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Highlights

Land amount meets demands of urbanization, food, and ecology

Spatial conflicts widely exist among land multidemands

Priorities of land demands affect urbanization pattern, crop yield, and ecology

The priority of food > ecology > urbanization gives the best outcome in China

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How to balance land demand conflicts to guarantee sustainable land development

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SUMMARY

Severe arable land loss and ecological problems raise attention to protect/develop land for food and ecology demand. Spatial conflict appears in front of multidemand for urbanization, food, and ecology. Our study took China as an example and explicitly outlined spatial preference of urbanization, food, and ecology. From the aspect of land amount, there are enough lands to support multidemand with a surplus of agriculture land of 45.5 $\times$ 10^6 ha. However, spatial conflict widely appears among the multidemands. We tested the impacts of different priorities on urban pattern, crop yield, and ecology and found the priority of food > ecology > urbanization gave the best outcome. Our results verified the importance of including priority of land multidemand to avoid confusion and increase efficiency in the implementation of land policies.

INTRODUCTION

Humanity entered the 21st century with 7.6 billion people, and the global population is expected to grow to 9.2 billion by 2050.[1,2] The growing population continues to fuel competition for already limited land resources to meet the demand for housing, food, and ecology.[3] Urbanization rate is projected to reach 70% by 2050, requiring 90–150 million ha more land for urban area. Food production is estimated to require 120 million ha more land to close the yield gap by 2050.[1] The post-2020 biodiversity framework, an important strategic plan for ecological conservation, calls for least 30% land and sea areas globally conserved. Increasing demands continue questioning whether the limited land resource is able to simultaneously support urbanization, food, and ecology. Spatial conflict under such multi-demand makes a need of assessing priority impacts on land sustainability.

China may act as a good example showing great efforts to achieve sustainable development against high pressure from growing population. China occupies the third largest area in the world and supports about 22% of the world's population with only 7% of the world's arable land.[4] Maintaining basic food self-sufficiency is always an important concern of the government. Over the past 3 centuries, the growing demand for food has led to the expansion of agricultural land and the decrease of forest area. However, the growth and globalization of China's economy in recent decades has led to a loss of over 2 million ha of arable land, most of which has been urbanized.[5–8] The expansion of agriculture and urban land has both resulted in high levels of ecological degradation. As a consequence, China faces major problems related to urban expansion by overpopulation, food security by arable land loss, and ecological degradation by urbanization or food security.[9]

The Chinese government started emphasizing the demand of food and ecology by adjusting its land use policies. In 2009, the government issued a policy of the highest level (call redline policy in China) to meet land resource demand from food, i.e., Redline of Arable Land Policy (RAL). RAL delineates a bottom line to maintain at least 120 million ha of arable land and strictly prohibits converting those lands to urban to ensure domestic food security. To meet the ecology demand, in 2002, the government issued the world's largest government-financed ecological restoration program, i.e., the Grain for Green policy, which increased forest cover by 4%, gaining around \$216 billion ecological benefit by 2010.[10] This ecological restoration program will continue and aim to increase the forest cover from 23.5% in 2015 to 25% in 2030. In 2014, another redline policy was published to conserve ecology: the Ecological Conservation Redline Policy (ECR). ECR promises to promote protected areas (PAs) over 2.4 million km^2 by 2030,[11] covering over 25% of the China mainland.

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These land use policies tend to balance multidemand of land resource but showed potential conflict and unexpected negative outcomes to sustainability. For instance, the Grain for Green policy reduced area of agriculture land[10]; the RAL policy shifted urban expansion pressure from agriculture to ecological land, leading to a loss of over 2000 ha of forest by urban encroachment.[5] Studies have been carried out to discuss sustainable development meeting a specific goal, such as arable land protection for food security and establishment of PAs for ecological conservation.[11–13] However, a question raises that when spatial conflict occurs between land multidemands, what is the suitable priority order to achieve land sustainable development.

Our study focused on conflicts between urbanization, food, and ecology. We calculated and mapped their land demand and identified the potentially spatial conflict. We then designed scenarios based on different priorities (Table 1), projected land uses in 2030 through a land use/cover change (LUCC) model, and assessed the impact on urban pattern, crop yield, and ecology. Accordingly, we suggested priority of land demand under conflicts. Our results are meant to support the improvement of policies aimed at sustainable land use in China, seeking to establish an integration between rapid urbanization, food security, and ecological improvement that could be replicated around the world.

RESULTS

Land conflicts between urbanization, food, and ecology

From the aspect of amount of demand, there is no conflict among urbanization, food, and ecology (Table 2). From 2015 to 2030, urbanization requires 12.9×10^6 ha, 8.3×10^6 ha of which is expected to be converted from agriculture land; reforestation needs 11.3×10^6 ha, and 6.2×10^6 ha is from agriculture. Based on agriculture land of 2015, when maintaining the 120×10^6 ha by RAL, there are lands of 60×10^6 ha possibly being transferred for other uses, which completely meets the land demand of 14.5×10^6 ha by urbanization and reforestation.

When we turned to the spatial aspect, land demand conflicts widely occur between urbanization, food, and ecology (Figure 1), especially for that between urbanization and food. Urbanization occurs mostly in the eastern region from 2015 to 2030, a politically and economically key region of China (Figure S1). Urbanization is most evident in the capital and economic zone of the Yangtze River Delta. This region is an economic powerhouse and has many millions of migrants from less-developed areas of China. Arable land in China is mainly distributed in northeastern, and eastern, parts surrounding several important economic zones (Figure S2). Around 52% of newly urban land from 2015 to 2030 have been and would be converted from arable land under no limitation (e.g., implementation of RAL), leading to arable land loss of 6.8×10^6 ha (Figure 1A).

