

Global Ecology and Conservation

journal homepage: www.elsevier.com/locate/gecco



Future global conflict risk hotspots between biodiversity conservation and food security: 10 countries and 7 **Biodiversity Hotspots**

Jianqiao Zhao^{a,b,1}, Yue Cao^{c,d,1}, Le Yu^{a,b,*}, Xiaoping Liu^{e,f}, Rui Yang^{c,d}, Peng Gong^{b,g}

^a Department of Earth System Science, Ministry of Education Key Laboratory for Earth System Modeling, Institute for Global Change Studies, Tsinghua University, Beijing 100084, China

^b Ministry of Education Ecological Field Station for East Asian Migratory Birds, Beijing 100084, China

^c Institute for National Parks, Tsinghua University, Beijing 100084, China

^d Department of Landscape Architecture, School of Architecture, Tsinghua University, Beijing 100084, China

e Guangdong Key Laboratory for Urbanization and Geo-simulation, School of Geography and Planning, Sun Yat-sen University, Guangzhou 510275, China

^f Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai), Zhuhai 519082, China

^g Department of Geography and Department of Earth Sciences, University of Hong Kong, Hong Kong 999077, China

ARTICLE INFO

Keywords: Biodiversity conservation Food security Sustainable development Protected areas Land use and land cover change

ABSTRACT

Balancing biodiversity conservation and food security is the key to global sustainable development. However, we know little about the future global conflict risk hotspots between biodiversity and food security at both country and Biodiversity Hotspots (BHs) levels. First we calculated land use intensity index (LUII) based on future land use simulation, incorporated data on species richness(including birds, mammals and amphibians) and introduced the Global Food Security Index (GFSI). Then we used local indicators of spatial association (LISA) and bivariate choropleth map to identify the future global conflict risk hotspots between biodiversity conservation and food security. These include 10 countries (including Congo (Kinshasa), Sierra Leone, Malawi, Togo, Zambia, Angola, Guinea, Nigeria, Laos, Cambodia) and 7 BHs (Eastern Afromontane, Guinean Forests of West Africa, Horn of Africa, Indo-Burma, Mediterranean Basin, Maputaland-Pondoland-Albany and Tropical Andes). Special attention needs to be paid to these hotspots to balance biodiversity conservation and food security.

1. Introduction

The United Nations Sustainable Development Goal 2 aims to end hunger and achieve food security (Godfray et al., 2010). Faced with rapidly growing crop demand, expansion and intensification of agricultural land has become a prevailing phenomenon (Foley et al., 2005), since technical limitations (Tester and Langridge, 2010) and negative synergies from increasing yield (Phalan et al., 2016)

¹ Contributed equally

https://doi.org/10.1016/j.gecco.2022.e02036

Received 17 June 2021; Received in revised form 22 January 2022; Accepted 24 January 2022

Available online 26 January 2022

2351-9894/© 2022 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

Corresponding author at: Department of Earth System Science, Ministry of Education Key Laboratory for Earth System Modeling, Institute for Global Change Studies, Tsinghua University, Beijing 100084, China.

E-mail address: leyu@tsinghua.edu.cn (L. Yu).

hinder the strategy which aims to increase yield and then spare land for wild nature. Besides agriculture, urban expansion changes land use and exerts cumulatively negative impacts on nature (Mcdonald et al., 2008). As a result, increasing land use intensity and more resources (such as water, pesticides and fertilizer) inputs for agriculture will lead to the loss, fragmentation and degradation of natural habitats (Tilman et al., 2001), contributing to global biodiversity decline (Butchart et al., 2010). Specifically, species richness will be seriously threatened due to the expansion of human footprint (Newbold et al., 2015).

In this context, satisfying food demands while conserving biodiversity simultaneously is crucial to the global sustainable development (Tscharntke et al., 2012). The conservation of species richness depends on effective conservation and restoration measures (Newbold et al., 2015), especially strategies targeted at species and habitats vulnerable to future environmental change (Pereira et al., 2010). Hence, conflict risk hotspots between biodiversity conservation and food security need to be identified (Molotoks et al., 2017). Studies which integrated and analyzed species richness of different taxonomic classes as a whole may miss conflict risk hotspots essential for one specific taxonomic class (Kehoe et al., 2017; Shackelford et al., 2015; Sonter et al., 2020). Of the few studies which took different taxonomic classes into account, most mainly focused on the relationship between land use change related to agriculture and biodiversity, ignoring dramatic urban growth and its potential impacts on nature (Delzeit et al., 2017; Zabel et al., 2019).

