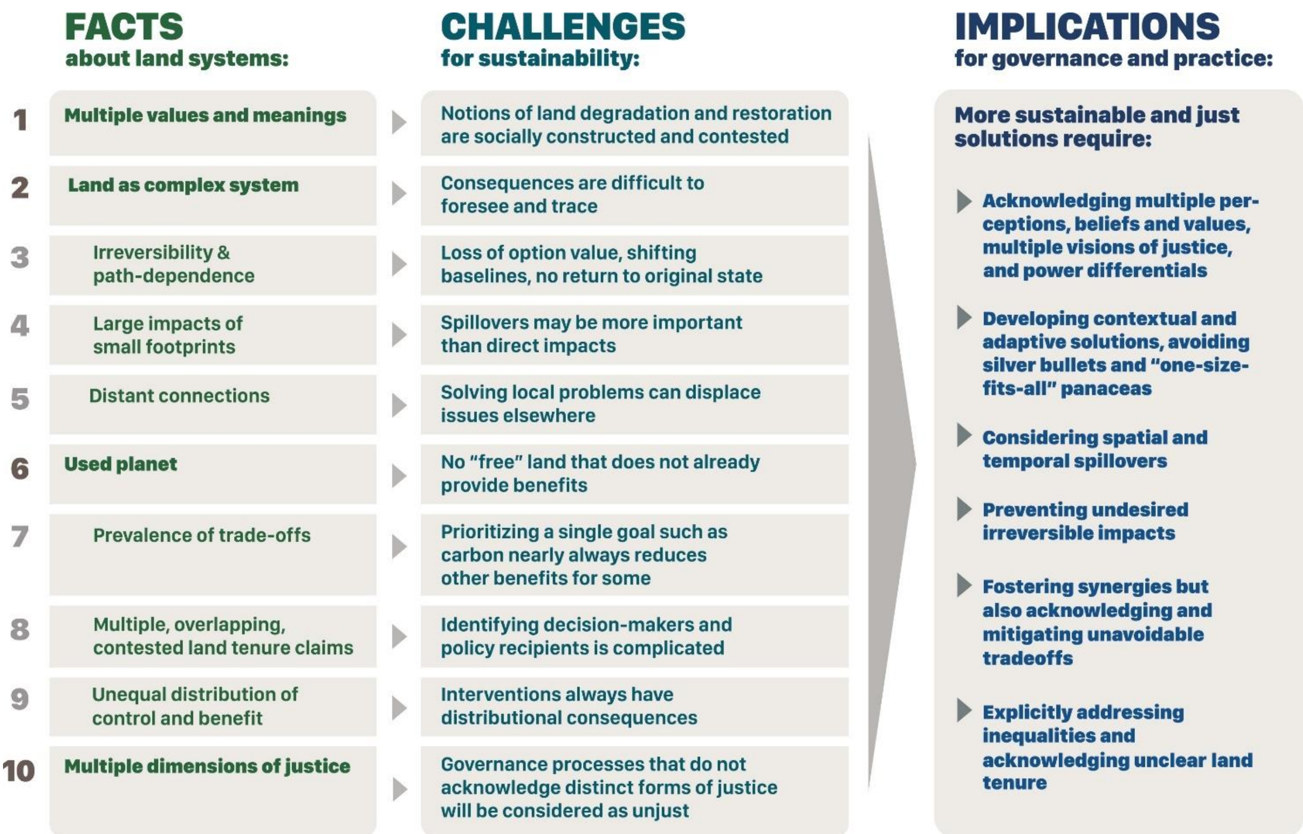

Figure 1 Ten empirical realities about land systems (Meyfroidt et al., 2022).

1.2 Natural footprints accounting and ecological network analysis

Ecological footprint accounting, aiming to quantify the human consumption of natural contributions (Rees, 1992), is widely used to evaluate the pressure of human activities on the environment (Wu et al., 2021). Since it was firstly introduced in 1992, ecological footprint has act as a key index to measure human needs of natural resources (L. Zhang et al., 2021), such as water (Hoekstra & Mekonnen, 2012; Ridoutt et al., 2018), land (Bruckner et al., 2019; Dorninger et al., 2021), energy (Lan et al., 2016), carbon (Berrill et al., 2020; Lenzen et al., 2018), or multiple footprints(Brizga, 2020; Steen-Olsen et al., 2012). Considering the wide range of interactions within socio-economic systems, the necessity of assessing both direct and indirect impacts of human activities have largely been recognized (Matuštík & Kočí, 2021; Patterson et al., 2017). With the help of Input-Output analysis, the ecological footprint approach has evolved tremendously and has been applied to national environmental accounting (Patterson et al., 2017; United Nations, 2021), planetary boundary assessments (Wu et al., 2021), and environmental sustainability assessments (Wiedmann & Allen, 2021). This enables us to identify the virtual linkage between the supply and demand of land resources through supply chains, revealing the tele-coupling of land use (Laroche et al., 2020; Seto et al., 2012), showing the internal linkages between different regions and sectors (Chen et al., 2019), and creating ecological networks based on virtual flows (Bodin et al., 2019).

Ecological network analysis (ENA) is a systematic way to evaluate the relationships between system components. It provides a perspective of the environment, based on general system theory and input-output analysis (Fath, 2012; Fath et al., 2007). The ENA method was originally used for systematic analysis for energy transfers through food networks in ecology, and subsequently applied to discover urban metabolisms (Fath et al., 2019; Morris et al., 2021). Derocles et al. (2018) highlight the importance and potential of ENA in future biomonitoring programs, to fill the gap of lacking numeric biomonitoring indicators to characterize the mechanisms that underpin ecosystem functioning. Y. Zhang et al., (2010) integrated throughflow analysis with utility analysis, to identify the network structure and ecological relationships within the urban metabolism system, and relationships among the metabolic system's energy components. Fang & Chen (2015) used ecological network analysis to study the network structure and ecological interactions in an urban water metabolic system in the Heihe River Basin, demonstrated that the balance between efficiency and redundancy is placed on the left side of the resilience curve with less efficiency and more redundancy. Shi et al. (2021) utilized ENA approach to reveal how the Northeast Revitalization Plan reshaped the socioeconomic and energy system in Jilin province of China, identified the dominance of exploitation relationships among the sectors, shown the complicated effect of revitalization efforts on the urban metabolic system.

1.3 Urban land supporting the "world's factory"

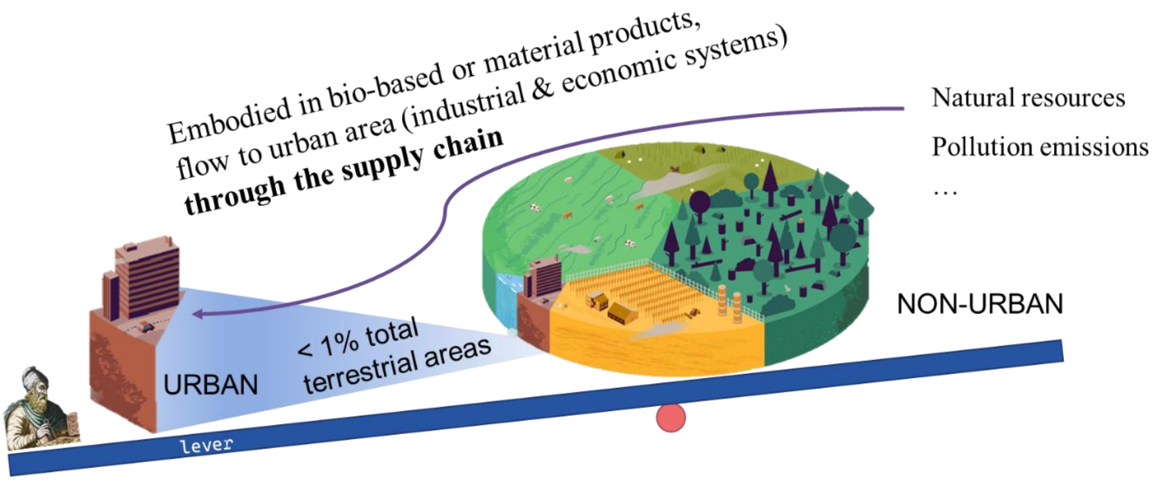

Figure 2 A conceptual representation of urban land leverage for embodied natural resources.

As an essential resource for economic and industrial production, urban land area has been consistently increased all over the world since 1840s as a notable feature of industrial and economic evolution (Dorninger et al., 2021). China is known as the "world's factory" and most populated. The pressure on land resources brought by industrial manufacturing and human consumption has promoted expansive and rapid land cover change and related environmental problems within China country (Chen et al., 2022; Wang et al., 2018). Urban land expansion not only causes direct environmental consequences such as deforestation, biodiversity loss, and pollution, but also act as a leverage that causes vast amounts of embodied natural resources consumption through global trade and supply chains (Bettencourt, 2020; Foley et al., 2005b).

Cities have a profound and far-reaching impact on the environment and society beyond their borders due to their population density, economic significance, degree of affluence and the consequent global demand for resources (Wiedmann & Allen, 2021). However, in contrast to agricultural land, the urban land is generally evaluated as an entirety and lacks comprehensive intersectoral surveys. Most of the land use dataset remains the urban land area as a single category "urban land" or "impervious land", and the land footprint of non-agricultural economic sectors are mainly considering only the land areas embodied in bio-based products. Until this point, the urban land analysis has been primarily restricted to a coarse sectoral level or focused mainly on the global and national scales.

To obtain a fine-scale urban land database for China, we established a bottom-up model to estimate the entity-level urban land use estimation model with emerging geographic data and novel methods (Xie et al., 2022). The model was utilized to identify the entity-level urban land use areas, and sum up at city level and province level to generate the land footprint and land use intensity dataset with multi-regional and multi-sectoral attributes.

In this study, based on a pre-established multi-regional and multi-sectoral land use dataset, a hybrid network model will be applied to study the interwoven connections of built-up land use among sectors and regions in China. Environmentally extended input–output analysis will be incorporated to evaluate the land resource flow, and Ecological network analysis will be adopted to evaluate the cycling and resilience of each region of China. The relationships among regions and sectors be identified in national and regional network systems. Incorporating built-up land into the resource metabolism study will bring new insights into regional sustainable development and resource metabolism, promoting resilient cities and sustainable land management.

Research Questions:

- How are urban land resources used and allocated within China’s industrial and socio-economic system?
- How are urban land resource utilizations driven and linked by trade?
- How are the network properties of the urban land flow system?

2. Methods

2.1 Research boundary

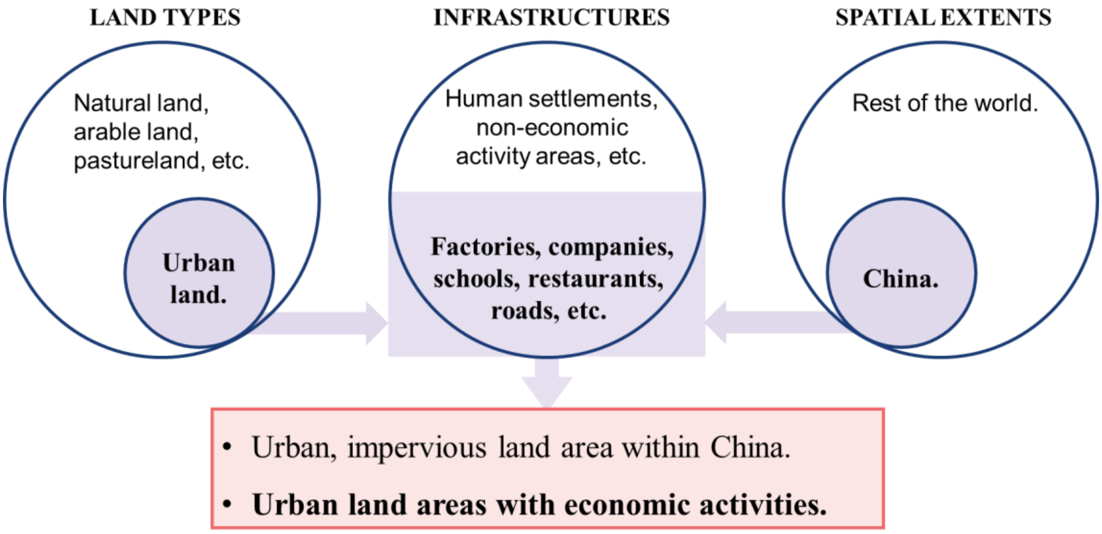

Figure 3 Research boundary of this study.

In this study, we focus on the urban land use associate with economic activities in China. Specifically, the area of cultivated land, forests, garden land, and water bodies are not taken into account. Land uses unrelated to human economic activities, such as human residential areas and land of public benefit, are not counted.

2.2 Urban land use dataset of China

To obtain a fine-scale urban land database for China, we established a bottom-up model to estimate the entity-level urban land use estimation model with emerging geographic data and novel methods, including point of interest (POI) data, road network data, and natural language processing (Xie et al., 2022). We applied the land use estimation model to the whole country, and a multi-regional built-up land use dataset with fine spatial and sectoral attributes was generated.

The land use estimation model included three modules: 1) A land parcel segmentation model, which divided the city into small patches to improve the accuracy of the POI boundary delineation; 2) An economic sector classification model, which classified the POIs based on their attributes; and 3) A land boundary delineation model, which outlined the boundary for each POI. The specific processes of each sub-model can be seen in (Xie et al., 2022).

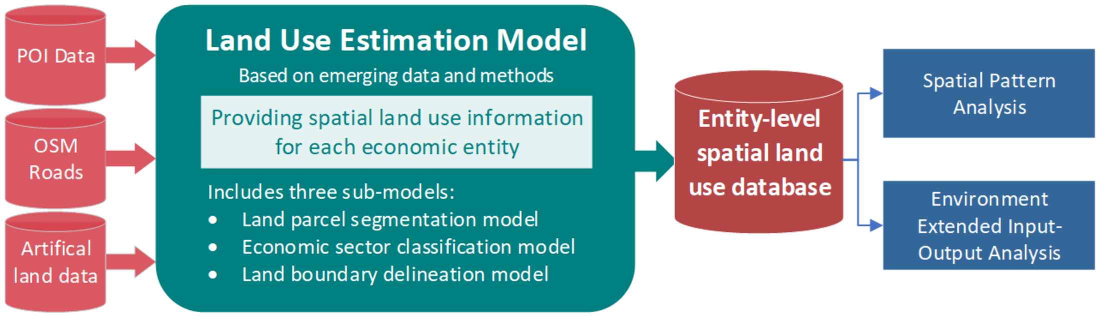

Figure 4 The framework of the land use estimation model (Xie et al., 2022).

The land parcel segmentation model was used to generate the land parcels with road network data from OpenStreetMap data. The interconnected and intertwined road network system divides the city into a series of parcels of different sizes. Each land parcel has one or several economic entities, which was represented by the POI data. After obtaining the base land parcels, the POIs were screened and classified into the corresponding economic sector through the economic sector classification model. The classification was achieved in two ways, one was based on the original classification of POIs, and the other was achieved by an automatic classifier. The classifier was based on natural language processing and trained by an enterprise information dataset.

The land boundary delineation model was used to identify the estimated boundary and then calculate the land area taken by each economic entity. The Voronoi diagram was applied to delineate the land boundaries within each land parcel, and the surrounding roads controlled each POI's demarcation. The VD results were spatially combined with the artificial impervious surface layer, which was obtained from Gong et al. (2020), and the artificial impervious land use area for each POI was quantified. Finally, the VD results were integrated according to the economic sectors, and the adjacent patches in the same sector were combined to obtain the land occupation of the 42 sectors.

2.3 Input-Output Analysis

Environmentally extended input-output analysis was used to evaluate the land resource flow, and ecological network analysis was adopted to evaluate the network properties of each region of China. The investigation comprised 30 Chinese provinces due to data availability, Hongkong, Macao, and Taiwan are not accounted.

We used a nested-IO dataset which embedded the Chinese provincial Multi-Regional Input-Output (MRIO) database in the global GTAP database, allowing to trace how each sector in each province trades with other countries globally (Mi et al., 2017). The disaggregation and combination of the Chinese Input-output table and the GTAP MRIO can be illustrated in two steps: 1) Firstly converted China's MRIO Table from 42 sectors over 31 provinces to 30 sectors over 30 provinces. 2) Then combined China's MRIO table with the GTAP Global MRIO Table.