Table 1. Summary of designed scenarios

Scenario no.	Priority	Explanation
S0	–	BAU (business as usual)
S1	URB > ECO > FOOD	No limits on urban expansion or reforestation
S2	URB > FOOD > ECO	No limits on urban expansion; reforestation is not allowed to encroach arable land
S3	ECO > URB > FOOD	Urban expansion is not allowed to encroach arable land. No limits on reforestation
S4	ECO > FOOD > URB	Urban expansion is not allowed to encroach arable land or ECR area. No limits on reforestation
S5	FOOD > URB > ECO	Urban expansion and reforestation are not allowed to encroach arable land
S6	FOOD > ECO > URB	Urban expansion is not allowed to encroach arable land or ECR area; reforestation is not allowed to encroach arable land

ECO, ecological conservation and restoration; ECR, Ecological Conservation Redline policy; FOOD, arable land protect; URB, urban expansion.

Table 2. Comparison of land demand and supply

Land transformation (10^6 ha)	Demand (10^6 ha) Total	Agriculture land	Available agriculture land (10^6 ha)	Surplus (+) or deficit (−) of agriculture land (10^6 ha)
Urban expansion	12.9	8.3	60	
Reforestation	11.3	6.2		
Sum	24.2	14.5	60	45.5

Following ECR's guidance, we mapped the expanded PAs by 2030 (Figure S3), namely the land demand for ecological conservation. Considering the existing PAs and the areas that could be potential conservation units, we verified that 36% of the Chinese territory could be protected, within the range of 25–36% estimated by previous studies.[11,14] The total to be protected, in association with existing PAs, would represent 44% of the carbon storage capacity in ecosystems, 61% of the soil conservation capacity, and 48% of the water retention. New PAs in association with existing PAs would also protect 70% of areas susceptible to water erosion and 68% of areas susceptible to desertification. Overlapped land of ECR and urbanization was 2.1×10^6 ha, making up 16.54% of newly expanded urban land (Figure 1B).

Reforestation would occur mostly in northeastern and southwestern parts of China (Figure S4). It showed low conflict to urbanization land demand with overlapping lands of 0.4×10^6 ha, accounting for 1.56% of newly expanded urban land (Figure 1C). Reforestation would take 6×10^6 ha of land from agriculture, of which 2.2×10^6 ha would be from arable land, accounting for 20.16% of reforestation land from 2015 to 2030 (Figure 1D).

Impacts of a different priority on urban pattern

Priority of urbanization, food, and ecology made two distinct urban landscapes (Figure 2). When we gave priority to urbanization, urban accumulation would be strengthened in eastern China (Figure 2A). This accumulation was particularly obvious along the railway and major road lines in Beijing-Tianjin-Hebei and Yangtze delta urban agglomerations. Changing priority to ecology, i.e., no urban expansion in ECR area, had little impacts on this accumulation (Figure 2B) because (1) overlapping area of urbanization and ECR only made up 16% of urbanization land and (2) ECR area was mostly distant away from the railway or road line. Implementation of ECR shifted urban area away with a median distance of 14.4 km and a maximum distance of 29.9 km, comparing to urban expansion under no limitation.

When giving priority to food over urbanization, i.e., implementation of RAL, urban accumulation was weakened along the railway and road lines (Figures 2C and 2D). This was because urban and traffic development preferred to locating surrounding arable land for the convenience of grain transportation. Strict protection of arable land obviously would change urban landscape in 2030, but will not shift newly expanded urban land to very distant area, indicating by a median distance of 28.8 km and maximum distance of 64.7 km, away from urban expansion under no limitation (Figure 2). When giving priority to food and ecology over urbanization, i.e., implementation of RAL and ECR, newly expanded urban land showed a median distance of 14.9 km and maximum distance of 33.6 km to that under no limitation.

Newly expanded urban land under different priorities showed similar distance to traffic networks (Figure 2). Under no limitation, newly expanded land is on average 19.6 km and 5.2 km away from the railways and main roads, respectively. Implementation of ECR shifted the newly expanded urban close to the traffic network by prohibiting built-up area expansion in PAs. Implementation of RAL or both RAL and ECR shifted the newly expanded urban land away by less than 2 km away from the railways and less than 0.5 km away from the main roads on average.

Impacts of different priority on food and ecology

Scenarios S4 – S6 showed better outcome in food and ecology than scenarios S1 – S3 (Figure 3). They (S4 – S6) increased crop yield by 6.82–7.97 billion tons, C stock by 15.12–15.16 PgC, and tree richness by 978–1086 species than the ''business as usual'' (BAU) scenario. Scenarios S4 – S6 have in common the priority of food over urbanization, while scenarios S1 – S3 are on the contrary. On the premise of