In this study, we aim to uncover future spatial relationships between land use intensity and species richness of mammals, birds and amphibians, and to identify global future conflict risk hotspots between biodiversity conservation and food security. To do this, we calculate the Land Use Intensity Index (LUII), which takes both agricultural land and urban area into consideration (Peng et al., 2016; Jiang, Yu, 2019). Land use's potential impacts on species richness of birds, mammals and amphibians (Pimm et al., 2014; Jenkins et al., 2013) are assessed separately. Then we identify High-High spatial clusters between biodiversity and LUII using local indicators of spatial association (LISA) (Anselin, 1995) at 10-km resolution. These High-High spatial clusters imply locations where high species richness are threatened by land use intensification. We subsequently identify future high spatial auto-correlation (HSA) areas for countries and BHs. Countries and BHs with high proportion of HSA areas and low value of Global Food Security Index (GFSI) are defined as conflict risk hotspots, demanding forward-looking measures and effective management.

2. Materials and methods

This analysis is conducted separately for countries and BHs in 2030, 2050 and 2100 to identify future global conflict risk hotspots (Fig. 1). On the one side, to reflect future land use intensity, we calculate 10-km LUII in 2030, 2050 and 2100 from a 1-km resolution dataset which simulates and maps future global land-use and land-cover change (Global LUCC) under 8 different scenarios. We adopt LUII and maps of total species richness and use Local Indicators of Spatial Association (LISA) to discern HSA areas under each future scenario and areas showing HSA in all 8 future scenarios (HSA-8). Then the area proportion of HSA-8 areas (HSA-8%) is calculated for each country and each BH. On the other side, we calculate Global Food Insecurity Index (GFISI) from GFSI. Based on bivariate choropleth map, we identify countries and BHs belonging to the high HSA-8% & high GFISI type and these areas are future global conflict



Fig. 1. Technical route of the analytical process. Yellow represents input datasets. Blue represents intermediate outputs. Purple represents the processing of input datasets and intermediate outputs. Green represents the final outputs, that is, conflict risk hotspots identified.

2.1. Calculation of LUII based on Global LUCC

In order to calculate LUII (Peng et al., 2016; Jiang et al., 2019) and then analyze future land use intensity for 2030, 2050 and 2100, we use 1-km resolution Global LUCC, which simulates future land cover/land use from 2020 to 2100 at a 5-year interval. Chen et al. use the Future Land-Use Simulation (FLUS) model, which adopts the mechanisms of machine learning and cellular automata, to produce Global LUCC (Chen et al., 2020). Global LUCC contains 7 land types, including water, forest, grassland, bare land, cropland, urban land and snow/ice. This dataset considers both the shared socioeconomic pathways (SSPs) and the representative concentration pathways (RCPs) and provides projections from 2020 to 2100 under 8 kinds of scenarios, including SSP1-RCP1.9, SSP1-RCP2.6, SSP2-RCP4.5, SSP3-RCP7.0, SSP4-RCP3.4, SSP4-RCP6.0, SSP5-RCP3.4 and SSP5-RCP8.5. The five SSPs describe future changes in demographics, economy, technology, policies and natural resources as follows (Neill et al., 2017). SSP1 represents a sustainable pathway which values human well-being and takes the green road. SSP2 represents middle of the road in which development follows classic patterns in history. SSP3 is regional rivalry pathway with attenuated globalization and prevailing fragmentation. SSP4 represents a divided pathway which stresses rising inequality and declining social cohesion both across and within countries. SSP5 is characterized by massive exploitation of fossil fuel resources and rapid economic growth. RCPs depict plausible climate outcomes in aspects of emissions, concentrations and land cover/use (Van Vuuren et al., 2011), providing predicted radiative forcing by 2100 from less than 1.9 W/m⁻² to more than 8.5 W/m⁻². The combined scenarios of SSPs and RCPs represent different levels of societal vulnerability and radiative forcing (Neill et al., 2016).