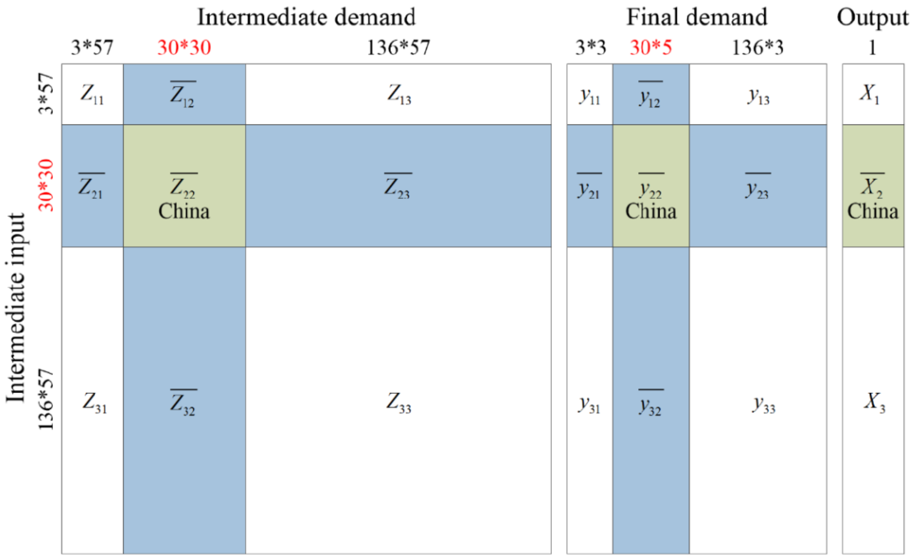

Figure 5 The conceptual figure of China-GTAP nested MRIO model (Mi et al., 2017)
1) Matrices for China's domestic structure in GTAP are replaced by Chinese MRIO directly (in green); 2) Matrices for China's international exports and imports are calculated under the assumption that international exports (or imports) of a sector in a province are distributed in the same proportion as China's exports (or imports) of the sector (in blue); 3) Matrices for other countries do not change (in white).

2.4 Ecological network Analysis

Based on a pre-established multi-regional and multi-sectoral land use dataset, an ecological network model was applied to study the interwoven connections among sectors and regions in China for the year 2012. Then we handled each province or municipality as a separate network in the ENA, with economic sectors as nodes, virtual urban land flows as linkage.

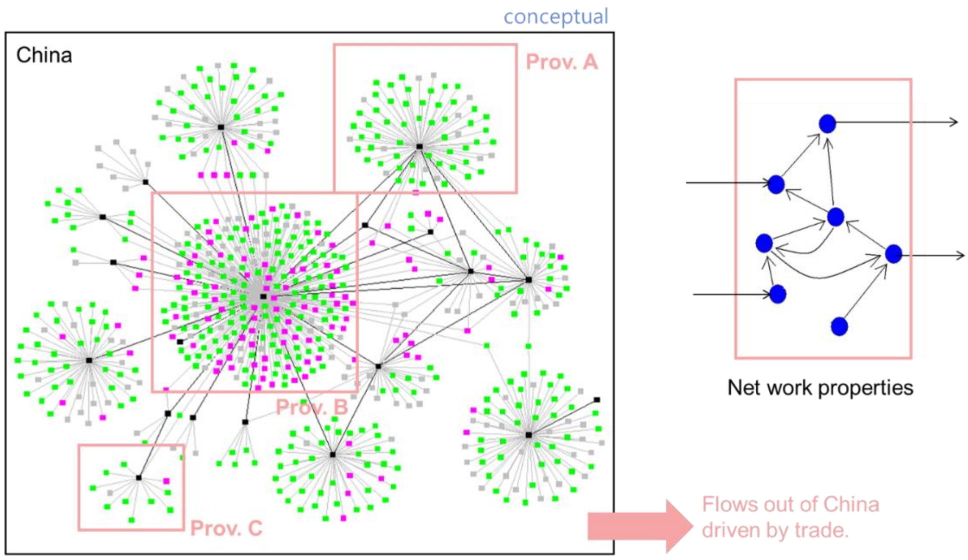

Figure 6 Conceptual framework of how we conduct the Ecological network analysis

3. Results

3.1 Accounting urban land footprint in China

3.1.1 Spatial distribution of urban land footprints

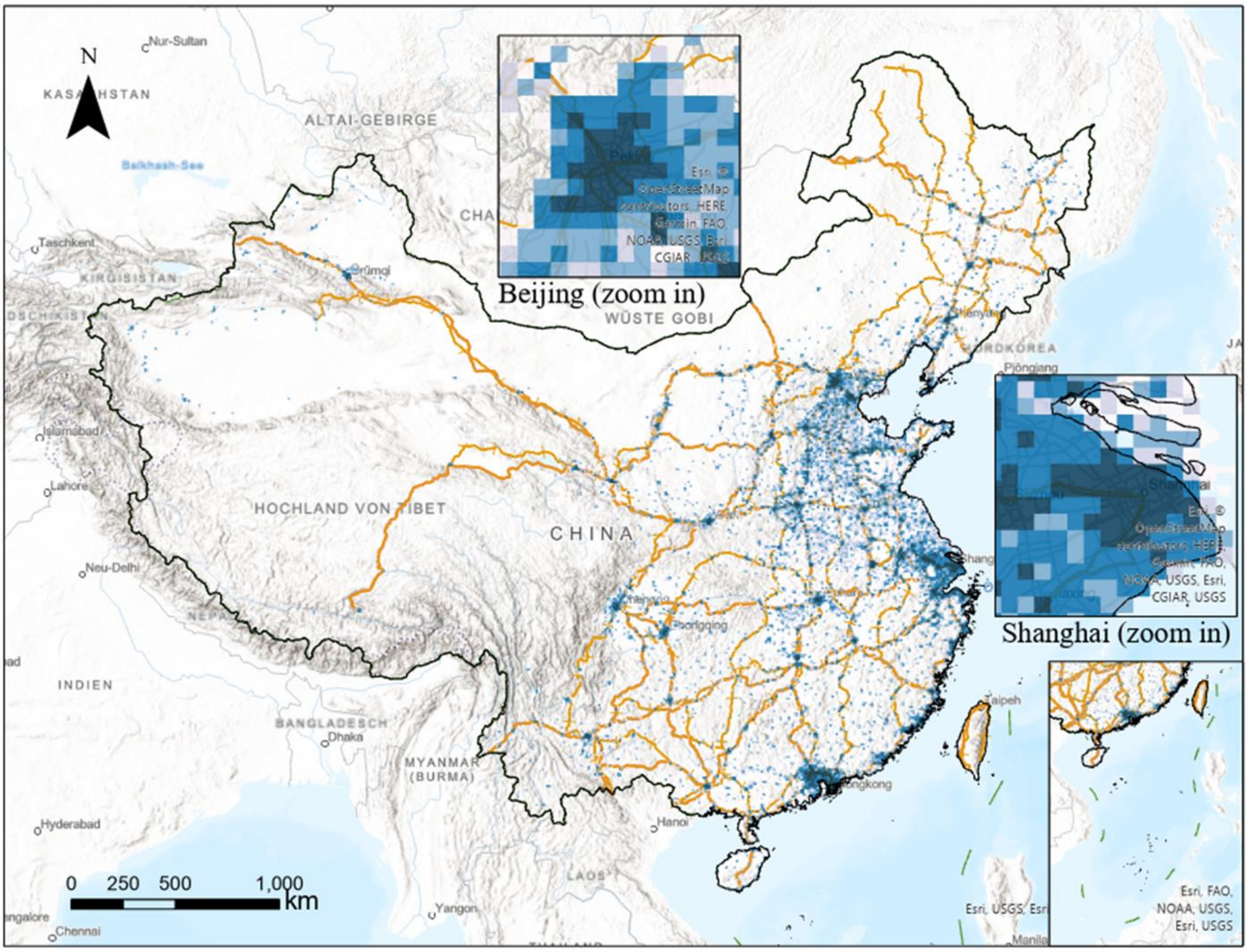

Figure 7 Urban land use related to economic activities in China of the year 2012.

Land use footprints shown by 10km grids, colour concentration represents the amount of urban land use footprint associated with economic activity within the grid. Only artificial impervious land surfaces are counted. Major roads and railways are shown as yellow lines. Due to data availability, Hong Kong, Macau and Taiwan regions are not included.

The urban land footprint related to economic activities of China's 31 provinces totalled 3.13 million hectares in the year of 2012. Figure 7 shows the spatial distribution of urban land footprints. The land footprint is mainly located in the coastal areas of eastern China, with big cities as the center of hot spots. Among them, the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions shown significant spatial agglomerations. The land use of economic activities presents obvious spatial correlation with the main traffic arteries, with the hot spots of urban land use were commonly presented at the intersection of traffic arteries. As the two most important megacities, the land footprint distribution in Beijing and Shanghai is shown in zoom-in windows, showing the spatial details of land use within them. Appendix figures S8-15 show the spatial distribution information of land use in seven typical industries respectively. Although it is similar in terms of national distribution, the spatial pattern of land use shows obvious differences among economic industries, which can be clearly identified from the enlarged windows of Beijing and Shanghai. This shows that the pressure of different types of economic activities on land resources and related environmental impacts presents spatial heterogeneity.

3.1.2 Urban land footprint from production-based and consumption-based perspective

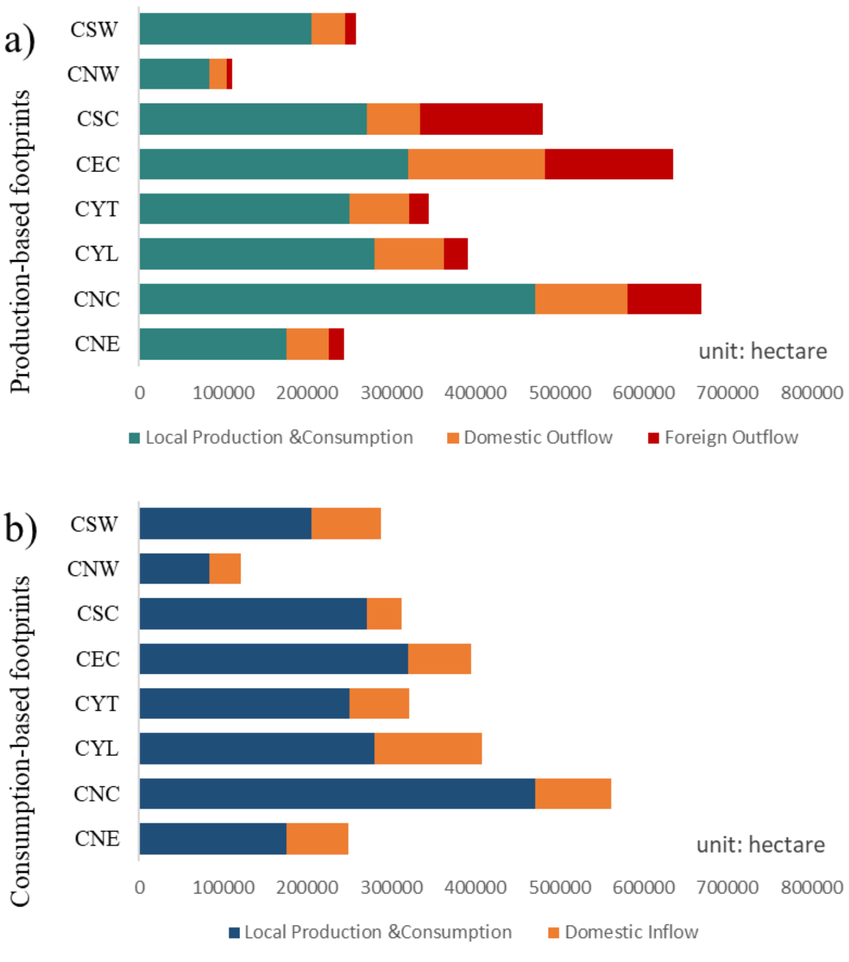

Figure 8 Production-based and Consumption-based urban land footprints of 8 regions within China.

The total land footprints are decomposed into local production for local use, domestic flow and foreign export (only for the production-based land footprint), distinguished by different colours. Abbreviations: CNE, northeast of China; CNC, north coast of China; CYL, Yellow River midstream of China; CYT, Yangtze River midstream of China; CEC, east coast of China; CSC, south coast of China; CSW, southwest of China; CNW, northwest of China.

Figure 8 illustrates the land footprint of each region in China. The production-based footprint shows the actual urban land area used for economic activities, while the consumption-based footprint identifies the urban land hectares required to meet final demand through the supply chain. Based on the input-output matrix and the land coefficient vector, we decomposed the total land footprints to four types: local production for local consumption, local production for domestic consumption, local production for international consumption, and local consumption drives domestic production in other regions. The result shows that the coastal region (CNC, CEC, CSC) had the highest land footprint on the production side, followed by the two major midstream regions (CYT, CYL), while the northwest of China (CNW) shown the lowest. Although the north coast of China (CNC) had the highest total production-based footprint, the majority (471999ha, 70.5%) was consumed locally. In contrast, 49.5% of the production-based footprint of the east coast of China (CEC) was driven by externally regions, with a land footprint of 161,990 ha (25.5%) driven by domestic consumption, and 152,807 ha (24%) driven by foreign export. The region north coast of China (CNC) had the largest consumption-based footprint (561847 ha), followed by Yellow River midstream of China (CYL) and CEC with 408266 ha, 394854 ha, respectively. The biggest external pulling effect was demonstrated by the Yellow River midstream of China (CYL), which drove 128465 hectares of external land use.

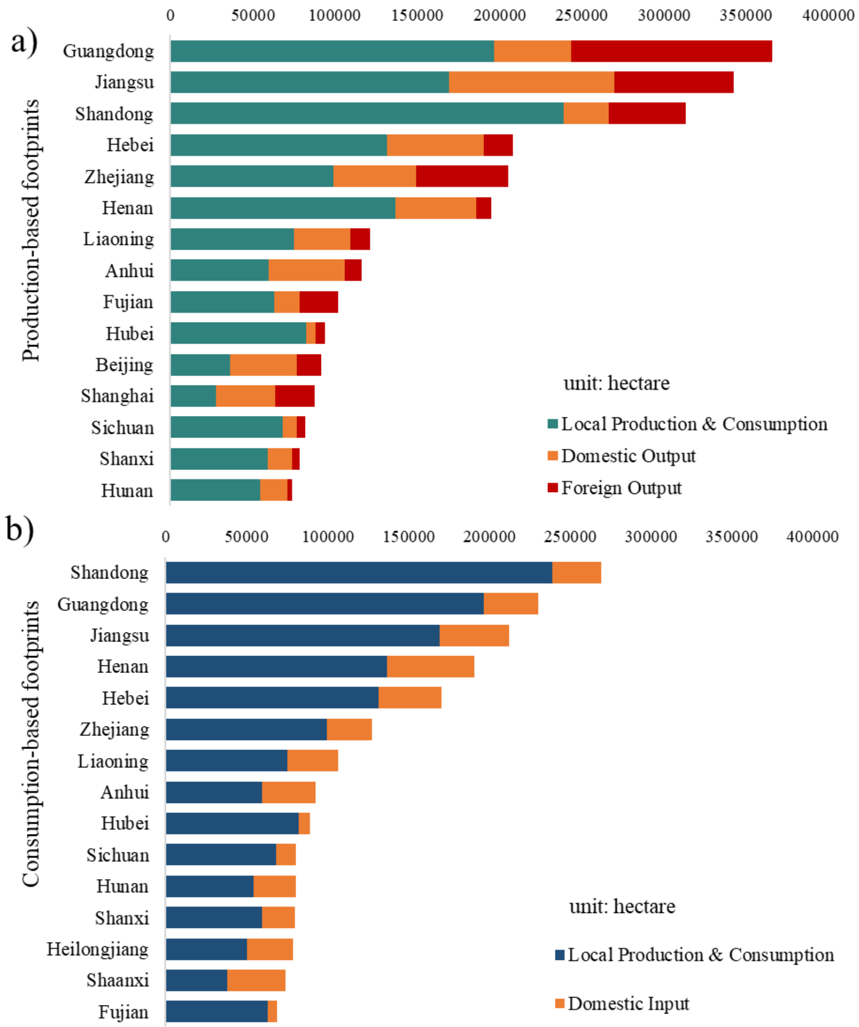

Figure 9 The top-15 provincial urban land footprints from production-based and consumption-based accounting.

The total land footprints are decomposed into local production for local use, domestic flow and foreign export (only for the production-based land footprint), distinguished by different colors.

Guangdong, Shandong, and Jiangsu remained the three highest provinces of land footprint from both production and consumption side. Guangdong province presented more export-oriented economic features demonstrated through its land footprint, with foreign outflows accounting for 72.4% of its overall outflows, compared to 42.1% in Jiangsu Province. The land footprint varied by provinces, with the top six accounting for 52% of total national land use on the production side and 45.2% on the consumption side (Figure 9). Bi-map shows the mismatch between high production-based and consumption-based footprints (Figure 10). Coastal areas (NC, EC, SC) provided 57% direct land footprints, shows the role of priority region of economic activities. High production-based footprints were mainly found in the east coastal provinces, with high industrially developed, while high consumption-based footprint was mainly related to the provincial population (Supplementary).