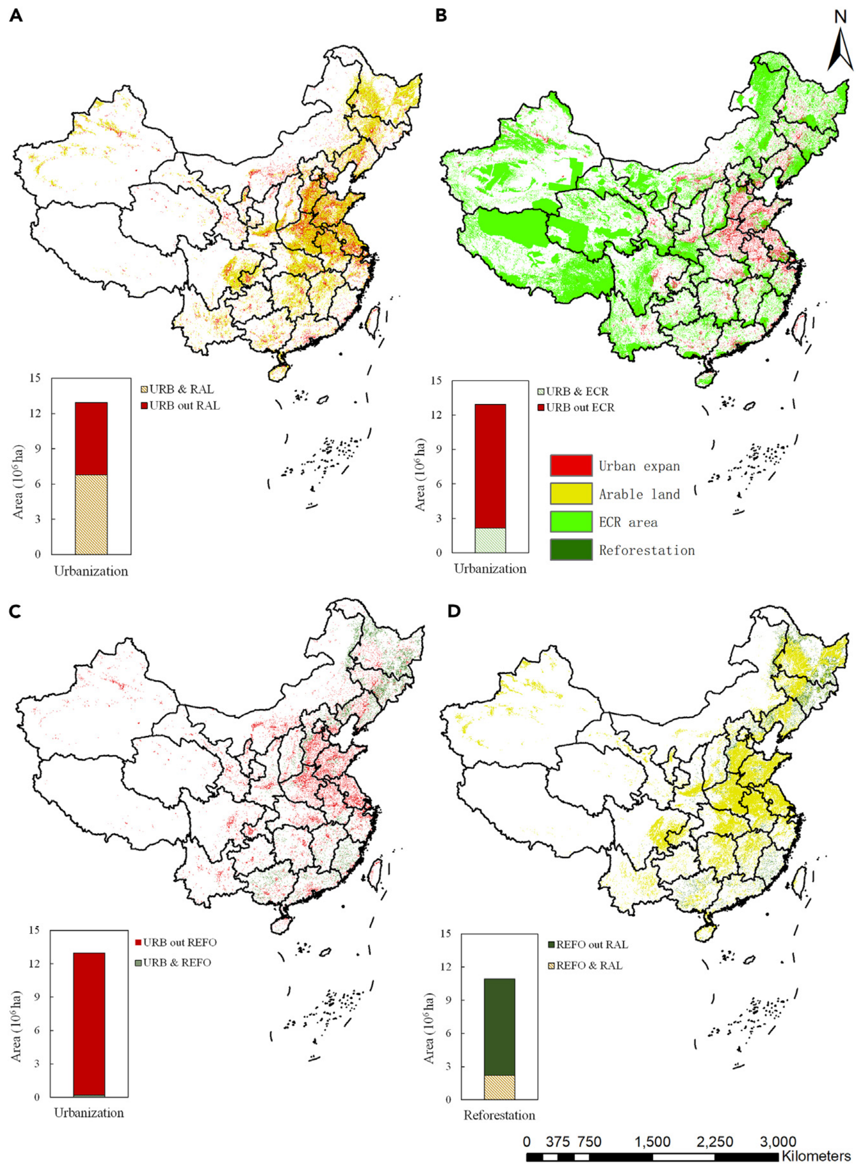

Figure 1. Spatial conflict between land multidemands

(A) Distribution of newly expanded urban land by 2030 and protected arable land.

(B) Distribution of newly expanded urban land by 2030 and protected areas identified by the Ecological Conservation Redline (ECR) policy.

(C) Distribution of newly expanded urban land and newly reforested land by 2030.

(D) Distribution of newly reforested land by 2030 and protected arable land. For maps of newly expanded urban land, arable land, ECR, and newly reforested land, refer to Figures S1–S4.

giving first priority to urbanization, ecology before food did not improve ecology. Compared with the scenario S1 (order: URB > ECO > FOOD), scenario S2 (order: URB > FOOD > ECO) saved around 0.08 billion in crop yield and showed 6.37-PgC higher C stock and 256 more tree richness. When ecology is prioritized over food, we allow arable land to be converted to forest, which is more fertile and has higher soil organic carbon (SOC) than agriculture land as it supports more crop yields. However, tree planting on organic soils increased soil respiration and decreased SOC, which canceled out the increment in C stocks in tree biomass and resulted in net C loss.[15–17] This also explained slight improvement in ecology under scenario S3 (order: ECO > URB > FOOD) although giving ecology the highest priority.

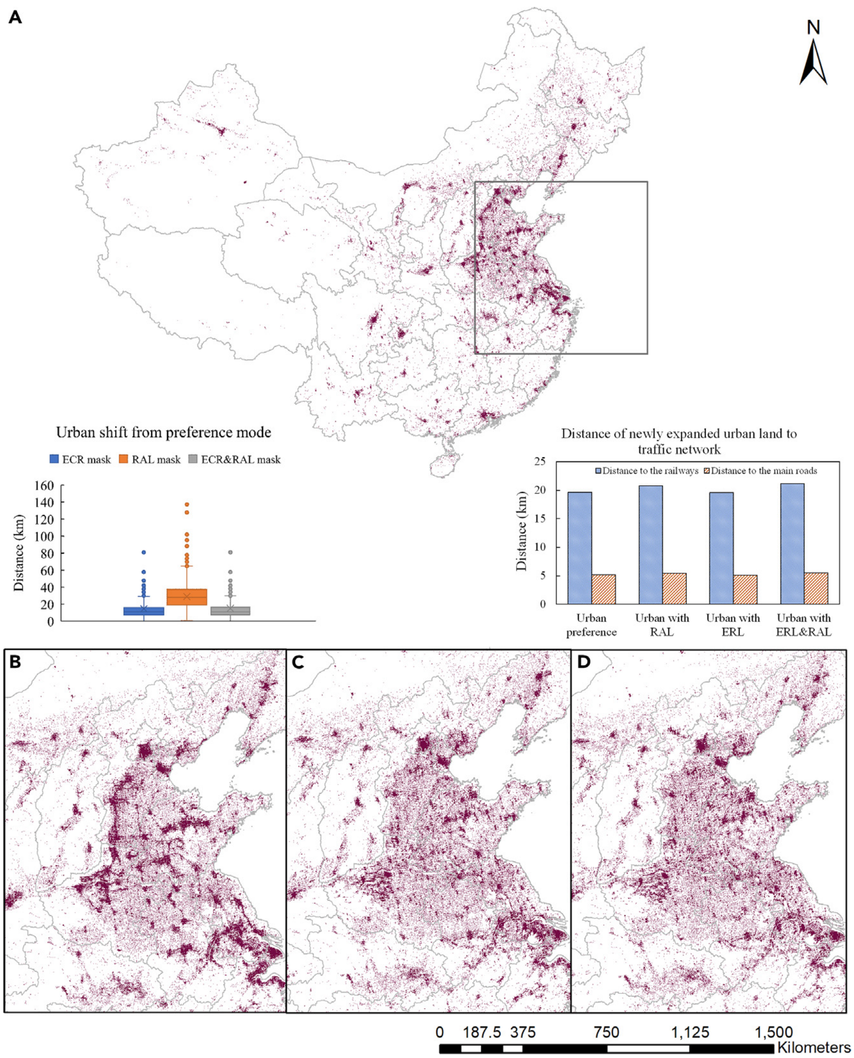

Figure 2. Urban landscape in 2030 under different expansion modes

(A) Under "urban preference" mode, referring to urbanization priority, which has no limits on urban expansion.