Human activities, such as agricultural land expansion driven by food demands and urban expansion due to increasing population, have greatly jeopardized global biodiversity (Mcdonald et al., 2008; Jones et al., 2018). It is therefore meaningful to identify the future change of land use intensity and its potential threats on high-biodiversity regions (Zabel et al., 2019). Based on Global LUCC, we calculate an index named LUII to reflect future land use intensity for 2030, 2050 and 2100. *LUII* is calculated according to Eq.(1) and Eq.(2).

$$LUII' = 100 \times \sum_{i=1}^{4} (A_i \times C_i), \quad LUII' \in [100, \quad 400]$$
(1)

$$LUII = \frac{LUII' - 100}{300}, \quad LUII \in [0, 1]$$
(2)

Where *LUII*' represents the weighted average intensity for each pixel with a 10-km resolution to match the resolution of species richness map; A_i represents the land use value for the i-th land cover class, according to Table 1; C_i represents the area proportion of the i-th future land use; *LUII* represents the final index, which is the normalization of *LUII*'.

2.2. Exploration of the future relationship between LUII and species richness

To explore the future relationship between LUII and each one of birds, mammals and amphibians, we apply the bivariate local Moran's I by Local indicators of spatial association (LISA) at ecoregion scale (Anselin et al., 1995). Global spatial autocorrelation is not considered in this study because spatial heterogeneity is high on a global scale. In the LISA method, we calculate adaptive kernel inverse distance weights as spatial weight matrix.

Data used for biodiversity maps total species richness of global terrestrial birds, mammals and amphibians with a spatial resolution of 10 km (Pimm et al., 2014; Jenkins et al., 2013). This dataset obtains original data from BirdLife International and International Union for Conservation of Nature, which involves 10,033, 5270 and 6188 species of birds, mammals and amphibians. It is the most widely used and most reliable global species richness dataset with relatively high accuracy.

It is at ecoregion scale that we apply LISA method, involving 867 terrestrial ecoregions which contain distinct natural communities and endemic species (Olson et al., 2001). For each ecoregion, the mean LUII for 2030, 2050 and 2100 under each scenario and the mean species richness of birds, mammals and amphibians are calculated. Then bivariate local Moran's I, a local indicator of spatial association, is applied at ecoregion scale, simulating the future relationship between LUII and each one of birds, mammals and amphibians. The statistical significance for the spatial relationship is at 0.05 level, according to Monte Carlo randomization procedure with 999 permutations. High-High spatial clusters imply locations where high species richness are threatened by land use intensification. Low-Low spatial clusters indicate areas with both low species richness and low potential for future land use intensity. High-Low

Table 1

Classification of land types and the corresponding land type value. Unused land mainly consists of saline-alkali land, sand land, barren soil land, barren rock land (Peng et al., 2016). Ecological land refers to land with less human disturbance and more inhabitable for wildlife, such as natural vegetation. Agricultural land is defined as land used for cultivation of crops and animal husbandry. Construction land is used for buildings and structures, satisfying residential, industrial, transport and infrastructure purposes.

Land type	Unused land (A1)	Ecological land (A2)	Agricultural land (A3)	Construction land (A4)
Land types of Global LUCC	bare land, snow/ice	water, forest, grassland	cropland	urban area
Land type value	1	2	3	4

J. Zhao et al.

spatial clusters mean that high species richness and low LUII coexist in future. Low-high spatial clusters mean that low species richness and high LUII coexist in the future.

2.3. Identification of countries' and BHs' HSA-8 areas

For each year (2030, 2050 or 2100) under each scenario, there are three kinds of spatial associations, including associations between LUII and bird, mammal, amphibian richness respectively. Accordingly, we identify HSA areas and HSA-8 areas, separately for countries and BHs at an ecoregion scale.

There are currently 36 BHs, which are not only rich in biodiversity but also severely threatened. Only areas where more than 1500 endemic species of vascular plants inhabit and meanwhile over 70% of primary native vegetation vanishes are defined as BHs (Hoffman et al., 2016). According to Conservation International, these 36 BHs cover only 2.4% of Earth's land surface while shelter more than 50% of endemic plant species and almost 43% of endemic bird, mammal, reptile and amphibian species. Only terrestrial regions in BHs are included in this study.

Firstly, for each year under each scenario, regions where LISA between LUII and all three kinds of species richness presents High-High spatial clusters are identified as HSA areas for countries; regions where LISA between LUII and any one of species richness presents High-High spatial clusters are identified as HSA areas for BHs.