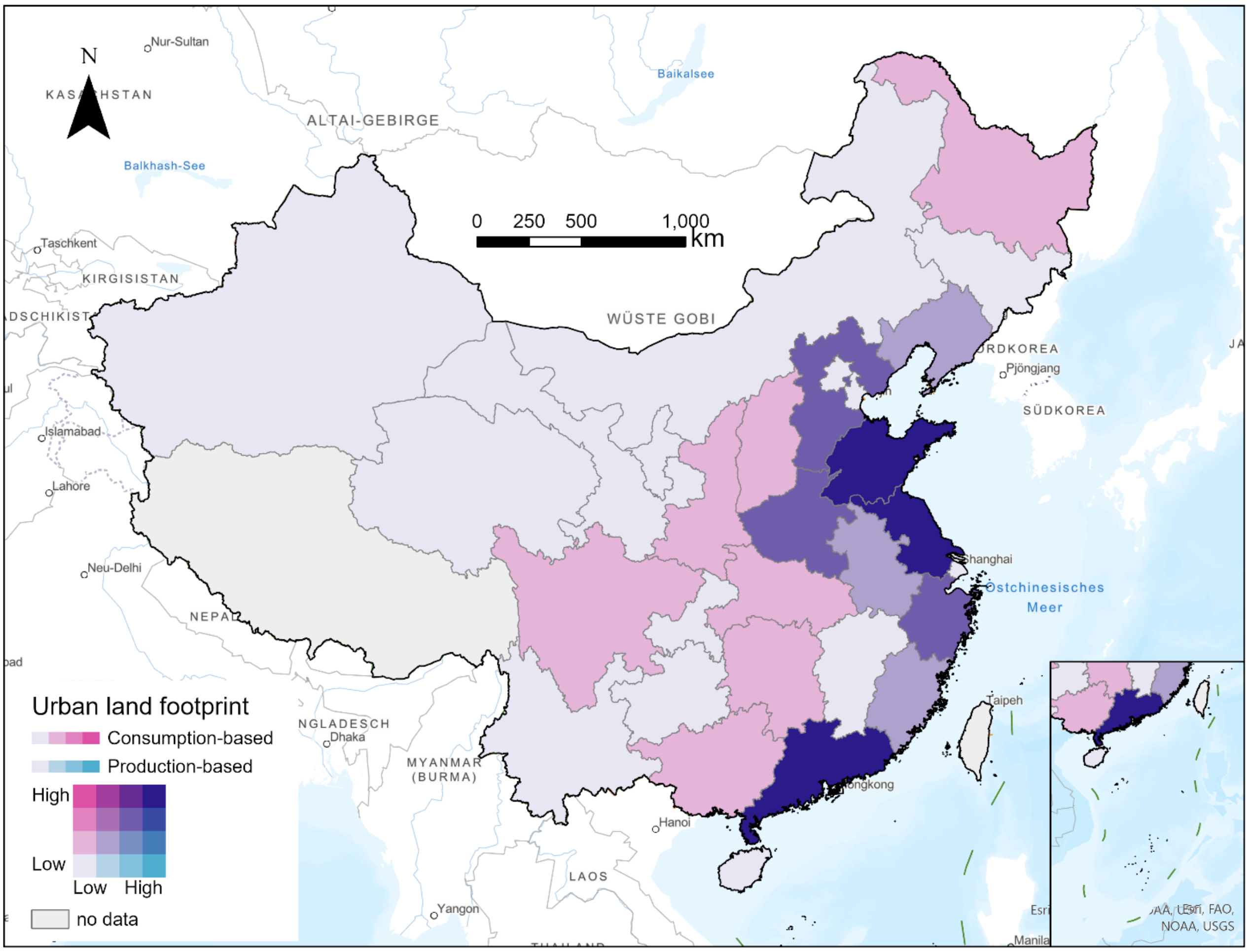

Figure 10 Bi-map of provincial land footprint within China from both production-based and consumption-based perspective.

3.2 The virtual urban land flows and consumption drivers

3.2.1 Land virtual flow driven by foreign consumptions

In terms of the final demand drivers of land flows, the results indicate that 85% of the urban land use in China was driven by domestic consumptions, with 15% due to foreign consumptions. From a global view, North America and Western European were the two main importers of China's urban land. The United States was the top importer, accounting for 103,785 ha, 21.8% of all the foreign consumptions. Followed by Japan, Germany, and South Korea with land importation of 42,522 ha, 24,358 ha, and 17,304 ha, respectively. Coastal provinces (NC, EC, SC), with highly developed industries, were the primary urban land exporters, providing 81.5% total foreign outflows.

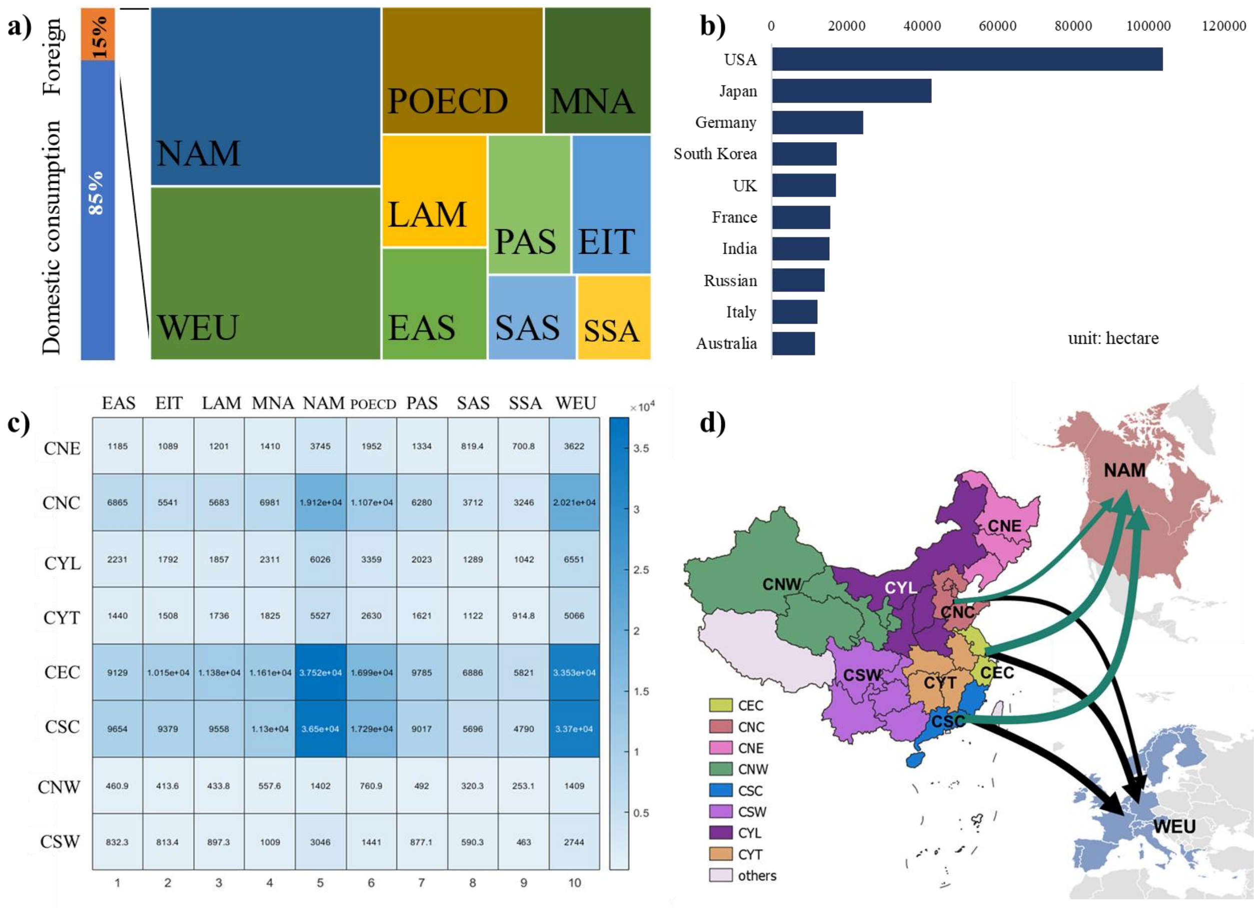

Figure 11 virtual land flow driven by final demand of foreign countries.

a) Tree diagram illustrating the amount of final consumption driving China's urban land footprint in 10 foreign regions; b) Top 10 countries globally driving China's urban land footprint; c) Virtual flow matrix of urban land between 8 regions in China and 10 regions abroad, with grid colors representing the amount of virtual flows; d) Virtual linkages between China and the 2 main foreign drivers, the top 6 virtual urban land flow pathways are shown on the map.

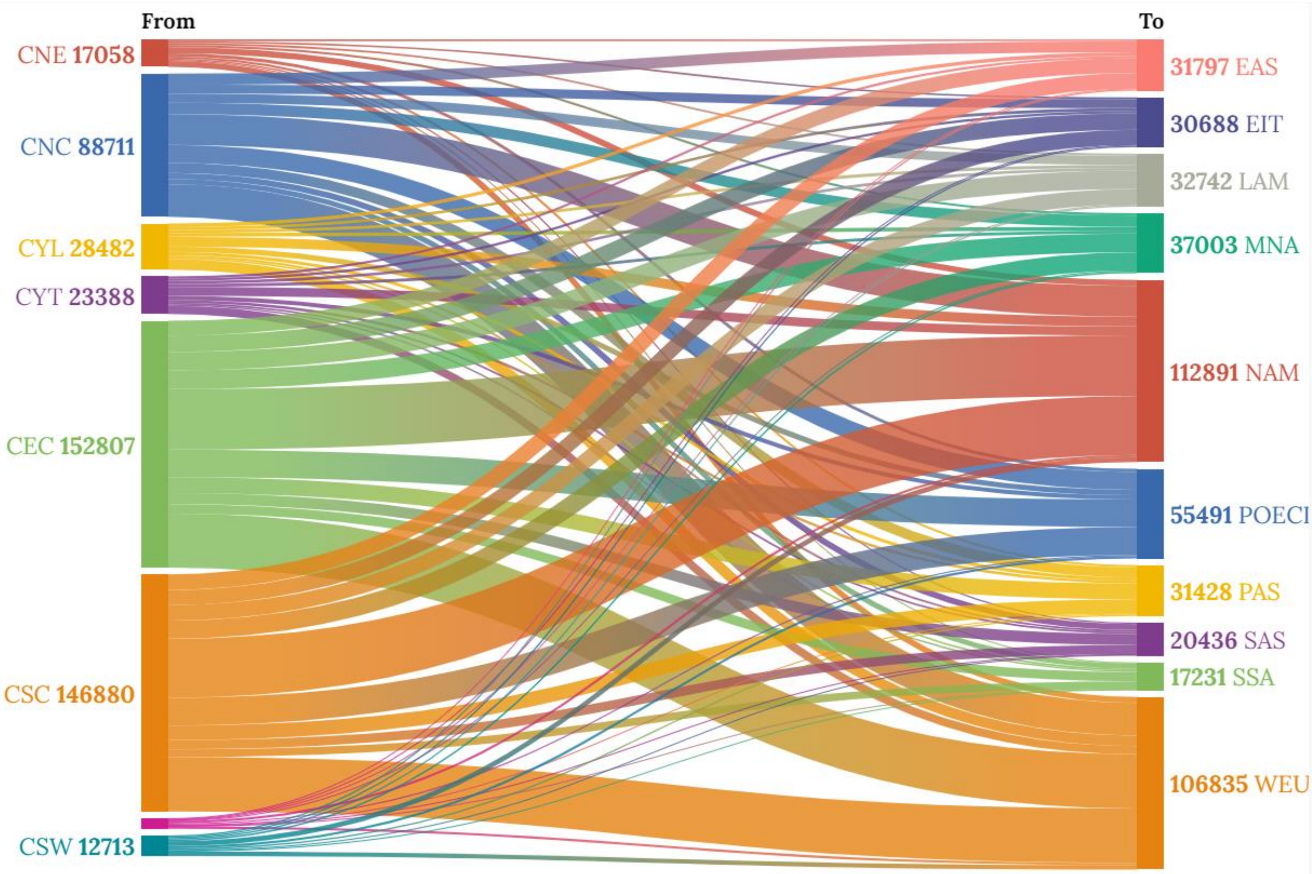

Figure 12 Global flows of embodied urban land used in China associated with the foreign final demand in 2012.

The left side of the sanger diagram shows the urban land use in 8 regions in China, the right side depicts the land embodied in the final consumption of 10 foreign regions.

3.2.2 Land virtual flow driven by domestic consumptions

From a general view, the results show a main trend that urban land flows from the eastern area of China to the western area. Figure 13 demonstrates that the net importers of urban land are mainly distributed in the inland areas of China, while the net exporters are in the east coast areas. From a regional perspective, coastal areas were the main domestic net land exporters, with CEC being the highest with a domestic net land flow of 87,836 ha, followed by CSC and CNC with 20,766 and 19,256 ha, respectively. CYL and CNE were the most important domestic urban land importer with 45,013 ha and 22,310 ha, respectively. The map illustrates the top 14 net flow routes, and Jiangsu was the main source (10/14) of these land flows. In terms of provincial land flows, the province accounting for the most domestic flows was Jiangsu (57,328 ha), followed by Hebei (20,244 ha). This implies that a large amount of land in Jiangsu and Hebei was embodied in products as a supply to other provinces.

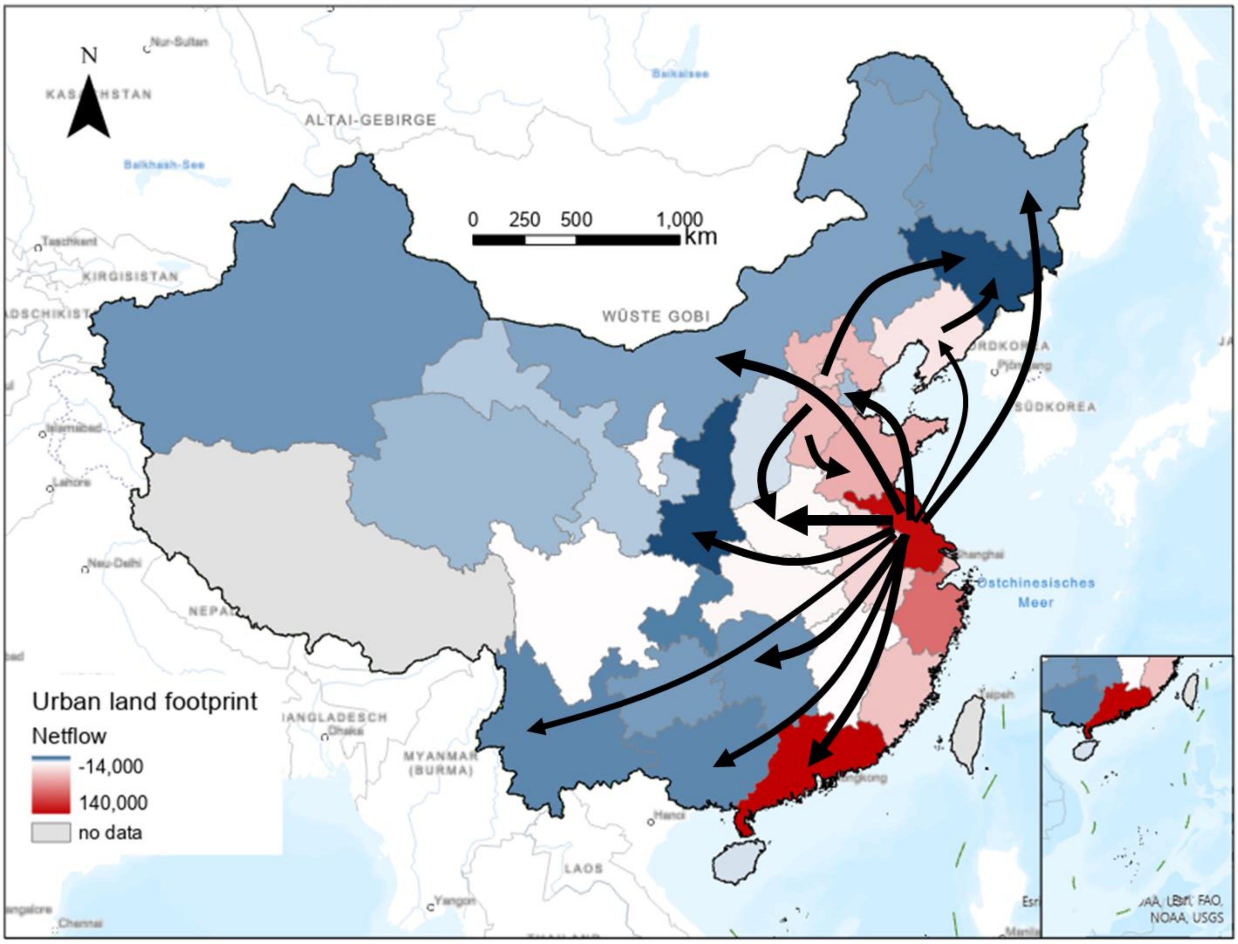

Figure 13 Net virtual land flow within China.

The province's color represents its role in the domestic virtual land flow network (blue represents net importers, red represents net exporters). The arrows indicate the 14 main net land flow pathways.