(B) Under "urban preference" refers to urbanization priority, which has no limits on urban expansion.

(C) Under "urban with ECR" refers to giving priority to ecology over urbanization, which does not allow urban expansion encroaching protected areas.

(D) Under "Urban with ECR&RAL" refers to giving priority to food and ecology over urbanization, which does not allow urban expansion encroaching arable land and protected areas.

Of all 6 scenarios, S6 with a priority of FOOD > ECO > URB had the best outcome on crop yield and ecology.

DISCUSSION

In response to crop yield loss, ecological and environmental degradation from rapid economic development, China stressed the importance in sustainable development and invested heavily, such as land resources, in arable land protection, ecological restoration, and conservation. These efforts proved to be a success in maintaining crop production and improving ecosystem services.[18] Sustainable land use becomes more challenge for the next decade, with population achieving the peak by 2030 in China. Our work provides new insight into dealing with spatial conflict of land multidemand. We calculated there would be enough land to support urbanization, food, and ecology (Table 2), but spatial conflict widely existed that

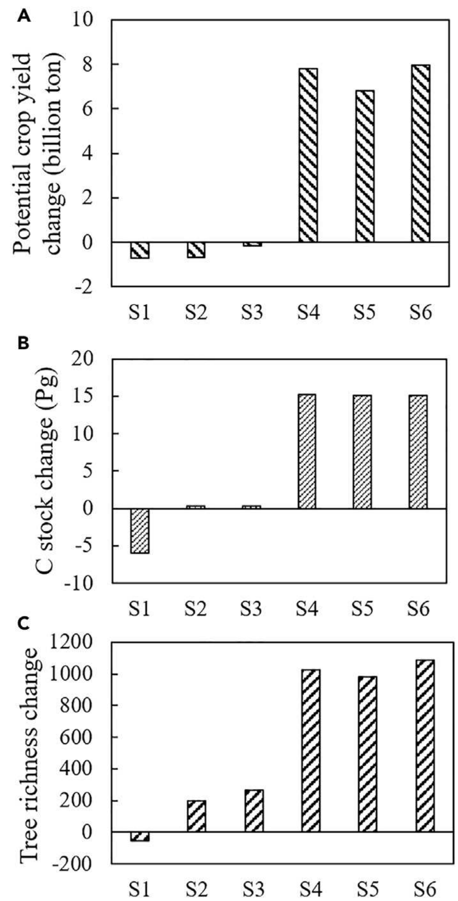

Figure 3. Impacts of different scenarios on crop yield, carbon stock and tree richness

(A) Changed crop yield compared to the BAU (business as usual) scenario in 2030.

(B) Changed carbon stock.

(C) Changed tree richness. Scenario S1 is of the order URB > ECO > FOOD; S2 is URB > FOOD > ECO; S3 is ECO > URB > FOOD; S4 is ECO > FOOD > URB; S5 is FOOD > URB > ECO; S6 is FOOD > ECO > URB. Detailed explanation of each scenario refers to the Table 1; changed carbon stock within protected areas refers to Figure S5.

over 50% urban and over 20% reforestation intended to encroach arable land (Figure 1). Different priorities highly influenced outcomes of land development.

Urbanization priority influences on food and ecology

Ongoing rapid urbanization was projected to reach 70% by 2050 in China. With such trend, urbanization has been considered a main driver of LUCC. These lands only covered 4.3% of the mainland of China but were a major contributor to the national land use change and a threat to food security.[6] The land surrounding cities often contains fertile soil and showed strong competing interests between urbanization and food. Historic LUCC in China gave priority to urbanization and threatened crop production. From 1980 to 2010, 57.61% of built-up land was converted from arable land, resulting in an arable land loss of 3.18×10^6 ha.[19] Food imports are a potential solution that could be used by China to meet its food requirements.[1] However, as China becomes dependent on food imports, it also becomes vulnerable to peaks in commodity prices, restrictive tariffs, among other problems that can affect its import capacity and consequently affect national food security.[20,21] Sustainable urban development mitigates crop yield loss, but the sustainable mode from the shared socioeconomic pathways still has 50–63% of newly expanded urban lands converted from croplands, leading to 1–4% reduction of global crop production.[7] Based on our modeling results, giving priority to urbanization led to crop yield losses of 0.65–0.76 billion tons compared with the BAU scenario (Figure 3).

In addition to crop yield loss, urbanization leads to ecological degradation. Urban land was not much converted from ecological land. But urbanization and the resultant arable land loss encroached forest and grassland. This indirect encroachment on ecological land from urbanization has been widely observed in urban agglomerations such as Beijing-Tianjin-Hebei region and Yangtze delta region.[19] Our results also showed that despite a small conflict between urbanization and ecology (Figure 1), urbanization priority still leads to 5.97 PgC of carbon stock loss by 2030 at most (Figure 3).

Food priority influences on urban pattern, crop yield, and ecology

Giving priority to food over urbanization is efficient in terminating crop yield loss by urban expansion (Figure 3). Such a shift in priority is not easy. In the early 1990s, the Chinese government issued the General Land use Plan to protect arable land and control the scale of built-up land, but this plan was proved inefficient to effectively stop the rapid loss of arable land by urbanization.[22–24] In 2009, RAL was published to strictly protect arable land from urban expansion but took 9 years to terminate arable land loss until 2018. Arable land still reduced by 7.5 million ha from 2010 to 2020 based on the second and third national land surveys.