Secondly, aimed at each year, we count the number for each ecoregion of its being identified as HSA areas among all 8 scenarios, respectively for countries and BHs. Then regions identified as HSA areas for 8 times are HSA-8 areas in the current year. Identifying HSA-8 areas can reduce uncertainty due to different future scenarios and better reflect the possibility and strength of conservation conflicts. HSA-8% of each country and each BH is calculated subsequently.

Similarly, for each taxonomic class, regions where LUII and species richness show High-High spatial relationship are identified as HH areas under all 8 scenarios are HH-8 areas. We further calculate area proportion of HH-8 areas (hereafter referred to as HH-8%) for countries and BHs.

2.4. Calculation of GFISI

We use 2019 GFSI (The Economist Intelligence Unit, 2019) to calculate GFISI. GFSI assesses food security conditions for 113 countries, involving both developing and developed countries. The higher the value of GFSI, the more optimistic the condition of the country's food security. GFSI 2019 incorporates 34 distinct indicators which assess the driving factors of food security. It is built in the light of three crucial aspects, including affordability, availability, and quality and safety(https://foodsecurityindex.eiu.com/). Affordability is calculated from 9 indicators and involves factors about change in average food costs, proportion of population under global poverty line, gross domestic product per capita, agricultural import tariffs, presence and quality of food safety net programmes and farmers' access to financing. Availability is calculated from 14 indicators and involves factors about sufficiency of supply, public expenditure on agricultural research and development, agricultural infrastructure, volatility of agricultural production, political stability risk, corruption, urban absorption capacity and food loss. Quality and safety is calculated from 11 indicators and involves factors about dietary diversity, nutritional standards, micronutrient availability, protein quality and food safety.

GFISI is calculated according to Eq.(3). Since GFSI is a country-scale index, we cut BHs into many parts by countries' boundaries and each part has consistent GFSI value with the country it is located in.

$$GFISI = 1 - GFSI/100 \tag{3}$$

Where GFSI ranges from 0 to 100, 100 means the highest food security; GFISI show opposite trend with GFSI and is normalized.

2.5. Identification of future global conflict risk hotspots between biodiversity conservation and food security

The correlation between HSA-8% and GFISI reflects potential future conflicts between biodiversity conservation and food security. To catch this, the spatial relationships for both countries and BHs are respectively depicted through bivariate choropleth map.

Based on equal interval classification of HSA-8%, countries or BHs are divided into three types, that is, low type, medium type and high type. Similarly, based on equal interval classification of GFISI, countries or BHs are divided into low type, medium type and high type. Further, we combine countries' or BHs' types of HSA-8% and types of GFISI and classify them into three-by-three types. These three-by-three types include low HSA-8% & low GFISI, low HSA-8% & medium GFISI, low HSA-8% & high GFISI, medium HSA-8% & low GFISI, medium HSA-8% & medium GFISI, medium HSA-8% & medium GFISI, medium HSA-8% & high GFISI, medium HSA-8% & high GFISI, high HSA-8% & low GFISI, high HSA-8% & medium GFISI and high HSA-8% & high GFISI. The combinations of HSA-8% and GFISI are depicted in bivariate choropleth maps. Countries and BHs belonging to the high HSA-8% & high GFISI type are identified as conflict risk hotspots, as regions having high GFISI may require more agricultural lands in the future to increase food production, which will further increase the potential conflict between biodiversity conservation and food security. Similarly, there are bivariate choropleth maps reflecting the relationships between HH-8% and GFISI for each taxonomic class.





(c) 2100

Fig. 2. Global regions of high LUII and high species richness of birds, mammals and amphibians. HSA areas of each year are classified in to 3 types, according to the number of scenarios under which these areas show HSA.



(b)



Fig. 3. Spatial associations between HSA-8% and GFISI. The numbers in the matrices indicate the number of countries included in each of the 9 types.

3. Results

3.1. Global regions of high LUII and high species richness for mammals, birds and amphibians

Fig. 2 shows the global regions of high LUII and high species richness for mammals, birds and amphibians from statistically significant (P < 0.05) local indicators of spatial association for 2030(Fig. 2a), 2050(Fig. 2b) and 2100(Fig. 2c). HSA areas for countries are identified as regions where LISA between LUII and all three kinds of species richness presents High-High spatial clusters. We count the number of scenarios under which 10-km pixels are identified as HSA areas for countries. This number ranges from 1 to 8 since Global LUCC provides 8 different future scenarios. We classify HSA areas into 3 types according to this number: 1–4, 5–7 and 8. According to natural breaks for GFSI, countries belonging to the highest type of GFSI are bordered with blue and those belonging to the lowest type of GFSI are bordered with red.