3.3 Urban land metabolism from ecological network perspective

3.3.1 Country level network properties

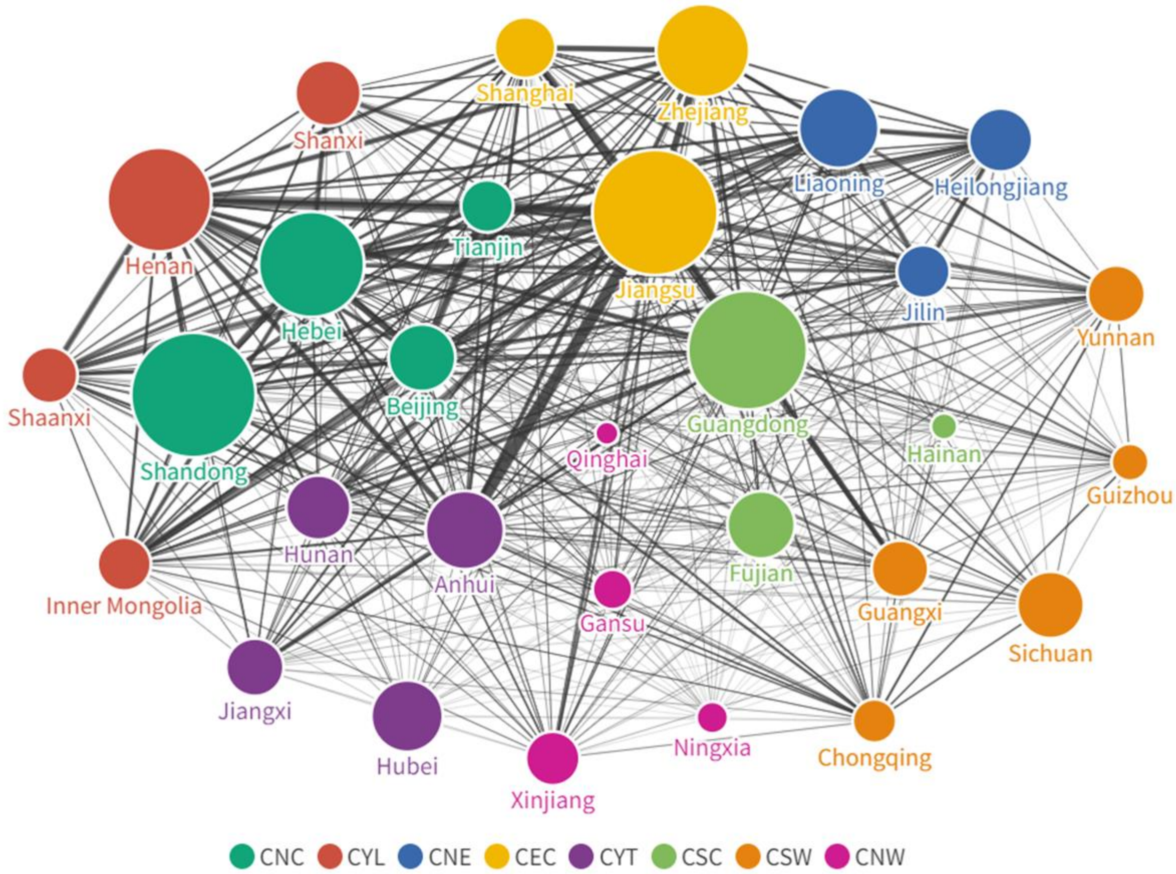

Figure 14 Network relations between Chinese provinces.

The virtual linkage of land among provinces are shown in Figure 14. China's eight regions are colored differently. The production-based land footprints are represented by the node size. The virtual land flow between the nodes is indicated by the interwoven connection lines, and the thickness represents the amount of virtual land flows. There are extensive trade links among the Chinese provinces and the network structure is complex. Regionally, the three regional networks of CNC, CEC, and CYL are more closely linked, which indicates a high degree of interconnectedness and integration of the socio-economic system in this region.

3.3.2 Province level network properties

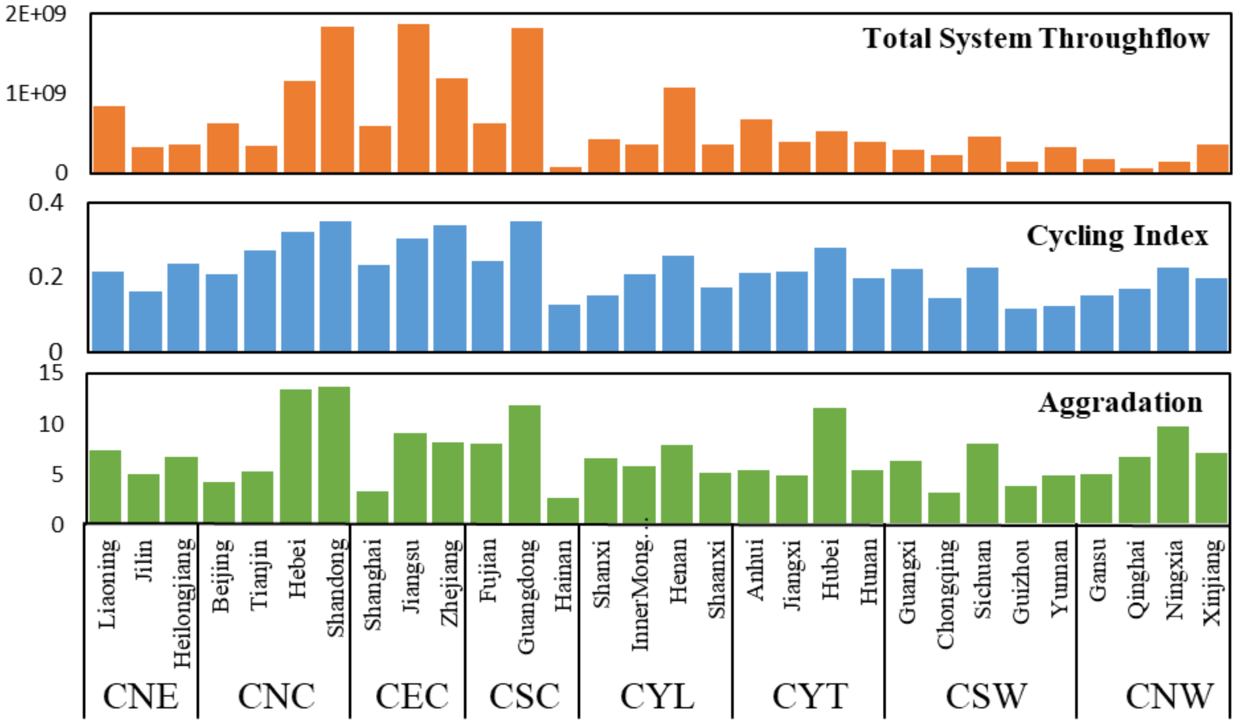

Figure 15 Properties of provincial virtual land flow network in China.

Each province or municipality was handled as a separate network in the ENA, with 42 economic sectors as nodes. Total system throughflow (TST) shows the total amount of virtual land flows through the network system. Jiangsu shows the highest TST value, while Qinghai was the lowest. Cycling Index (CI) shows how much of the flow would revisit the same node multiple times before exiting the system, associated with the ability of a system to re-use material and avoid loss, leading to a better efficiency. Aggradation shows the average path length of virtual land flows. Coastal areas (CNC, CEC, CSC) shown relatively high TST, CI, and Aggradation indexes, that the industrially developed provinces, as the main virtual land outflow areas, also exhibit a more complex network structure, with higher total system throughflow, more resource flow pathways, longer path length, and greater circularity. Shanghai, Beijing shown relatively high Cycling Indexes while relatively low TST and Aggradation index, revealed the resource was cycling in shorter pathways.

4. Discussion

1. spatial patterns of land use and differences between provinces.

The urban land usage was concentrated in the southeast coast and has aggregation characteristics at regional, provincial and more detailed spatial levels. These spatial characteristics and differences in land use patterns imply differences in the characteristics of various human activities. These differences can be observed at a finer urban level as well as at the industrial level (Xie et al., 2022). Furthermore, beyond land use footprint accounting, mapping and analysing the spatial characteristics of land provides a more nuanced view of land use and its associated environmental impacts. The spatial land use dataset can be linked with other spatial databases, provide insights for pollutant emission, spatial carbon accounting, or future land projections (Akbar et al., 2019; Ginebreda et al., 2018; Mishra et al., 2021).

Besides, cities are considered to have small footprints but large impacts, with a large number of embodied resources. The spatial characteristics of land can provide new insights about the trade linkage and production flows, the spatial distance, and the environmental impacts by transportation. Furthermore, the economic value and scarcity of land is tied to its spatial location, and then affects the industry development and land management. Zhao et al. (2019) used comparative advantage theory to examine the key driver of virtual water exports in China, and found that the land productivity was the main forces shaping the virtual water flow pattern, explains the difference from "virtual water hypothesis".

Furthermore, spatial attributes can act as a bridge to integrate current industrial and economic sector land use status with future climate and risk into an integrated framework (Cook-Patton et al., 2021; Lei et al., 2014; Lyu et al., 2020). How are future climate risks and catastrophic shocks spatially distributed, and how do they affect socioeconomic systems? These can be further discussed and analysed in the future study.

2. Land trade drive and virtual circulation

In this study, we used an input-output approach to simulate the virtual flow of land resources and identify the drivers of global final consumption on land use in China. These results supported the interconnectedness of the global land. From the perspective of virtual flows, almost half of the production-side land in industrially developed provinces were driven by final demand from external regions. For example, 41.4% of the urban land use in Shanghai was driven by domestic final consumption of other regions, and 27% was driven by foreign countries.

From the country level, 15% of China's national urban land footprint was driven by foreign final consumption. While for a single province, this proportion can reach 33.5% (Guangdong Province). Understanding these tele-coupling characteristics helps to understand the dynamic interactions and spillovers between land requirements and economic activities in human system (Bruckner et al., 2015;

Liu et al., 2018). America was the top importer of China's urban land, accounting for 21.8% of all the foreign consumptions, reflects the close trade linkage. There are broad spaces for US-China-EU cooperation in land protection, sustainable consumption, jointly promote sustainable management, and global climate change resolution (Bryan et al., 2018; Lewis, 2020; Schreurs, 2019).

Different from the land use transfer associated with agricultural production, urban land use exhibits different virtual transfer patterns. We found that the virtual flows were mainly from industrially developed areas to less developed areas, reflecting that urban land was embedded in industrial products and flows virtually with trade networks. In the future, specific industry-scale or product-scale analysis can correlate the urban land footprint as a supplement to the life cycle impact assessment (LCIA) factor (De Baan et al., 2013; Kuipers et al., 2019; Scherer et al., 2021), providing data supplements for Life Cyle Assessment and other industrial ecology methods.

5. Conclusion

Through a fine-grained spatial and sectoral identification of urban land take, we introduced a direct land footprint analysis into the industrial and socioeconomic systems. This enables the investigation of the relationship between economic activities and direct land requirements, as well as the urban land resource use in relation to industrial products. In this study, using a pre-established multi-regional and multi-sectoral land database, we conducted input-output analysis and ecological network analysis to examine the urban land footprints, spatial distributions and virtual flows. According to our findings, the urban land footprint associated with economic activity in China's 30 provinces totalled 3.13 million hectares in 2012. Spatial imbalances between the production and consumption footprints were found. Intensive urban land use occurred mostly in China's coastal areas. Guangdong, Shandong, and Jiangsu remained the top three provinces with the largest land footprints on both the production and consuming sides. In terms of the final demand drivers of land flows, the results revealed that domestic final consumption accounted for 85% of urban land usage in China, with foreign final consumption accounting for 15%. Globally, North America and Western Europe were the two largest importers of China’s urban land. From ecological network perspective, industrialized regions exhibited more complex network structures, with higher total system throughflow, more resource flow paths, longer path length, and greater circularity. Our results revealed the association between human socioeconomic activity with direct land demand and virtual land flows. In the future, multi-resource nexus analysis can be utilized to understand the leveraging effect of urban land use on other resources to enable future sustainable development analyses. The urban land use dataset can also cooperate with spatially environmental databases to reveal new insights and deeper understanding for spatial resource nexus and land management.

6. References

Akbar, T. A., Hassan, Q. K., Ishaq, S., Batool, M., Butt, H. J., & Jabbar, H. (2019). Investigative Spatial Distribution and Modelling of Existing and Future Urban Land Changes and Its Impact on Urbanization and Economy. *Remote Sensing*, *11*(2), 105. https://doi.org/10.3390/rs11020105

Barnes, A. D., Allen, K., Kreft, H., Corre, M. D., Jochum, M., Veldkamp, E., Clough, Y., Daniel, R., Darras, K., Denmead, L. H., Farikhah Haneda, N., Hertel, D., Knohl, A., Kotowska, M. M., Kurniawan, S., Meijide, A., Rembold, K., Edho Prabowo, W., Schneider, D., … Brose, U. (2017). Direct and cascading impacts of tropical land-use change on multi-trophic biodiversity. *Nature Ecology & Evolution*, *1*(10), 1511–1519. https://doi.org/10.1038/s41559-017-0275-7

Berrill, P., Miller, T. R., Kondo, Y., & Hertwich, E. G. (2020). Capital in the American carbon, energy, and material footprint. *Journal of Industrial Ecology*, *24*(3), 589–600. https://doi.org/10.1111/jiec.12953

Bettencourt, L. M. A. (2020). Urban growth and the emergent statistics of cities. *Science Advances*, *6*(34), eaat8812. https://doi.org/10.1126/sciadv.aat8812

Betts, M. G., Wolf, C., Ripple, W. J., Phalan, B., Millers, K. A., Duarte, A., Butchart, S. H. M., & Levi, T. (2017). Global forest loss disproportionately erodes biodiversity in intact landscapes. *Nature*, *547*(7664), 441–444. https://doi.org/10.1038/nature23285

Bodin, Ö., Alexander, S. M., Baggio, J., Barnes, M. L., Berardo, R., Cumming, G. S., Dee, L. E., Fischer, A. P., Fischer, M., Mancilla Garcia, M., Guerrero, A. M., Hileman, J., Ingold, K., Matous, P., Morrison, T. H., Nohrstedt, D., Pittman, J., Robins, G., & Sayles, J. S. (2019). Improving network approaches to the study of complex social–ecological interdependencies. *Nature Sustainability*, *2*(7), 551–559. https://doi.org/10.1038/s41893-019-0308-0

Bonan, G. B. (2008). Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. *SCIENCE*, *320*(5882), 1444–1449. https://doi.org/10.1126/science.1155121

Borrelli, P., Robinson, D. A., Panagos, P., Lugato, E., Yang, J. E., Alewell, C., Wuepper, D., Montanarella, L., & Ballabio, C. (2020). Land use and climate change impacts on global soil erosion by water (2015-2070). *Proceedings of the National Academy of Sciences*, *117*(36), 21994–22001. https://doi.org/10.1073/pnas.2001403117

Bradford, M. A., Wieder, W. R., Bonan, G. B., Fierer, N., Raymond, P. A., & Crowther, T. W. (2016). Managing uncertainty in soil carbon feedbacks to climate change. *Nature Climate Change*, *6*(8), 751–758. https://doi.org/10.1038/nclimate3071

Brizga, J. (2020). The Unintended Side Effects of Bioplastics: Carbon, Land, and Water Footprints. *One Earth*, 9.

Bruckner, M., Fischer, G., Tramberend, S., & Giljum, S. (2015). Measuring telecouplings in the global land system: A review and comparative evaluation of land footprint accounting methods. *Ecological Economics*, *114*, 11–21. https://doi.org/10.1016/j.ecolecon.2015.03.008

Bruckner, M., Häyhä, T., Giljum, S., Maus, V., Fischer, G., Tramberend, S., & Börner, J. (2019). Quantifying the global cropland footprint of the European Union’s non-food bioeconomy. *Environmental Research Letters*, *14*(4), 045011. https://doi.org/10.1088/1748-9326/ab07f5

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

Chen, Y., Li, X., Liu, X., Zhang, Y., & Huang, M. (2019). Quantifying the teleconnections between local consumption and domestic land uses in China. *Landscape and Urban Planning*, *187*, 60–69.

Chen, Y., Zhang, Q., Cai, X., Zhang, H., Lin, H., Zheng, C., Guo, Z., Hu, S., Chen, L., Tao, S., Liu, M., & Wang, X. (2022). Rapid Increase in China’s Industrial Ammonia Emissions: Evidence from Unit-Based Mapping. *Environmental Science & Technology*, *56*(6), 3375–3385. https://doi.org/10.1021/acs.est.1c08369

Cook-Patton, S. C., Drever, C. R., Griscom, B. W., Hamrick, K., Hardman, H., Kroeger, T., Pacheco, P., Raghav, S., Stevenson, M., Webb, C., Yeo, S., & Ellis, P. W. (2021). Protect, manage and then restore lands for climate mitigation. *Nature Climate Change*, *11*(12), 1027–1034. https://doi.org/10.1038/s41558-021-01198-0

Creamer, R. E., Hannula, S. E., Leeuwen, J. P. V., Stone, D., Rutgers, M., Schmelz, R. M., Ruiter, P. C. de, Hendriksen, N. B., Bolger, T., Bouffaud, M. L., Buee, M., Carvalho, F., Costa, D., Dirilgen, T., Francisco, R., Griffiths, B. S., Griffiths, R., Martin, F., Silva, P. M. da, … Lemanceau, P. (2016). Ecological network analysis reveals the inter-connection between soil biodiversity and ecosystem function as affected by land use across Europe. *Applied Soil Ecology*, *97*, 112–124. https://doi.org/10.1016/j.apsoil.2015.08.006

De Baan, L., Alkemade, R., & Koellner, T. (2013). Land use impacts on biodiversity in LCA: a global approach. *The International Journal of Life Cycle Assessment*, *18*(6), 1216–1230.