Impedance of shifting priority to food lies in locating newly expanded urban lands to marginal land which may be distant and inconvenient for living. Our simulation results verified that changing priority between food and urbanization obviously affected urban pattern, breaking urban accumulation along the railway and road lines, but the cost is acceptable (Figure 2), indicated by similar distance of newly expanded urban land to traffic network under different expansion modes. Since 2008, the Chinese government proclaimed the ''4 trillion yuan stimulus packages'', 37.5% of which (i.e., 1.5 trillion yuan) was invested to improve infrastructure of railways and roads. A well-developed traffic network helps to decrease the cost of shifted urban land by RAL and makes it feasible to prioritize food over urbanization. Urban pattern under food priority fits the expectation of sustainable urban development by the government, which stressed the decentration and the importance of multicenter instead of mega-city expansion. For instance, Beijing has become the first mega city proposing to maintain development while reducing its scale by developing the subcenter in the next 5 years. Highly saved crop yield loss, acceptable cost, and decentralized urban pattern all support to give priority to food over urbanization.

Ecology priority influences on food and ecology

Land demand of ecology includes conservation and restoration. PA establishment has long been the dominant tool of ecological conservation to tackle the global ecological crisis, and especially to conserve biodiversity.[25–27] By 2018, 11800 PAs have been established in China, covering over 18% of the country's territory.[28] This ratio would be increased to 25–36% of the mainland claimed by the issued ECR policy. Reforestation is a typical tool of ecological restoration. The reforestation project in China has increased forest cover to 19% of national mainland in 2010[29] and plans to increase forest cover to 25% in 2030. PAs establishment and reforestation projects indicate China's attention on ecology.

Overlapping area of urbanization and ecology makes up 16% (PAs of ECR) and less than 2% (reforested land) of newly expanded urban land. Although urbanization causes severe ecological degradation, urban expansion does not directly take much land from ecological lands,[5] which explains low conflict between urbanization and ecology. This low competition contributes to the success of ecological policies. Based on the satellite data (2000–2017), China contributed to 25% of the global net increase in leaf area with only less than 7% of global vegetated area.[29] The national ecological conservation and restoration policies have shown ecological improvement of most ecosystem services increasing from 2000 to 2010, such as soil retention, flood mitigation, and water retention.[29] Within these 10 years (2000–2010), China experienced fast economic development, as well as increased ecosystem services, proving that improving ecosystem services and economic growth can co-exist.[18] Our results verified that low conflict between urbanization and ecology continues to next decade from 2015 to 2030 (Figure 1). Giving priority to ecology over urbanization did not change the urban pattern as much as giving priority to food. Still ECR implementation saved around 15 TgC of carbon stock from urbanization within the identified area of ECR from 2015 to 2030 (Figure S5).

The conflict between ecology and food has been widely recognized. Agricultural products loss is often regarded as the cost of PA establishment.[30,31] ECR expands PAs and promises not to disturb farming activities.[11] Therefore, we analyzed the conflict between arable land and reforestation, instead of PAs expansion (Figure 1). Over 50% of reforestation from 1999 to 2019 occurred in agricultural land, converting over 34 million ha agriculture to natural vegetation. However, the crop yield increased from 508.39 million tons to 663.84 million tons in the same period.[10] On one hand, improvement of agriculture techniques, such as mechanization and fertilization, increased the unit crop yield. On the other hand, reforestation targeted at agricultural land with low productivity and high ecological frangibility, such as land in steep slope (>25°), therefore gained ecological benefit with small crop yield loss. Our study distinguished arable land from agricultural land. Conflict decreased therefore from 5.8×10^6 ha of agricultural land to 2.2×10^6 ha of arable land, which led to a crop yield loss of 1.15 billion tons. Our results showed that attention was still required on reforestation encroaching arable land. Protection of these arable lands (i.e., giving priority to food over ecology) not only saved crop yield loss but also benefited ecology (Figure 3).

Importance of explicit spatial information and priority to achieve sustainable land development

To achieve sustainable development, land strategies are proposed and sometimes suggest land quantity for the specific demand. Spatial allocation is however mostly missed. For instance, Aichi target 11 requires to protect 17% of each global ecoregion. This ratio is promoted to 30% by COP15, while missing explicit spatial suggestions makes PAs expansion inefficient in conservation. Global PAs established by 2014 were proved to fail targeting places with high concentrations of threatened vertebrate species.[30] Chauvenet et al. (2020) proved that different PA acquisition strategies had distinct results in realizing COP15 goal and proposed to include explicit ecoregional representation within the new post-2020 PA target.[31]

China experiences inefficiency and confusion of land policies implementation because of the lack of spatial information. By the end of 2014, PAs spanned 15% of China's mainland but poorly covered areas of high ecosystem services or biodiversity.[32] RAL delineates the bottom line of 120 million ha arable land. Without mapping the arable land, RAL is implemented as strict protection of agricultural land, which becomes a main impedance of RAL implementation. It also led to a negative impact on ecology as the pressure of urban expansion was transferred from agriculture to ecological land. Moreover, the spatial ambiguity of land use also causes unnecessary land conversion. Since World Food Program gave warning of global food crisis in 2021, some forests that had been converted from cropland were observed to return to farmland in China. Previous studies verified the importance of spatial allocation in achieving a specific land-development goal.[13,31,33] Land policies start incorporating explicit information such as ECR in China, explaining the way to identify PAs.[34] Our study took China as an example and affirmed enough land resources to realize demand of urbanization, food, and ecology. Priority should be determined to solve spatial conflict between different demands to achieve land sustainable development. Accordingly, spatial information not only helps to realize a specific land policy but is essential to properly allocate varied demand. Although spatial contradiction widely exists between multiple demands of economic development, food security, and ecological conservation, land area is still the first guarantee of a specific land policy. For instance, the post-2020 biodiversity framework promoted conservation area from 17% to 30% while the explicit spatial allocation was assigned to individual country. Despite scientific discussions on land use planning based on resource competitions, land use policies, especially for national level, still emphasize meeting the land area demand of the specific aspect. This would cause confusion that land area is sufficient to support multidemands while spatial allocation can hardly meet the demand. We took China as a case study and mapped preferred spatial allocation of urbanization, food security, and ecological restoration and conservation. Our results clearly showed the spatial conflicts between land multidemands. Although some local studies on land use planning tried to test scenarios of resources competition,[35,36] the equally important land policies are vague in their priority. Our study indicated the necessity to include explicit spatial information in land policies in addition to area requirement. Still further studies are required to test our proposition in other regions.