4	r	`
	2	1
	d	

Country	Birds	Mammals	Amphibians	Conflict risk hotspots
Angola				
Cambodia				
Congo (Kinshasa)				
Ethiopia				
Guinea				
Laos				
Malawi				
Nigeria				
Sierra Leone				
Syria				
Togo				
Zambia				

(b)

Fig. 4. Conflict risk hotspots for countries. (a) Locations of these 10 countries. (b) Conditions of three taxonomic classes. These 10 countries are in comparison with 2 countries which for at least one year are classified into the high HH-8% & high GFISI type for at least one taxonomic class. Orange denotes that for 2030, 2050 and 2100, this country is in the high HH-8% & high GFISI type for taxonomic classes or identified as conflict risk hotspots. Green denotes that for 2030, 2050 and 2100, this country is not in the high HH-8% & high GFISI type for taxonomic classes or is not identified as conflict risk hotspots. Purple denotes that this country belongs to different HH-8% & GFISI types for 2030, 2050 and 2100.

Most HSA areas are identified as HSA-8 areas, since they show statistically significant spatial associations between LUII and biodiversity under all 8 scenarios. Though land use varies with different future scenarios, HSA areas of high LUII and high richness for three taxonomic classes show great spatial consistency under all scenarios. Land use's pressure on biodiversity is apparent globally,







(b)





Fig. 5. BH regions of high LUII and high species richness of birds, mammals and amphibians. HSA areas of each year are classified in to 3 types, according to the number of scenarios under which these areas show HSA.

especially in the United States, Latin America, Sub-Saharan Africa, Central Europe, Southern Europe, Belarus, Ukraine, South Asia, China, Japan, South Korea, North Korea and Southeast Asia. In addition, there is prevailing intensified land use among various scenarios in the United States, Brazil, Argentina, Sub-Saharan Africa, Europe, South Asia, China, Myanmar and Thailand. Venezuela, Laos



Fig. 6. Spatial associations between HSA-8% and GFISI. The numbers in the matrices indicate the number of BH regions included in each of the 9 types.

and many African countries with low GFSI are not only faced with critical challenge of food insecurity but also simultaneously threatened by potential biodiversity loss. Even in some high GFSI countries, species richness is threatened by intensified land use, including the United States, Canada, Japan, Australia, Germany, France and Portugal.

3.2. Spatial associations between HSA-8% and GFISI

Fig. 3 shows the spatial associations between HSA-8% and GFISI for 2030 (Fig. 3a), 2050 (Fig. 3b) and 2100 (Fig. 3c). Countries are classified into 9 types based on equal interval for both HSA-8% and GFISI. Countries lack of GFISI data are filled with white.

The maps show that though many countries have to tackle the trade-offs between biodiversity conservation and food security, few are classified into the high HSA-8% & high GFISI type which simultaneously suffers from both jeopardized biodiversity due to the intensified land use and severe food insecurity. Most vulnerable countries are located in Central Africa, West Africa, Southeast Asia and South Asia. For one thing, these tropical regions provide habitats for massive species and show high species richness. For another, these less developed regions face food-insecure problems and have experienced fast population and economic growth with cropland and per capita income increasing over the past several decades, which poses anthropogenic threats to biodiversity (Tilman et al., 2017).



(a)

Code	BH nart	Birds	Mammals	Amphibians	Conflict risk hotspots
1.1	Eastern Afromontane (Ethiopia)	Dirdo		Timpinotano	connect that notopoto
1.2	Eastern Afromontane (Malawi)				
1.3	Eastern Afromontane (Mozambigue)				
1.4	Eastern Afromontane (United Republic of Tanzania)				
1.5	Eastern Afromontane (Zambia)				
2.1	Guinean Forests of West Africa (Cameroon)				
2.2	Guinean Forests of West Africa (Nigeria)				
2.3	Guinean Forests of West Africa (Sierra Leone)				
2.4	Guinean Forests of West Africa (Togo)				
3	Horn of Africa (Ethiopia)				
4.1	Indo-Burma (Cambodia)				
4.2	Indo-Burma (Laos)				
5	Maputaland-Pondoland-Albany (Mozambique)				
6	Mediterranean Basin (Syria)				
7	Tropical Andes (Venezuela)				