Derocles, S. A. P., Bohan, D. A., Dumbrell, A. J., Kitson, J. J. N., Massol, F., Pauvert, C., Plantegenest, M., Vacher, C., & Evans, D. M. (2018). Chapter One - Biomonitoring for the 21st Century: Integrating Next-Generation Sequencing Into Ecological Network Analysis. In D. A. Bohan, A. J. Dumbrell, G. Woodward, & M. Jackson (Eds.), *Advances in Ecological Research* (Vol. 58, pp. 1–62). Academic Press. https://doi.org/10.1016/bs.aecr.2017.12.001

Dorninger, C., von Wehrden, H., Krausmann, F., Bruckner, M., Feng, K., Hubacek, K., Erb, K.-H., & Abson, D. J. (2021). The effect of industrialization and globalization on domestic land-use: A global resource footprint perspective. *Global Environmental Change*, *69*, 102311. https://doi.org/10.1016/j.gloenvcha.2021.102311

Eugenia Kalnay & Ming Cai. (2003). Impact of urbanization and land-use change on climate. *Nature*. https://doi.org/10.1038/nature01675

Fang, D., & Chen, B. (2015). Ecological Network Analysis for a Virtual Water Network. *Environmental Science & Technology*, *49*(11), 6722–6730. https://doi.org/10.1021/es505388n

Fargione, J., Hill, J., Tilman, D., Polasky, S., & Hawthorne, P. (2008). Land Clearing and the Biofuel Carbon Debt. *Science*, *319*(5867), 1235–1238. https://doi.org/10.1126/science.1152747

Fath, B. D. (2012). Overview of Network Environ Analysis: A systems analysis technique for understanding complex ecological systems. *Biologi Italiani*, 8.

Fath, B. D., Asmus, H., Asmus, R., Baird, D., Borrett, S. R., de Jonge, V. N., Ludovisi, A., Niquil, N., Scharler, U. M., Schückel, U., & Wolff, M. (2019). Ecological network analysis metrics: The need for an entire ecosystem approach in management and policy. *Ocean & Coastal Management*, *174*, 1–14. https://doi.org/10.1016/j.ocecoaman.2019.03.007

Fath, B. D., Scharler, U. M., Ulanowicz, R. E., & Hannon, B. (2007). Ecological network analysis: Network construction. *Ecological Modelling*, *208*(1), 49–55. https://doi.org/10.1016/j.ecolmodel.2007.04.029

Field, J. L., Richard, T. L., Smithwick, E. A. H., Cai, H., Laser, M. S., LeBauer, D. S., Long, S. P., Paustian, K., Qin, Z., Sheehan, J. J., Smith, P., Wang, M. Q., & Lynd, L. R. (2020). Robust paths to net greenhouse gas mitigation and negative emissions via advanced biofuels. *Proceedings of the National Academy of Sciences*, *117*(36), 21968–21977. https://doi.org/10.1073/pnas.1920877117

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I. C., Ramankutty, N., & Snyder, P. K. (2005a). Global Consequences of Land Use. *Science*, *309*(5734), 570–574. https://doi.org/10.1126/science.1111772

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I. C., Ramankutty, N., & Snyder, P. K. (2005b). Global Consequences of Land Use. *Science*, *309*(5734), 570–574. https://doi.org/10.1126/science.1111772

Gao, J., & Pesaresi, M. (2021). Downscaling SSP-consistent global spatial urban land projections from 1/8-degree to 1-km resolution 2000–2100. *Scientific Data*, *8*(1), 281. https://doi.org/10.1038/s41597-021-01052-0

Ginebreda, A., Sabater-Liesa, L., Rico, A., Focks, A., & Barceló, D. (2018). Reconciling monitoring and modeling: An appraisal of river monitoring networks based on a spatial autocorrelation approach - emerging pollutants in the Danube River as a case study. *Science of The Total Environment*, *618*, 323–335. https://doi.org/10.1016/j.scitotenv.2017.11.020

Goldstein, J. H., Caldarone, G., Duarte, T. K., Ennaanay, D., Hannahs, N., Mendoza, G., Polasky, S., Wolny, S., & Daily, G. C. (2012). Integrating ecosystem-service tradeoffs into land-use decisions. *PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA*, *109*(19), 7565–7570. https://doi.org/10.1073/pnas.1201040109

Haberl, H., Mbow, C., Deng, X., Irwin, E. G., Kerr, S., Kuemmerle, T., Mertz, O., Meyfroidt, P., & Ii, B. L. T. (2014). Finite Land Resources and Competition. *Rethinking Global Land Use in an Urban Era*, *14*, 36.

Hoekstra, A. Y., & Mekonnen, M. M. (2012). The water footprint of humanity. *Proceedings of the National Academy of Sciences*, *109*(9), 3232–3237. https://doi.org/10.1073/pnas.1109936109

Kuipers, K. J. J., May, R. F., Graae, B. J., & Verones, F. (2019). Reviewing the potential for including habitat fragmentation to improve life cycle impact assessments for land use impacts on biodiversity. *The International Journal of Life Cycle Assessment*, *24*(12), 2206–2219. https://doi.org/10.1007/s11367-019-01647-1

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

Lan, J., Malik, A., Lenzen, M., McBain, D., & Kanemoto, K. (2016). A structural decomposition analysis of global energy footprints. *Applied Energy*, *163*, 436–451. https://doi.org/10.1016/j.apenergy.2015.10.178

Laroche, P. C. S. J., Schulp, C. J. E., Kastner, T., & Verburg, P. H. (2020). Telecoupled environmental impacts of current and alternative Western diets. *Global Environmental Change*, *62*, 102066. https://doi.org/10.1016/j.gloenvcha.2020.102066

Lei, Y., Wang, J., Yue, Y., Yin, Y., & Sheng, Z. (2014). How adjustments in land use patterns contribute to drought risk adaptation in a changing climate—A case study in China. *Land Use Policy*, *36*, 577–584. https://doi.org/10.1016/j.landusepol.2013.10.004

Lenzen, M., Sun, Y.-Y., Faturay, F., Ting, Y.-P., Geschke, A., & Malik, A. (2018). The carbon footprint of global tourism. *Nature Climate Change*, *8*(6), 522–528. https://doi.org/10.1038/s41558-018-0141-x

Lewis, J. I. (2020). Toward a New Era of US Engagement with China on Climate Change. *Georgetown Journal of International Affairs*, *21*, 173–181. https://doi.org/10.1353/gia.2020.0032

Liu, J., Dou, Y., Batistella, M., Challies, E., Connor, T., Friis, C., Millington, J. D., Parish, E., Romulo, C. L., Silva, R. F. B., Triezenberg, H., Yang, H., Zhao, Z., Zimmerer, K. S., Huettmann, F., Treglia, M. L., Basher, Z., Chung, M. G., Herzberger, A., … Sun, J. (2018). Spillover systems in a telecoupled Anthropocene: Typology, methods, and governance for global sustainability. *Current Opinion in Environmental Sustainability*, *33*, 58–69. https://doi.org/10.1016/j.cosust.2018.04.009

Lyu, H.-M., Shen, S.-L., Zhou, A., & Yang, J. (2020). Risk assessment of mega-city infrastructures related to land subsidence using improved trapezoidal FAHP. *Science of The Total Environment*, *717*, 135310. https://doi.org/10.1016/j.scitotenv.2019.135310

Matuštík, J., & Kočí, V. (2021). What is a footprint? A conceptual analysis of environmental footprint indicators. *Journal of Cleaner Production*, *285*, 124833. https://doi.org/10.1016/j.jclepro.2020.124833

Meyfroidt, P., de Bremond, A., Ryan, C. M., Archer, E., Aspinall, R., Chhabra, A., Camara, G., Corbera, E., DeFries, R., Diaz, S., Dong, J., Ellis, E. C., Erb, K.-H., Fisher, J. A., Garrett, R. D., Golubiewski, N. E., Grau, H. R., Grove, J. M., Haberl, H., … zu Ermgassen, E. K. H. J. (2022). Ten facts about land systems for sustainability. *Proceedings of the National Academy of Sciences of the United States of America*, *119*(7), e2109217118. https://doi.org/10.1073/pnas.2109217118

Mi, Z., Meng, J., Guan, D., Shan, Y., Song, M., Wei, Y.-M., Liu, Z., & Hubacek, K. (2017). Chinese CO2 emission flows have reversed since the global financial crisis. *Nature Communications*, *8*(1), 1712. https://doi.org/10.1038/s41467-017-01820-w

Mishra, U., Hugelius, G., Shelef, E., Yang, Y., Strauss, J., Lupachev, A., Harden, J. W., Jastrow, J. D., Ping, C.-L., Riley, W. J., Schuur, E. A. G., Matamala, R., Siewert, M., Nave, L. E., Koven, C. D., Fuchs, M., Palmtag, J., Kuhry, P., Treat, C. C., … Orr, A. (2021). Spatial heterogeneity and environmental predictors of permafrost region soil organic carbon stocks. *Science Advances*, *7*(9), eaaz5236. https://doi.org/10.1126/sciadv.aaz5236

Morris, Z. B., Weissburg, M., & Bras, B. (2021). Ecological network analysis of urban–industrial ecosystems. *Journal of Industrial Ecology*, *25*(1), 193–204. https://doi.org/10.1111/jiec.13043

Patterson, M., McDonald, G., & Hardy, D. (2017). Is there more in common than we think? Convergence of ecological footprinting, emergy analysis, life cycle assessment and other methods of environmental accounting. *Ecological Modelling*, *362*, 19–36. https://doi.org/10.1016/j.ecolmodel.2017.07.022

Rees, W. E. (1992). Ecological footprints and appropriated carrying capacity: What urban economics leaves out. *Environment and Urbanization*, *4*(2), 121–130. https://doi.org/10.1177/095624789200400212

Ridoutt, B. G., Hadjikakou, M., Nolan, M., & Bryan, B. A. (2018). From Water-Use to Water-Scarcity Footprinting in Environmentally Extended Input–Output Analysis. *Environmental Science & Technology*, *52*(12), 6761–6770. https://doi.org/10.1021/acs.est.8b00416

Scherer, L., De Laurentiis, V., Marques, A., Michelsen, O., Alejandre, E. M., Pfister, S., Rosa, F., & Rugani, B. (2021). Linking land use inventories to biodiversity impact assessment methods. *The International Journal of Life Cycle Assessment*, *26*(12), 2315–2320. https://doi.org/10.1007/s11367-021-02003-y

Schreurs, M. A. (2019). Climate change politics in the US, China, and the EU: Climate science and the framing of climate action. In *The Evolving Relationship between China, the EU and the USA*. Routledge.

See, L., Georgieva, I., Duerauer, M., Kemper, T., Corbane, C., Maffenini, L., Gallego, J., Pesaresi, M., Sirbu, F., Ahmed, R., Blyshchyk, K., Magori, B., Blyshchyk, V., Melnyk, O., Zadorozhniuk, R., Mandici, M.-T., Su, Y.-F., Rabia, A. H., Pérez-Hoyos, A., … Fritz, S. (2022). A crowdsourced global data set for validating built-up surface layers. *Scientific Data*, *9*(1), 13. https://doi.org/10.1038/s41597-021-01105-4

Seto, K. C., Reenberg, A., Boone, C. G., Fragkias, M., Haase, D., Langanke, T., Marcotullio, P., Munroe, D. K., Olah, B., & Simon, D. (2012). Urban land teleconnections and sustainability. *PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA*, *109*(20), 7687–7692. https://doi.org/10.1073/pnas.1117622109

Shi, Z., Duan, H., Zhang, L., Hao, Y., Liu, X., & Xiong, X. (2021). Ecological network analysis of the energy metabolic system under the revitalizing process: Insight from the case of Jilin province, China. *Journal of Cleaner Production*, *326*, 129356. https://doi.org/10.1016/j.jclepro.2021.129356

Steen-Olsen, K., Weinzettel, J., Cranston, G., Ercin, A. E., & Hertwich, E. G. (2012). Carbon, Land, and Water Footprint Accounts for the European Union: Consumption, Production, and Displacements through International Trade. *Environmental Science & Technology*, *46*(20), 10883–10891. https://doi.org/10.1021/es301949t

Tietenberg, T. H., & Lewis, L. (2015). *Environmental & natural resource economics* (10th Edition). Pearson.

United Nations. (2021). *System of Environmental-Economic Accounting—Ecosystem Accounting*.

van Riper, C. J., Thiel, A., Penker, M., Braito, M., Landon, A. C., Thomsen, J. M., & Tucker, C. M. (2018). Incorporating multilevel values into the social-ecological systems framework. *Ecology and Society*, *23*(3), 25. https://doi.org/10.5751/ES-10047-230325

van Vliet, J. (2019). Direct and indirect loss of natural area from urban expansion. *Nature Sustainability*, *2*(8), 755–763. https://doi.org/10.1038/s41893-019-0340-0

Wang, C., Wang, Y., Wang, R., & Zheng, P. (2018). Modeling and evaluating land-use/land-cover change for urban planning and sustainability: A case study of Dongying city, China. *Journal of Cleaner Production*, *172*, 1529–1534. https://doi.org/10.1016/j.jclepro.2017.10.294

Wiedmann, T., & Allen, C. (2021). City footprints and SDGs provide untapped potential for assessing city sustainability. *Nature Communications*, *12*(1), 3758. https://doi.org/10.1038/s41467-021-23968-2

Wu, L., Huang, K., Ridoutt, B. G., Yu, Y., & Chen, Y. (2021). A planetary boundary-based environmental footprint family: From impacts to boundaries. *Science of The Total Environment*, *785*, 147383. https://doi.org/10.1016/j.scitotenv.2021.147383

Xie, W., Yu, H., Li, Y., Dai, M., Long, X., Li, N., & Wang, Y. (2022). Estimation of entity-level land use and its application in urban sectoral land use footprint: A bottom-up model with emerging geospatial data. *Journal of Industrial Ecology*, *26*(1), 309–322. https://doi.org/10.1111/jiec.13191

Zhai, M., Huang, G., Liu, L., Zheng, B., & Guan, Y. (2020). Inter-regional carbon flows embodied in electricity transmission: Network simulation for energy-carbon nexus. *Renewable and Sustainable Energy Reviews*, *118*, 109511. https://doi.org/10.1016/j.rser.2019.109511

Zhang, L., Godil, D. I., Bibi, M., Khan, M. K., Sarwat, S., & Anser, M. K. (2021). Caring for the environment: How human capital, natural resources, and economic growth interact with environmental degradation in Pakistan? A dynamic ARDL approach. *Science of The Total Environment*, *774*, 145553. https://doi.org/10.1016/j.scitotenv.2021.145553

Zhang, Y., Yang, Z., Fath, B. D., & Li, S. (2010). Ecological network analysis of an urban energy metabolic system: Model development, and a case study of four Chinese cities. *Ecological Modelling*, *221*(16), 1865–1879. https://doi.org/10.1016/j.ecolmodel.2010.05.006

Zhao, D., Hubacek, K., Feng, K., Sun, L., & Liu, J. (2019). Explaining virtual water trade: A spatial-temporal analysis of the comparative advantage of land, labor and water in China. *Water Research*, *153*, 304–314. https://doi.org/10.1016/j.watres.2019.01.025

Zheng, Q., Siman, K., Zeng, Y., Teo, H. C., Sarira, T. V., Sreekar, R., & Koh, L. P. (2022). Future land-use competition constrains natural climate solutions. *Science of The Total Environment*, 156409. https://doi.org/10.1016/j.scitotenv.2022.156409