Conclusion

Despite a well-studied strategy to realize sustainable land development from a specific aspect, such as arable land protection for food security, PA establishment for ecological conservation, and reforestation for ecological restoration, spatial conflict from land multidemands as well as the priority impact is still not clear. Our study identified spatial conflict between urbanization, food, and ecology and tested the impacts of different priorities on urban pattern, crop yield, and ecology. The results provide suggestions for their priority on potentially conflicted spots, taking China's domestic effort as an example. We stress the importance of including explicit spatial information of land development and affirm the feasibility of balancing urban sprawl, arable land protection, and ecological conservation/restoration. These issues are relevant not only to China but also to the sustainable development of the world. A greater understanding of potential land use changes will help protect high-quality arable land, provide scientific guidance for sustainable urban development, long-term planning of ecological conservation, and ensure a domestic food supply.

Limitations of study

Our study assumed a well-developed forest system when calculating ecological benefits of reforested land, which was not realistic for a 15-year simulation. Indeed, it is proved that reforestation may hardly achieve equal ecological level compared with natural forest.[37] The ecological level of reforested land depends on environment (e.g., soil fertility, moisture, temperature, precipitation) and managements. As our study aimed to test the impact of land policies priority, we assumed a forest-based system once lands were reforested, regardless of establishing time and other possible influences. Further studies are necessary to discuss how reforestation may affect the efficiency of ecological policies.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2023.106641.

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AUTHOR CONTRIBUTIONS

H.L., Y.J.Y., and B.S.S.-F. designed the research; H.L., and A.T.L.-F. performed research; H.L. and Y.J.Y. collaboratively analyzed the data; H.L., Y.J.Y., B.S.S.-F., and A.T.L.-F. wrote the article. S.Z. and J.D. contributed to data. All authors commented on the final manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Land use data	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences	https://www.resdc.cn/DOI/
Digital Elevation Map	ASTER (Global Digital Elevation Model	https://wist.echo.nasa.gov/~wist/api/imswelcome/
Precipitation	China Meteorological Administration	http://data.cma.cn/
Air temperature	China Meteorological Administration	http://data.cma.cn/
Software and algorithms		
DINAMICA EGO	Soares-Filho et al.[38]	https://www.dinamicaego.com/

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources and data should be directed to and will be fulfilled by the lead contact: Yujun Yi (yiyujun@bnu.edu.cn).

Materials availability

This study did not generate new unique reagents.

Data and code availability

- This paper analyzes existing, publicly available data. These accession numbers for the datasets are listed in the key resources table.
- This paper does not report original code.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

METHOD DETAILS

Data description

Data used includes land-use data for LUCC analysis, geographical, plant, soil and climate data for ES calculation. Detailed explanations were as following:

Land-use dataset was acquired from Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC). This data set was based on LandsatTM imagery between 1980 1990, 2000 and 2010, Landsat 8 imagery of 2015. The RESDC was built up by visual interpretation of images, and released maps at a spatial resolution of 30 m.

Geographical data referred to digital elevation map (DEM) at 90 m resolution from ASTER (Global Digital Elevation Model).

Plant data referred to 1:1 million Chinese vegetation map and crop potential yield map. The vegetation map is with 50 different vegetation species at 1 km resolution; the potential crop yield map is at 1 km resolution. Both maps were obtained from Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences.

Soil data used in this study included 1:1 million Chinese soil type map, soil organic carbon (SOC), soil texture, fraction of volumetric field capacity, permanent wilting, $CaCO_3$ content and root restricting layer depth. Among them, SOC, soil texture and fraction of volumetric field capacity and permanent wilting were obtained from Soil Data Centre, which was digitalized to 1 km resolution based on the Second National Soil Survey of 3758 soil profiles and the 1:1 million soil type map of China; $CaCO_3$ content was from Harmonized World Soil Database at 1 km resolution; root restricting layer depth was from SoilGrid system at 250 m resolution.[39]

Climate data included daily precipitation, daily air temperature, daily snow depth, daily wind speed and daily potential evapotranspiration. Gridded daily precipitation and air temperature with 0.5°*0.5° resolution, from China Meteorological Administration. The raw data were observed from 2400 stations over China and have been passed though strict quality controls, including identification of outliers, assessment of spatiotemporal consistency, and correction of suspect and erroneous data. The station observations were transformed to 0.5°*0.5° grid-based data by the ANUSPLIN software developed by Australian National University with thin plate smooth spline method, which is an interpolation scheme adopting three variables (longitude, latitude, altitude), the square pretreatment and three times spline. In addition, the digital altimetric data was introduced in order to weaken the effects of elevation on interpolation precision under the condition of Chinese special landscape. Daily snow depth were from Environmental and Ecological Science Data Center for West China, at 1 km resolution; wind speed and potential evapotranspiration were from ECMWF's Integrated Forecast System, at 1 km resolution.