(b)

Fig. 7. Conflict risk hotspots for BHs. (a) Locations of these 15 BH parts, involving 7 BHs. Labels correspond to the codes in (b). (b) Conditions of three taxonomic classes. Orange denotes that for 2030, 2050 and 2100, this BH part is in the high HH-8% & high GFISI type for taxonomic classes or identified as conflict risk hotspots. Green denotes that for 2030, 2050 and 2100, this BH part is not in the high HH-8% & high GFISI type for taxonomic classes.

3.3. Conflict risk hotspots: 10 countries

The ten countries classified into the high HSA-8% & high GFISI type (Fig. 3) are identified as future conflict risk hotspots at the national level (Fig. 4), including Congo (Kinshasa), Sierra Leone, Malawi, Togo, Zambia, Angola, Guinea, Nigeria, Laos, Cambodia (in descending order of GFISI). The list of countries identified as conflict risk hotspots keep the same for 2030, 2050 and 2100. Besides, for each taxonomic class, countries' conditions are shown in Fig. 4b and Fig. S1 (Appendix A). Considering that natural resilience at national level is stronger that at BH level, HSA areas at national level are defined as areas where all three taxonomic classes show HH in Section 2.3. Hence, Ethiopia and Syria are not conflict risk hotspots. However, birds and mammals are extremely vulnerable for 2030, 2050 and 2100 in Ethiopia while mammals are vulnerable for 2030 and 2050 but are facing less threats for 2100 in Syria. Though LUII varies with time, the spatial distribution of countries with most threated species richness shows great consistency across 2030, 2050 and 2100. This demonstrates that even the most environmentally friendly future scenarios, SSP1-RCP1.9 and SSP1-RCP2.6, are unable to mitigate potential conflicts and effective efforts towards these countries should be emphasized.

3.4. Conflict risk hotspots: 7 Biodiversity Hotspots

Fig. 5 shows BH regions of high LUII and high species richness for mammals, birds and amphibians from statistically significant (P < 0.05) local indicators of spatial association for 2030(Fig. 5a), 2050(Fig. 5b) and 2100(Fig. 5c). HSA areas for BHs are identified as regions where LISA between LUII and any one of species richness presents High-High spatial clusters. We count the number of scenarios under which 10-km pixels are identified as HSA areas for BHs. This number ranges from 1 to 8 since Global LUCC provides 8 different future scenarios. We classify HSA areas into 3 types according to this number: 1-4, 5-7 and 8. To match with the national-level index GFSI, BHs are cut into many parts by countries' boundaries and each one has consistent GFSI with the country it is located in. Whether a BH part is identified as with low or high GFSI depends on the country it belongs to as well.

Of 36 terrestrial BHs, species richness in most are facing potential impacts from intensified land use. In 2100, only in few BHs are all three taxonomic classes totally free from future threats due to intensified land use, including Chilean Winter Rainfall and Valdivian Forests, Polynesia-Micronesia, East Melanesian Islands, Southwest Australia, New Caledonia and New Zealand. In Madagascar and the Indian Ocean Islands, Coastal Forests of Eastern Africa, Wallacea, North American Coastal Plain, Tropical Andes and Mediterranean Basin, some regions are disturbed by intensified land use only under certain future scenario or even safe from potential intrusion. While in other BHs like Cerrado, Atlantic Forest, Indo-Burma, Himalaya, Horn of Africa and so forth, most areas are identified as HSA-8 areas.

BH parts are classified into 9 types based on equal interval for both HSA-8% and GFISI. Among 126 BH parts with GFISI data, 15 BH parts (involving 7 BHs) encounter high HSA-8% and high GFISI simultaneously and are identified as conflict risk hotspots for 2030 (Fig. 6a), 2050 (Fig. 6b) and 2100 (Fig. 6c).