7. Supplementary

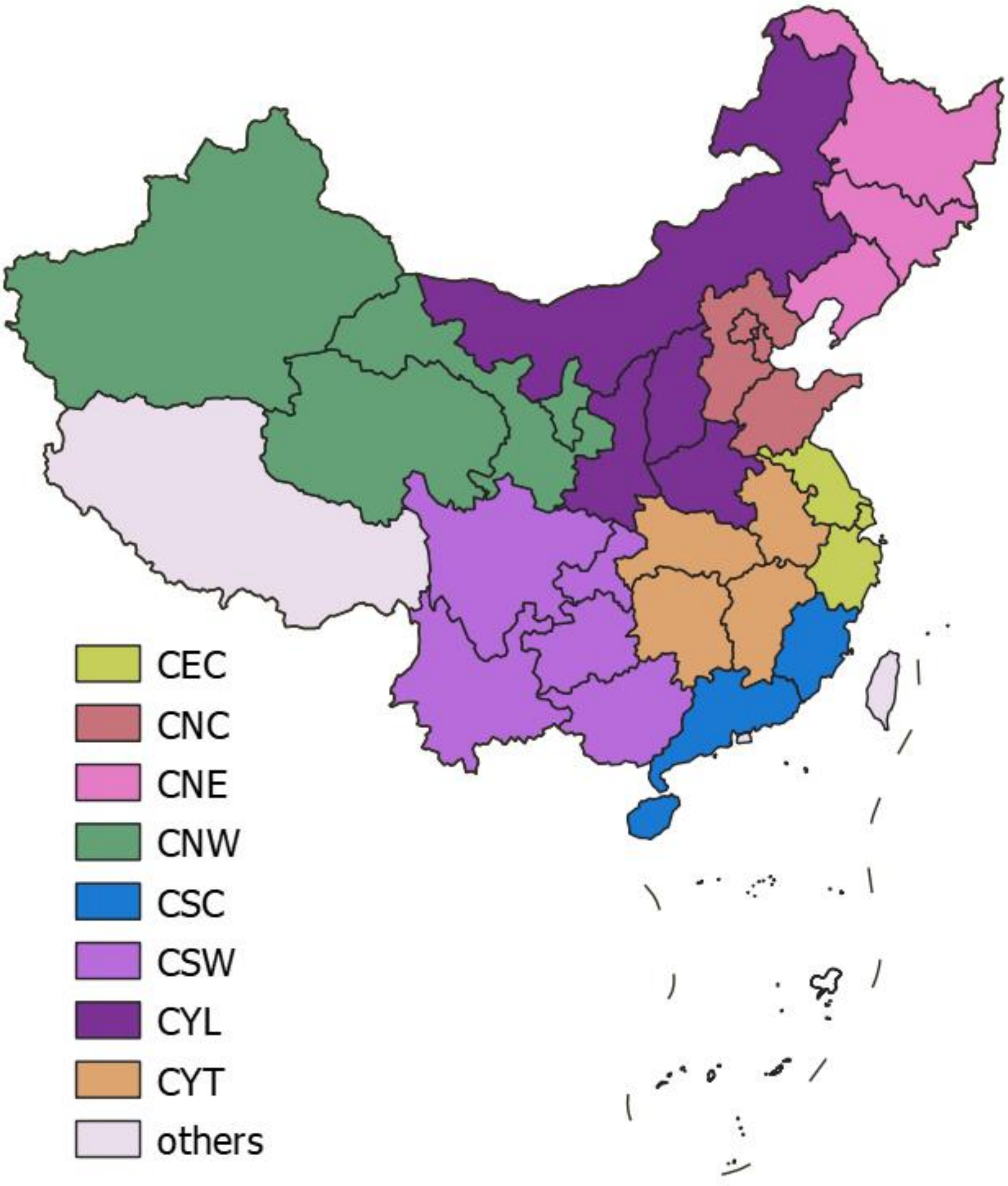

Figure S1 China's 8 regions.

Abbreviations: CNE, northeast of China; CNC, north coast of China; CYL, Yellow River midstream of China; CYT, Yangtze River midstream of China; CEC, east coast of China; CSC, south coast of China; CSW, southwest of China; CNW, northwest of China.

Table S1 Provincial codes, names, and classifications.

Code	Chinese name	English name	Region
110000	北京市	Beijing	CNC
120000	天津市	Tianjin	CNC

130000	河北省	Hebei	CNC
140000	山西省	Shanxi	CYL
150000	内蒙古自治区	Inner Mongolia	CYL
210000	辽宁省	Liaoning	CNE
220000	吉林省	Jilin	CNE
230000	黑龙江省	Heilongjiang	CNE
310000	上海市	Shanghai	CEC
320000	江苏省	Jiangsu	CEC
330000	浙江省	Zhejiang	CEC
340000	安徽省	Anhui	CYT
350000	福建省	Fujian	CSC
360000	江西省	Jiangxi	CYT
370000	山东省	Shandong	CNC
410000	河南省	Henan	CYL
420000	湖北省	Hubei	CYT
430000	湖南省	Hunan	CYT
440000	广东省	Guangdong	CSC
450000	广西壮族自治区	Guangxi	CSW
460000	海南省	Hainan	CSC
500000	重庆市	Chongqing	CSW
510000	四川省	Sichuan	CSW
520000	贵州省	Guizhou	CSW
530000	云南省	Yunnan	CSW
540000	西藏自治区	Tibet	Others (no data)
610000	陕西省	Shaanxi	CYL
620000	甘肃省	Gansu	CNW
630000	青海省	Qinghai	CNW
640000	宁夏回族自治区	Ningxia	CNW
650000	新疆维吾尔自治区	Xinjiang	CNW
710000	台湾省	Taiwan	others (no data)
810000	香港特别行政区	Hongkong	others (no data)
820000	澳门特别行政区	Macao	others (no data)

Table S2 Sectoral codes, names, and classifications.

Code	Sector Name	Primary Industry Name
1	Agriculture, Forestry, Animal Husbandry& Fishery	Agriculture
2	Mining and Washing of Coal	Mining
3	Extraction of Crude Petroleum and Natural Gas	Mining
4	Mining and Metal Ores	Mining
5	Mining and Quarrying of Nonmetal Ores and Other Ores	Mining
6	Manufacture of Food and Tobacco	Manufacturing
7	Manufacture of Textile	Manufacturing
8	Manufacture of Textile Wearing Apparel, Footwear, Caps, Leather, Fur, Feather, and Its products	Manufacturing
9	Processing of Timbers and Manufacture of Furniture	Manufacturing
10	Papermaking, Printing and Manufacture of Articles for Culture, Education and Sports Activities	Manufacturing
11	Processing of Refined Petroleum, Coking Products, Processing of Nuclear Fuel	Manufacturing
12	Manufacture of Chemicals and Chemical Products	Manufacturing
13	Manufacture of Nonmetallic Mineral Products	Manufacturing
14	Manufacture of Processing of Metals	Manufacturing
15	Manufacture of Fabricated Metal Products, Except Machinery and Equipment	Manufacturing
16	Manufacture of General and Special Purpose Machinery	Manufacturing
17	Manufacture of Transport Equipment	Manufacturing
18	Manufacture of Electrical Machinery and Apparatus	Manufacturing
19	Manufacture of Communication Equipment, Computer. and Other Electronic Equipment	Manufacturing
20	Manufacture of Measuring Instruments	Manufacturing
21	Other Manufacture	Manufacturing
22	Production and Supply of Electricity and Steam	Utility
23	Production and Distribution of Gas and Water	Utility
24	Construction	Construction
25	Transport, Storage & Post	Transportation
26	Wholesale and Retail Trade	Tertiary
27	Accommodation, Food and Beverage Services	Tertiary
28	Renting and Leasing, Business Services	Tertiary
29	Scientific Research and Development, Technical Services	Tertiary
30	Other Services	Tertiary

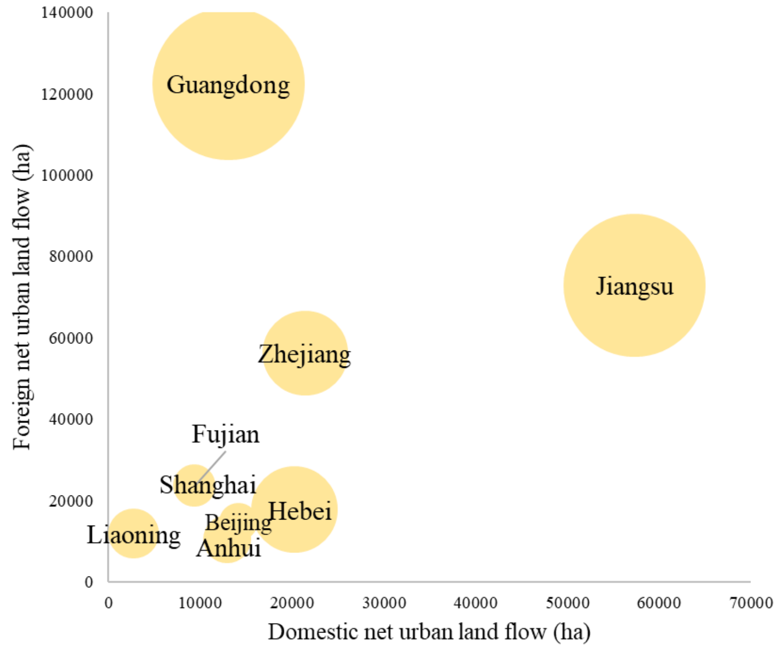

Figure S2 Scatter plot on the composition of net domestic and net foreign flows for major land exporters. *The size of the point represents the land footprint at its production end.*

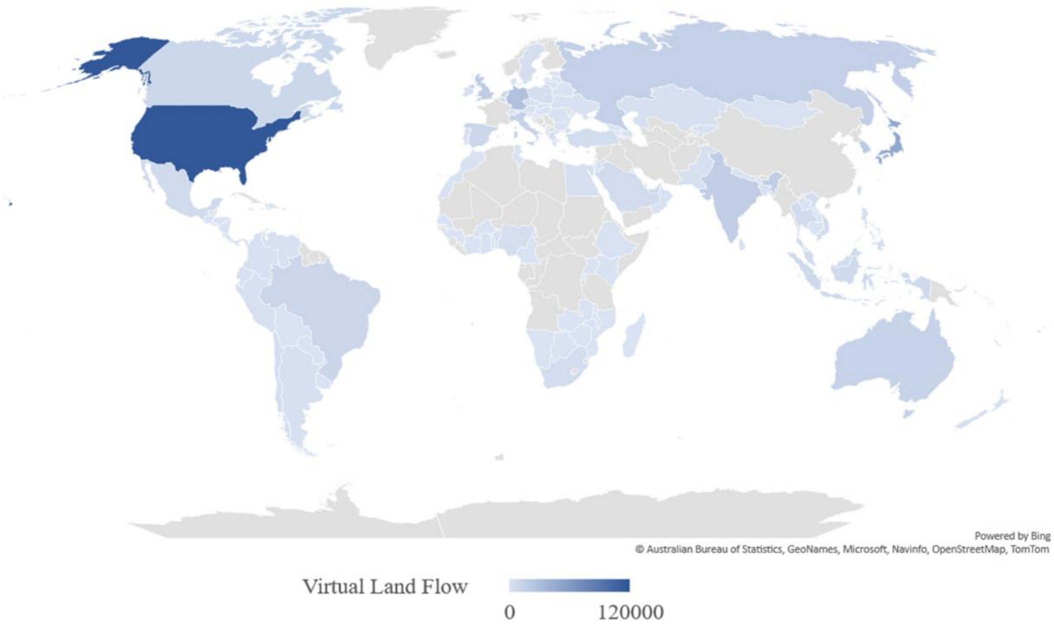

Figure S3 The amount of China's urban Land footprints driven by each foreign country.

Figure S4 Domestic virtual urban land netflows between 8 regions in China.

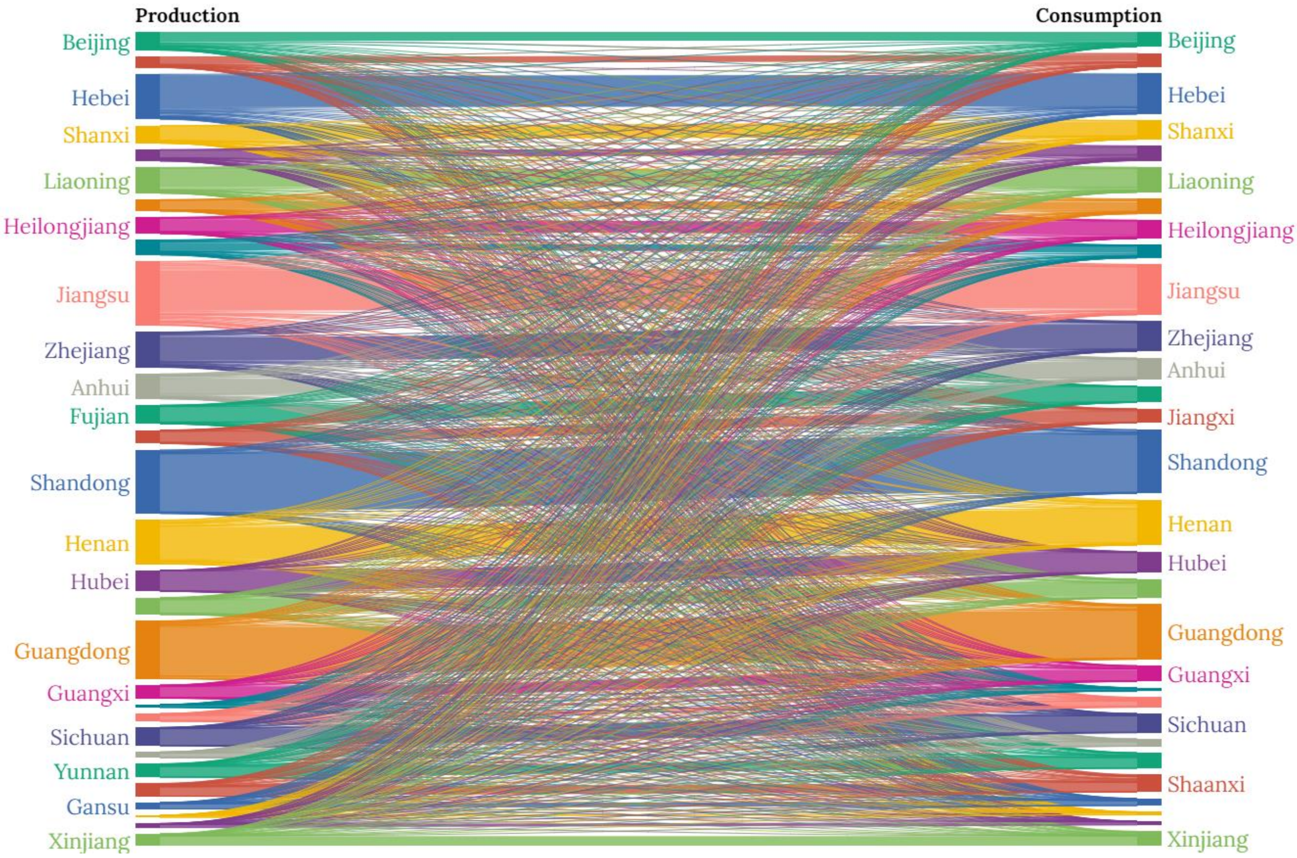

Figure S5 Domestic virtual urban land flows between 30 provinces in China.

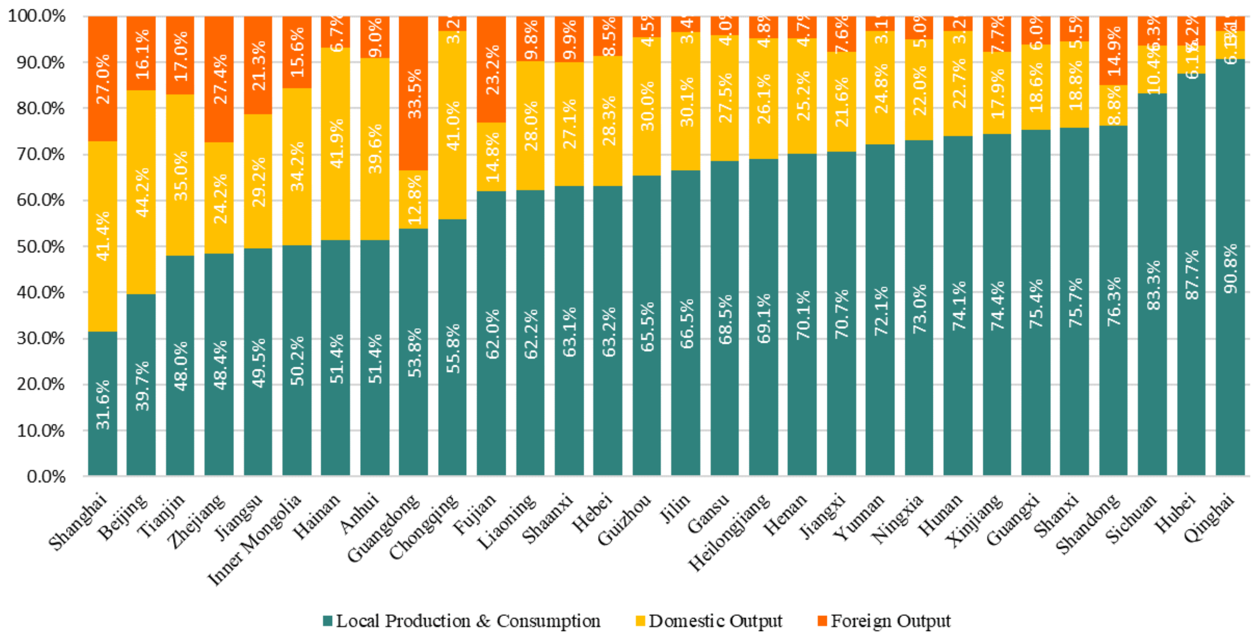

Figure S6 Proportion of urban land footprint driven by local or external regions in each province.