LUCC model description

We simulated LUCC with Dinamica EGO, an environmental modeling platform incorporating spatial analysis functions and developing spatial models. It was a cellular automated model that can simulate spatial variations in landscape dynamics and first used to simulate colonization at frontiers in the Amazon. Now this platform has been successfully applied on deforestation, urban expansion, infrastructure planning worldwide. Dinamica EGO was used for two steps: 1) mapping urbanization, reforestation, RAL and ECR; 2) simulating LUCC under different scenario settings.

We chose Dinamica EGO because it allowed to simulate LUCC per province and combine as a national map. As economic level differs from each province, simulating LUCC based on provincial level is more suitable and accurate than national level. In addition, ECR policy is a national policy but implemented on provincial level, which asks to identify protection area for each province. When simulating LUCC under different priorities/scenarios, we did not intend to outcome the ideal balance between different land demand competition but focused on discussing impact of priorities on urban pattern, food production and ecology. Though advanced land competition has been considered in LUCC model such as CLUMondo and CoMoLa, driving these advanced models require input such as transfer resistance parameters, land service.[40] Such spatial explicit information is hardly achievable. Land use policies also mostly emphasize land area demand instead of using complicate tool to balance the competition. Considering the land transfer resistance is subjective, our study made a simple assumption that each demand tended to occupy self-best land and chose Dinamica EGO to test impacts of priorities of different land policies.

The methodology used for LUCC simulation consists of eight steps: (I) calculate the transition matrices, (II) calculate the intervals for categorization of continuous variables, (III) calculate the coefficients of the evidence weights, (IV) analysis of the correlation of maps, (V) adjustment and execution of the model for the simulation of the LUCC, (VI) simulation validation, (VII) simulation and calibration run, and (VIII) projection of the final future scenario.

Initially, transition matrices and continuous variable ranges are calculated where the model suggests the classes that consider how representative each variable is in the area of study. With this result, can perform the next step where the coefficients of the evidence weights are calculated for the determinants applying the cellular automata theory. The spatial probability for each land use change is then obtained by summing up the WoE of each spatial determinant. We use dynamic determinants of land use change, such as distance to a specific land use type. For each time-step the dynamic distances are updated, the WoE is calculated and the spatial probability updated.

The next step is to analyze the correlation between thematic maps with a multi-criteria analysis that is formulated to predict future scenarios by comparing the initial year with the final year. All determinants must be spatially independent. In order to redefine the evidence weights, a set of correlation tests measuring Cramer's coefficients, contingency coefficient, and joint information uncertainty are applied for the detection of correlated variables. The fifth step is the adjustment and execution of the model for the simulation of the LUCC, where the Dinamica EGO is used from the transition matrix calculated in the first step to calculate the gross rates for the amounts of cells changed in the model. The calibration of the model was made by adjusting the following parameters: the proportion of the change demand that is allocated by the Expander rule and transferred to the Patcher rule, mean and standard deviation of the patch area and the neighborhood search window.

LUCC model construction and validation

The historical data on land use were obtained from the Environmental Sciences and Resources Data Center (RESDC) of the Chinese Academy of Sciences. These data are based on LandsatTM and Landsat 8 images. We used the period from 1980 to 2000 for calibration and 2000 to 2015 for validation. The land use maps were sampled for 250 m and include six land use classes: agriculture, forest, grassland, waterbodies, urban and unused Land (saline-alkalized land, beaches, sand lands, quagmire and bare rocks). We have modeled the seven major land use transitions identified in the period from 1980 to 2015: The transition from agriculture, pasture or forest to urban areas (Urbanization), the transition from forest and pasture to arable land and the transition from pasture and arable land to forest (Reforestation).

The transition probabilities are calculated based on spatial determinants obtained from the selection of multidisciplinary sources. We use 10 spatial determinants expressed as proximity: proximity to arable land, forests, grasslands, urban areas, large rivers, megacities (cities with a metropolitan area with a total population of more than 10 million people), existing PAs and railroads, and 5 biophysical variables (soil type, vegetation type, elevation, precipitation and average temperature).

The selection of the best LUCC model was made by means of the fuzzy similarity comparison test. The technique verifies the agreement between the observed and the simulated land use/cover datasets by obtaining the number of coincident cells within increasing window sizes of a neighborhood by means of a fuzzy neighborhood vector. Fuzzy similarity is a multi-resolution validation technique that derives the overall similarity using two types of membership: no fuzziness and fuzziness of location, within a neighborhood value.[41] We compared the minimum similarities between simulated and observed maps to the similarity of a random map with same number of changes and probability for all cells =0.5 (Neutral model).[38] The model performance was assessed based on the minimum fuzzy similarity measurement applied from a pixel-by-pixel to an 1×1 to 21x21 neighborhood window.

The minimum similarity fuzzy index obtained for the best model is ≈30% at a spatial resolution of 1.25 km^2, while the maximum similarity fuzzy index is ≈70% (Figure S6). These results indicate that 30% of the change pixels coincide in both land use maps in a cell-by-cell overlay. For the resolution and number of transitions being modelled, the obtained values for the minimum similarity fuzzy index suggest that the model are good and can be used in the simulation of land use change scenarios.[42,43] The similarity of the 2015 simulation was better than in the 2015 null model (A gain of 200% referring to relative increase in fitness in relation to its equivalent neutral model), indicating that the variables used represent an information gain compared with random distribution (Figure S6).

Land demand and conflict analysis for urbanization, food and ecology

We defined land demand of urbanization as newly expanded urban from 2015 to 2030; land demand of food as arable land under protection, referring to RAL, the highest-level policy in China to ensure food security; land demand for ecology as land for ecological conservation and for restoration. The former referred to land demand by PAs establishment, referring to ERL policy, which promised to assign over 25% Chinese mainland ecological conservation. The latter referred to reforestation program, which would increase the forest cover from 23.85% in 2015 to 25% in 2030.