The total land footprints are decomposed into local production for local use, domestic flow and foreign export (only for the production-based land footprint), distinguished by different colors.

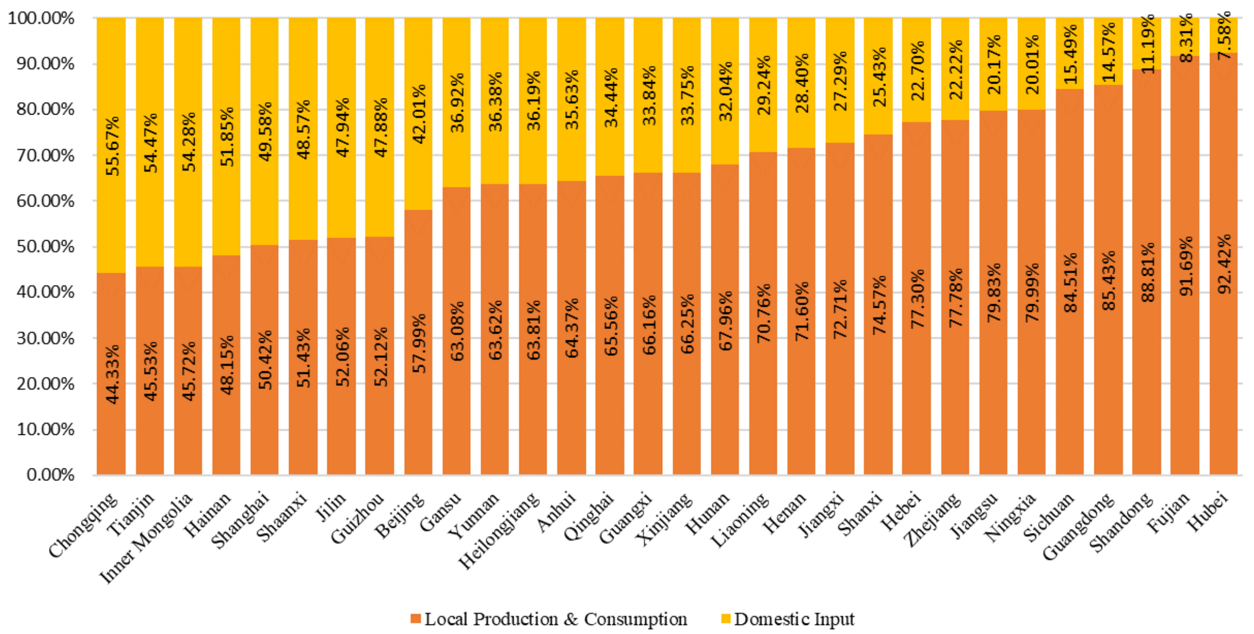

Figure S7 Proportion of sources of urban land footprint for final consumption by province.

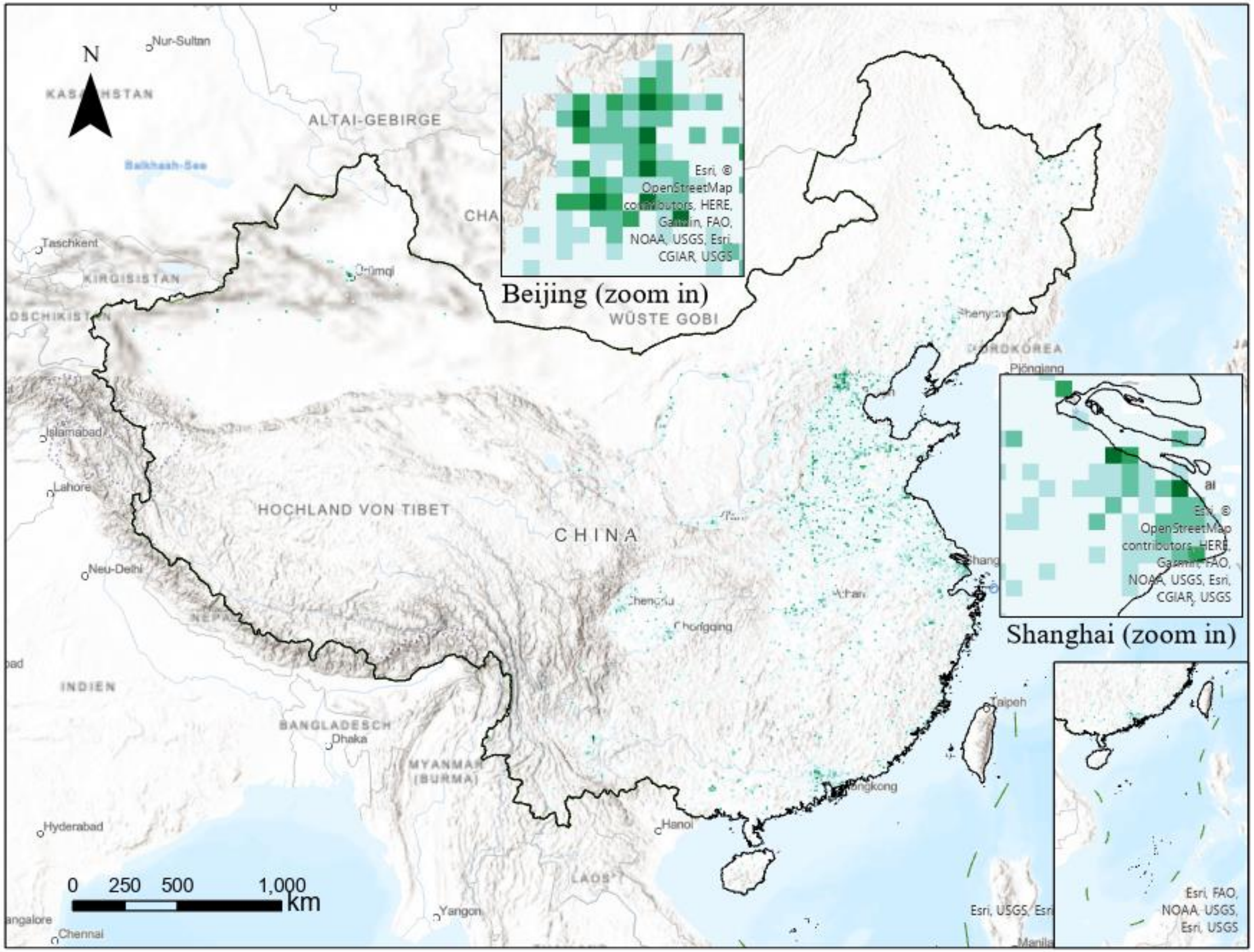

Figure S8 Spatial distribution of urban land use by the Agricultural Industry in China in 2012. Note: Only impervious urban land areas are accounted in this study.

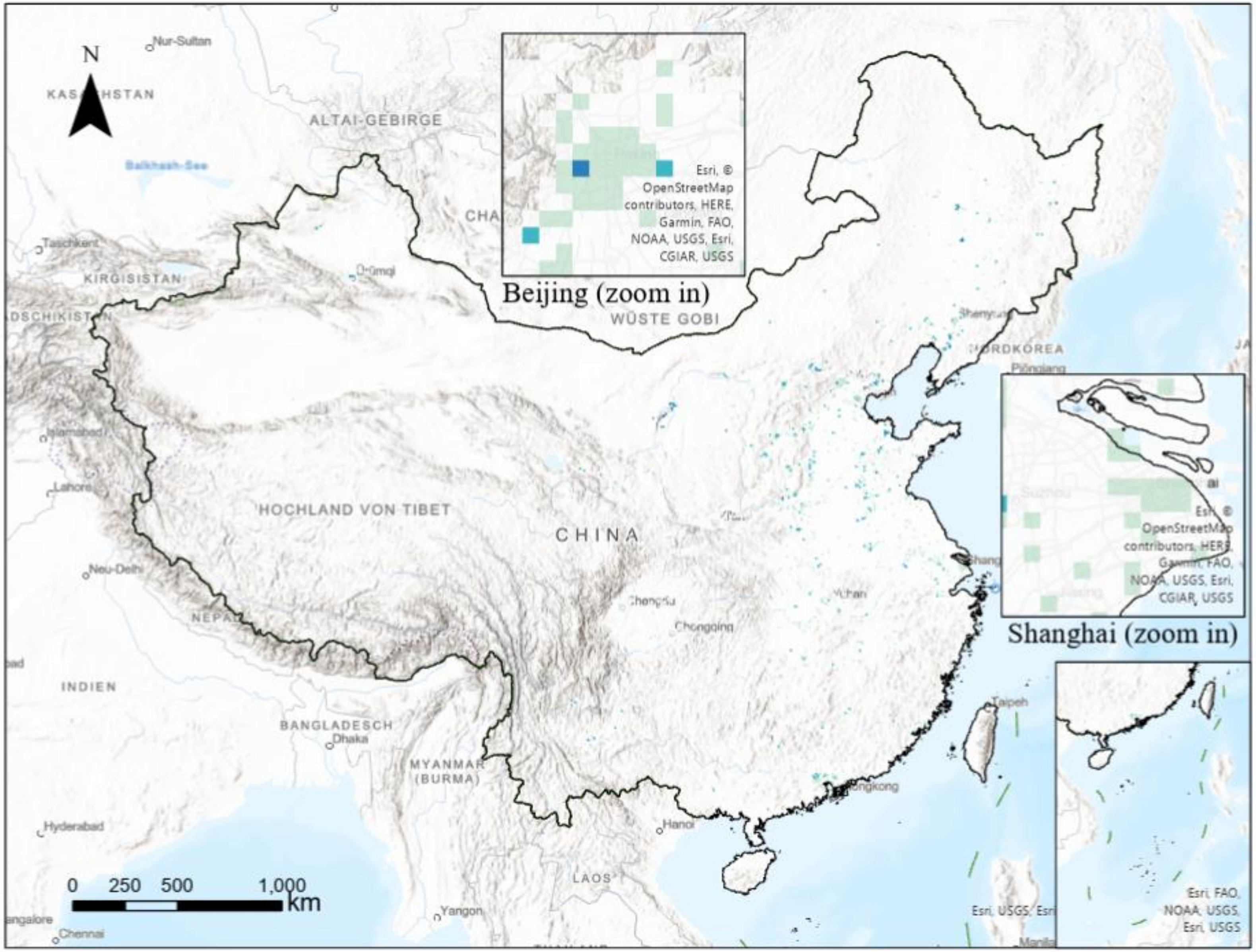

Figure S9 Spatial distribution of urban land use by the Mining Industry in China in 2012.

Note: Only impervious urban land areas are accounted in this study.

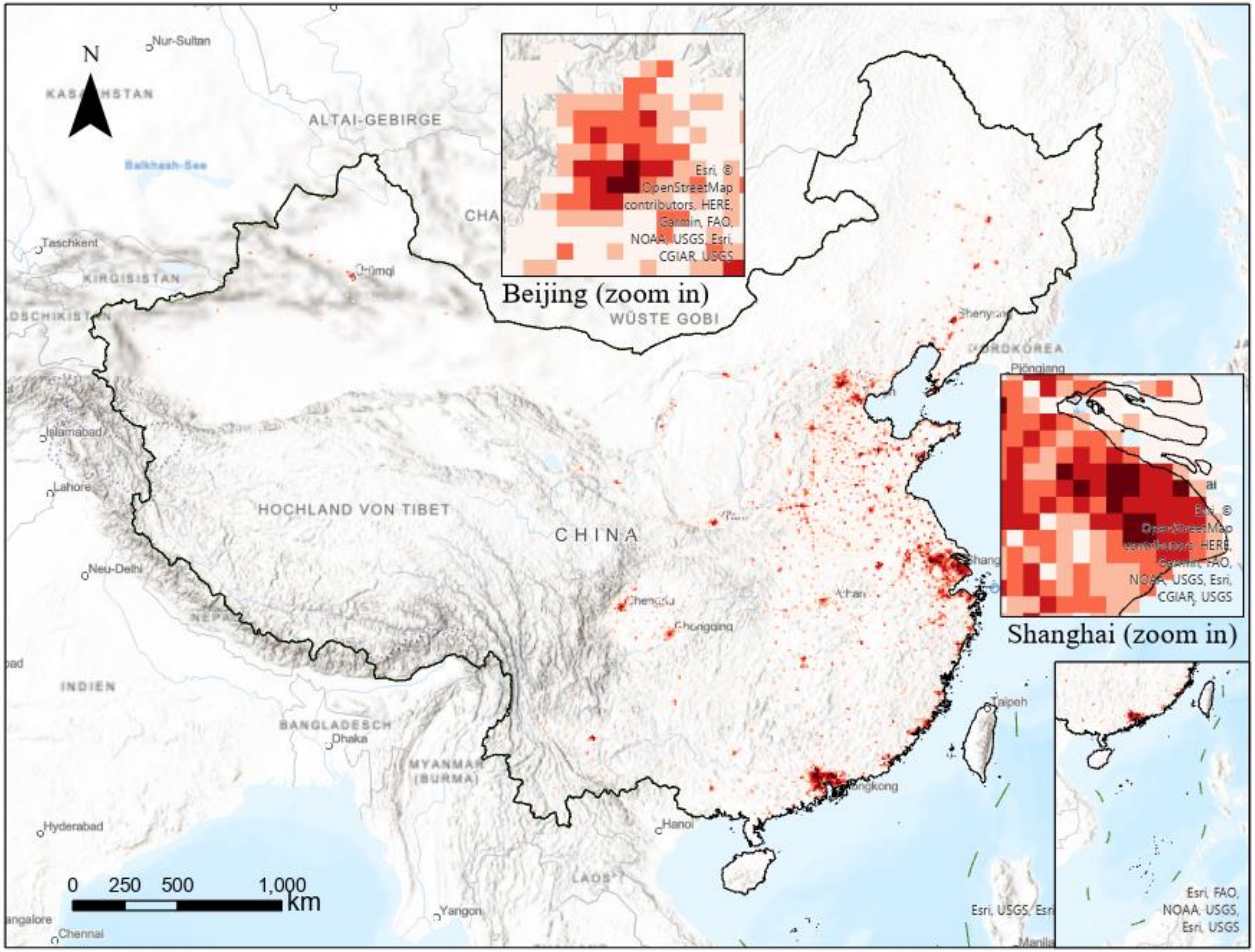

Figure S10 Spatial distribution of urban land use by the Manufacturing Industry in China in 2012.

Note: Only impervious urban land areas are accounted in this study.

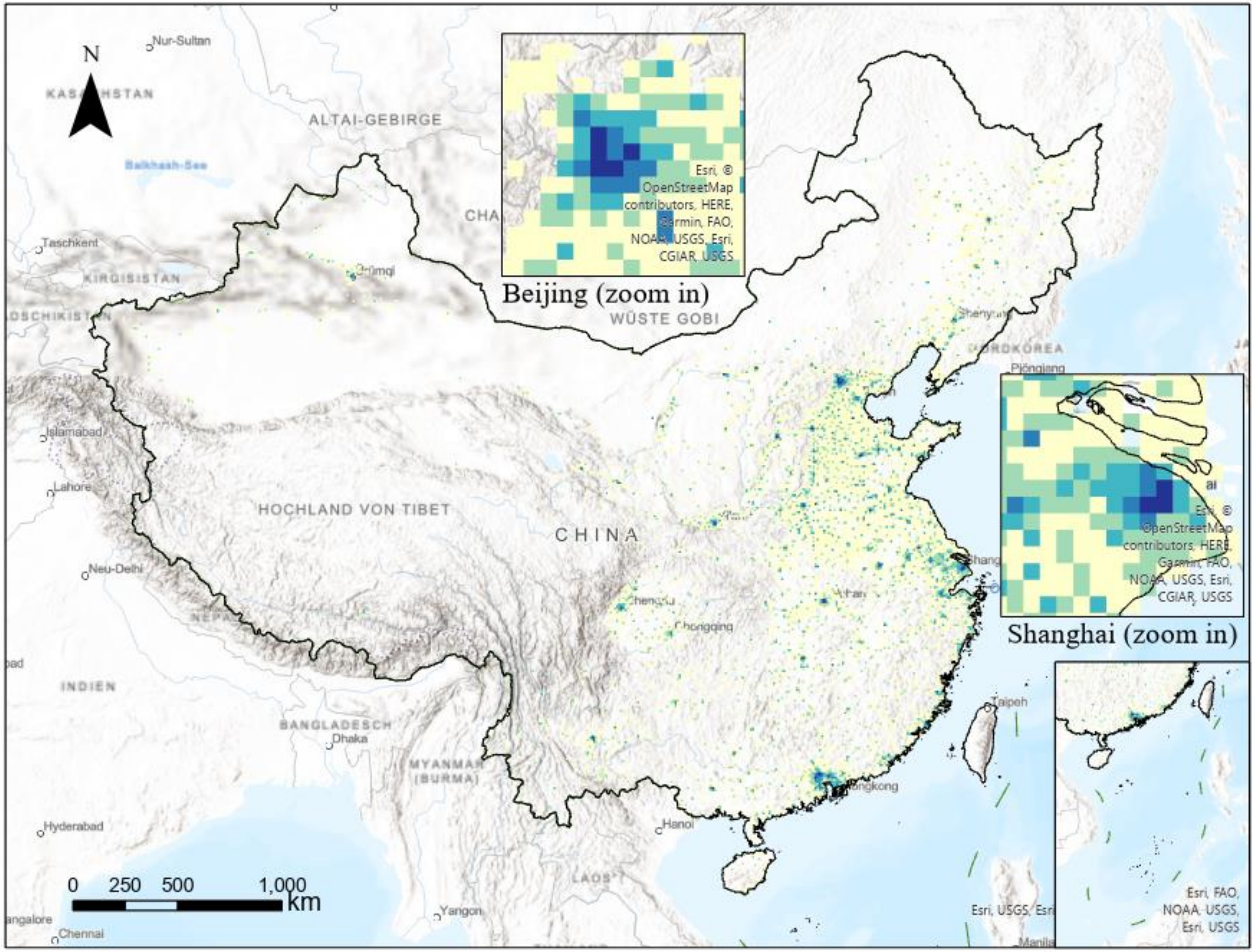

Figure S11 Spatial distribution of urban land use by the Tertiary Industry in China in 2012.

Note: Only impervious urban land areas are accounted in this study.

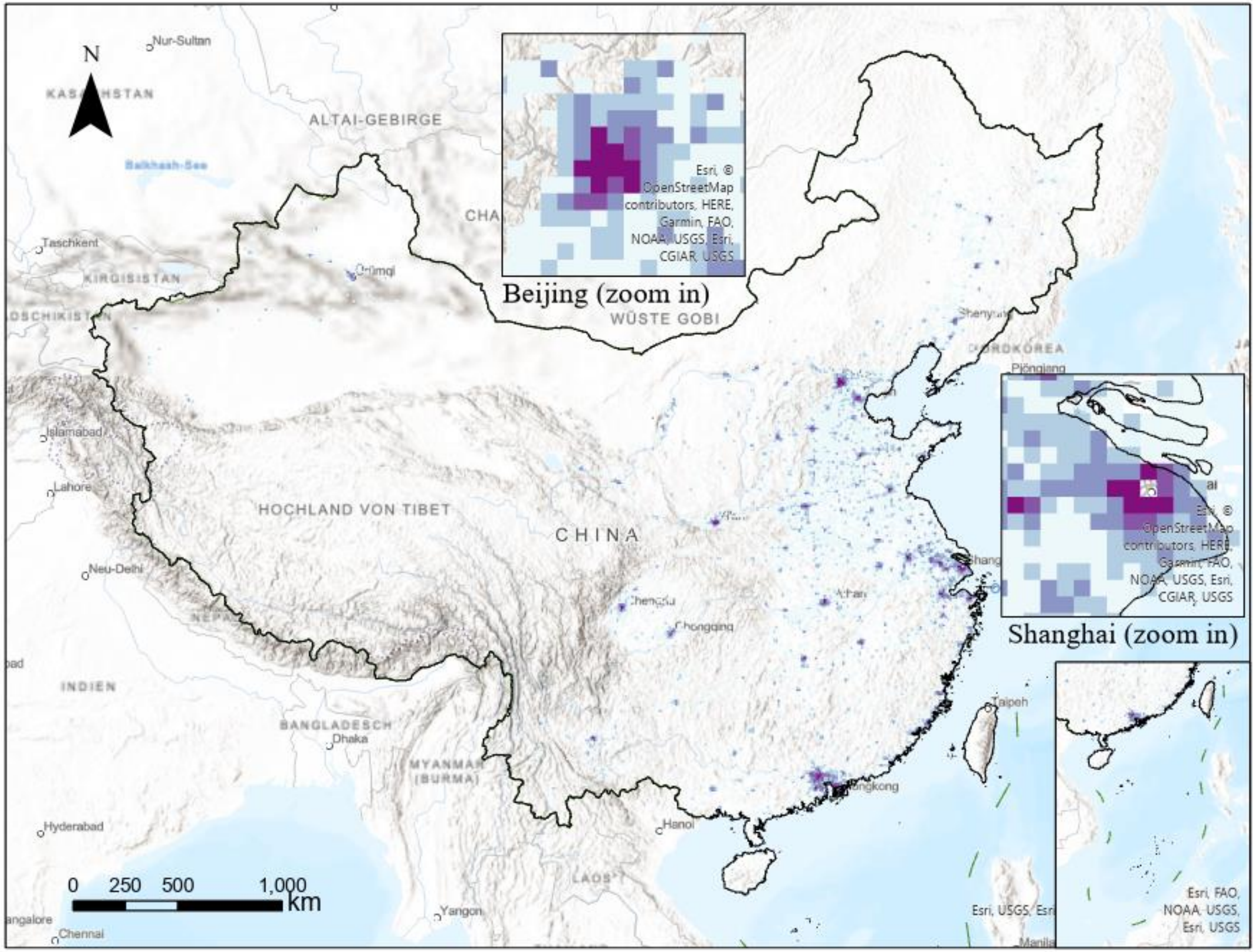

Figure S12 Spatial distribution of urban land use by the Transportation Industry in China in 2012.

Note: Only impervious urban land areas are accounted in this study.

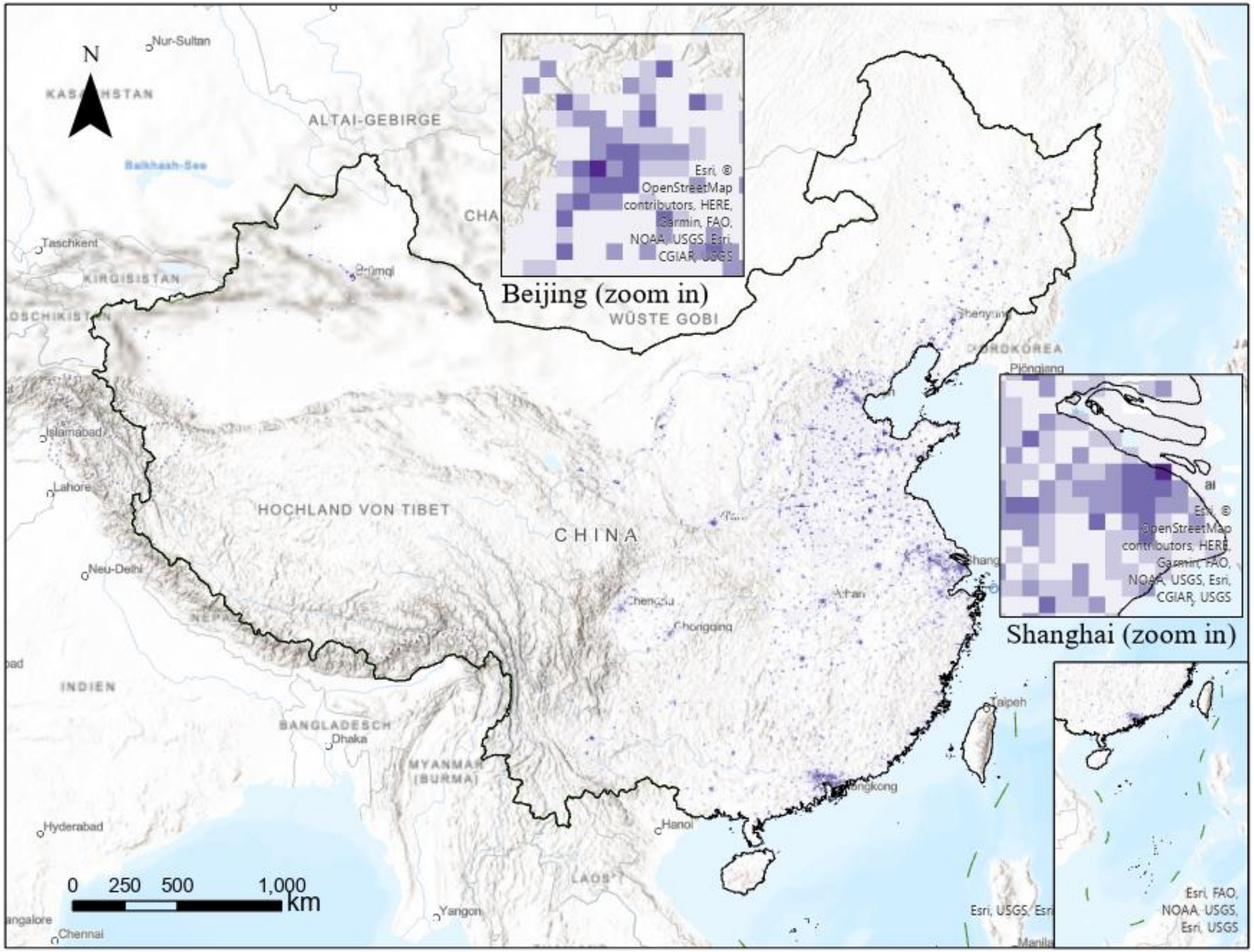

Figure S13 Spatial distribution of urban land use by the Utility Industry in China in 2012.

Note: Only impervious urban land areas are accounted in this study.

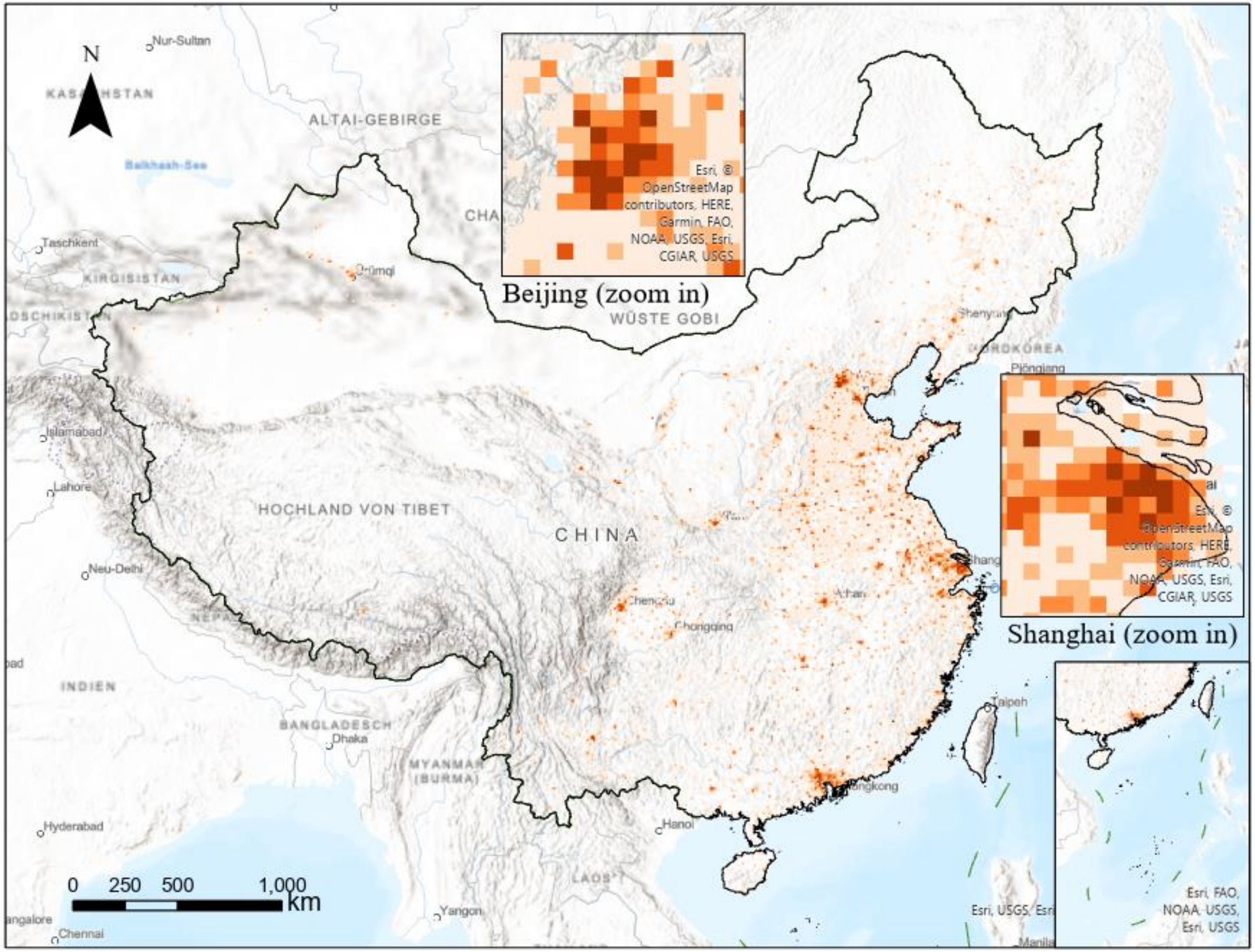

Figure S14 Spatial distribution of urban land use by the Construction Industry in China in 2012.

Note: Only impervious urban land areas are accounted in this study.

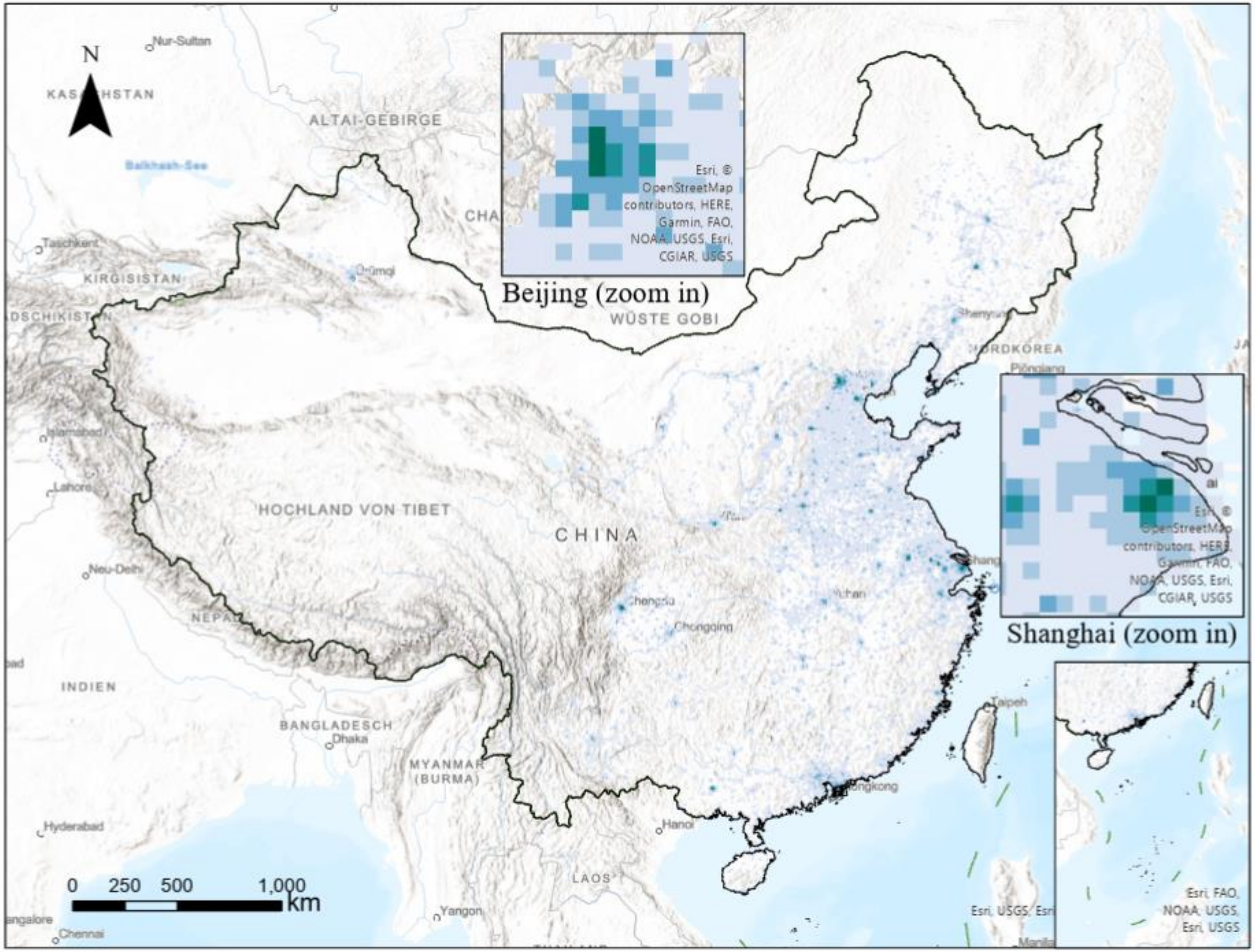

Figure S15 Spatial distribution of urban land use by residential in China in 2012.

Note: Only impervious urban land areas are accounted in this study.