Land demand of urbanization was calculated based on the predicted urbanization rate in 2030. We assumed a stable population density in urban from 2015 to 2030. Then urban land was calculated as following:

$$Land_{urb-2030} = \frac{Population_{2030} \cdot UrbRate_{2030}}{Population_{2015} \cdot UrbRate_{2015}} \cdot Land_{urb-2015} \qquad \text{(Equation 1)}$$

which, $Land_{urb-2030}$ and $Land_{urb-2015}$ is urban area in 2030 and 2015, respectively; $Population_{2030}$ and $Population_{2015}$ is population in 2030 and 2015, respectively; $UrbRate_{2030}$ and $UrbRate_{2015}$ is urban population in 2030 and 2015, respectively. $Population_{2030}$ and $UrbRate_{2030}$ were taken from Sun's study, which estimated urbanization rate and population in 2030 for each province in China. Spatial allocation of the increased urban land was mapped through the LUCC model (see "mapping urbanization and reforestation" for details).

Land demand of food security was 120×10^6 ha based on the RAL policy. The spatial allocation was mapped by identify agriculture land of high crop yield (see "mapping RAL and ECR" for details). Land demand of ECR was mapped by identifying area with high ecosystem services or high frangibility or high biodiversity (see "mapping RAL and ECR" for details). Land demand of reforestation was calculated based the increased forest cover rate. The spatial allocation of reforestation by 2030 was mapped through the LUCC model (see "mapping urbanization and reforestation" for details).

Mapping urbanization and reforestation

Urbanization and reforestation in 2030 were mapped using the LUCC model, respectively. Conversions from agriculture, forest and grassland to urban were included in the land transition matric to identify spatial preference for urbanization. Similarly, conversions from agriculture and grassland to forest were considered in the matric when mapping reforestation. Urbanization was modelled for each province considering the different urbanization rate at provincial level; while reforestation was modelled at the national level. Land demand of urban expansion was calculated from Equation 1 and assigned to agriculture, forest and grassland based on the ratio from 2000 to 2015 to obtain land transition matrices. Allocation of urban expansion was determined by the probability map, which was generated based on the weights of spatial determinants for certain land transition (see "LUCC model description" and "LUCC model construction and validation" for details). Land demand of reforestation was calculated based on the increased rate of 1.15% forest cover from 2015 to 2030. Land transition matric of reforestation included transition from agriculture to forest and grassland to forest, and was obtained in the same way of calculating urban expansion matric.

Mapping RAL and ECR

RAL and ECR were mapped by identifying land of high target value. RAL aims to protect arable land of 120×10^6 ha, while agriculture identified from the aerial image accounts for 180×10^6 ha, indicating a potential of 60×10^6 ha agriculture land for conversion to urban or ecological land. As there is no spatial information for the arable land, we assumed that the RAL should target at agriculture of high crop yield and mapped the land of 120×10^6 ha by top-ranking of crop yield, which was based on the crop yield map by Xu et al., 2017.

ECR was mapped following the guidance released by CMEP, which targeted lands that provide essential ecosystem services, ecologically fragile ecosystems and biodiversity *hotspots*. Ecosystem carbon storage capacity, soil conservation capacity, and water storage capacity of vegetation were selected as indictors for ecosystem services; the susceptibilities to water erosion and desertification were selected for ecologically fragile ecosystems; tree species richness was selected for biodiversity. The above 6 indicators were used to identify areas that should be protected using the "*top-ranking method*" according to the ECR guidelines.[11,34] ECR mapping was processed at provincial level and came to a national map in combination with current existing protected area in 2015. The proportion of ECR land proposed by each province was listed in Table S1.

Scenarios design

In addition to the business as usual (BAU) scenario (S0), we designed another 6 scenarios representing different priority of urbanization, food and ecology (Table 1). Priority was linked to the specific land policy. The S0 scenario used annual land transition rate observed over a 15-year period (2000 and 2015), applied as the annual rate of change for the simulation period. The S1 scenario simulated a priority of urbanization > ecology > food, under which urban or forest expansion occurred under no limitation. The S2 scenario simulated a priority of urbanization > food > ecology, under which urban expanded under no limitation but reforestation could not encroach arable land by RAL. The S3 scenario referred to a priority of ecology > urbanization > food, under which urban expansion was not allowed to encroach PAs of ECR. The S4 scenario referred to ecology > food > urbanization, under which urban expansion was not allowed to encroach area of ECR or RAL. The S5 scenario was for the priority of food > urbanization > ecology. Urban or forest expansion was therefore not allowed to encroach arable land by RAL. The last scenario S6 was set for the priority of food > ecology > urbanization. Urban expansion was not allowed to occur in the area of RAL or ERL, and reforestation was not allowed to take land from RAL. Scenarios were analyzed based on mask and overlay assessment. For instance, in S1 with the priority of urbanization > ecology > food, urbanization map was firstly determined by no limits on urban expansion. Since reforestation occurred only on agricultural land, then the urbanization map was used as the initial map for reforestation simulation. Instead, in S3 with the priority of ecology > urbanization > food, the reforestation was firstly determined by no limits. Then reforestation and ECR maps were used as a mask map, which allowed no urban expansion, to simulate urban expansion.

Impacts analysis of different scenarios

We analyzed impacts of different scenarios on urbanization, food and ecology. When urbanization was not assigned as priority (i.e. S3 – S6 scenarios), RAL or ECR implementation would shift urban away from its preferred allocation. We therefore took urbanization with no limit (i.e. S1 and S2) as the reference, and compared it to urban pattern under RAL limitation (i.e. S5), ECR limitation (i.e. S3), RAL and ECR limitation (i.e. S4 and S6). The distance of shifted urban land to its preferred allocation was calculated to indicate if the cost was acceptable. Impact on food was evaluated by calculating crop yield change of scenarios compared to BAU. Two ecological indicators were selected to calculate impact on ecology compared to BAU: carbon (C) stock and tree richness.