The conflict risk hotspots at the BH level keep the same for 2030, 2050 and 2100, including 7 BHs (Fig. 7), namely, Eastern Afromontane, Guinean Forests of West Africa, Horn of Africa, Indo-Burma, Mediterranean Basin, Maputaland-Pondoland-Albany and Tropical Andes. Besides, for each taxonomic class, BHs' conditions are shown in Fig. 7b and Fig. S2 (Appendix A). Considering BH's particular vulnerability, HSA areas at BH level are defined as areas where any one of taxonomic classes shows HH in Section 2.3. Even though, among 15 BH parts identified as conflict risk hotspots, 13 of them face conflict between all 3 taxonomic classes and food security. Conditions are better in Horn of Africa (Ethiopia) and Mediterranean Basin (Syria), where amphibians are free of conflicts. Similar to conflict risk hotspots for countries, conflict risk hotspots for BHs show consistency not only across spatial distribution but also across taxonomic classes.

4. Discussion

4.1. Recommendations for biodiversity conservation in the post-2020 era

The 15th Conference of the Parties to the United Nations Convention on Biological Diversity will adopt the post-2020 global biodiversity framework to guide the global biodiversity conservation in the next 10–30 years. In the 2050 goals and 2030 milestones, retaining the area of natural ecosystem and reducing the number of species that are threatened are critical. In this context, balancing biodiversity conservation and food security is one of the key issues and our results provide specific implications for the global policy. Our results provide implications in developing the sustainable development polices at global, national and regional levels. At the international level, international cooperation and mechanisms of assistance need to be further strengthened as most of the hotspots are located in developing countries. As suggested by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (IPBES et al., 2019), reviewing and renewing joint goals and targets, exchanging scientific knowledge and innovating in technologies contribute to transboundary environment conservation and establishment of effective cooperation mechanism. The 1st Draft of The Post-2020 Global Biodiversity Framework highlights increasing international financial support for developing countries (Secretariat of the Convention on Biological Diversity, 2021), which could mitigate the predicament of many hotspots identified in this study.

Of the 10 countries identified as conflict risk hotspots, 8 lie in Sub-Saharan Africa and 2 in Southeast Asia. These countries have high level of species richness, high level of future land use intensity, and high level of food insecurity. Thus, they will face the double dilemma of food insecurity and biodiversity loss in the future and may require more agricultural lands to increase food production, which will further increase the potential conflict between biodiversity conservation and food security. All of these 10 countries have very high GFISI value, and are concerned in all of the three core index issues including affordability, availability, quality and safety. Thus, comprehensive measures should be taken to improve the food security situation from all aspects in these countries, which requires more attention and careful management to minimize the negative impacts of future agricultural expansion on biodiversity conservation.

All of BHs identified as conflict risk hotspots are located in Sub-Saharan Africa, Asia and South America and belong to developing countries, except that some areas of Mediterranean Basin lie in Europe and North Africa. Similar to the situations of the countries, these BHs will face the double dilemma of food insecurity and biodiversity loss. BHs are regions with significant levels of biodiversity that is threatened by human habitation, which have the top priority for attention at the global scale. So, the BHs identified as future conflict



Fig. 8. Boxplots of GFSI's main factors for typical countries in 2100. (a) for affordability, (b) for availability, (c) for quality and safety, and (d) for natural resources and resilience. The number above each box represents the number of countries belonging to this type. Global p-value is shown in the top left corner. Pairwise comparison with each type and all types is shown in the top (*: p < = 0.05; **: p < = 0.01; ***: p < = 0.001; **: p < = 0.001; **: p < 0.001; **: p

risk hotspots are the "priorities in the priorities" in terms of balancing biodiversity conservation and food security.

4.2. Recommendations for conservation actions in typical countries

For typical countries with highest or lowest types of HSA-8% and GFISI, we show the main factors which influence GFSI of these countries (Fig. 8). In particular, the category of natural resources and resilience does not contribute to the overall score of GFSI 2019. Natural resources and resilience score is calculated from 21 unique indicators related with exposure, water, land, oceans, sensitivity, adaptive capacity and demographic stresses. There are significant differences among four types of countries in affordability, availability, quality and safety, especially affordability. In contrast, difference in natural resources and resilience is not significant. For the four types of countries, the policy focus on biodiversity conservation and improving food security should be different. For the 10 countries with high HSA-8 & high GFISI, biodiversity conservation should be the policy priority and for the 9 countries with low HSA-8 & high GFISI, food security should be the policy priority. While for the 26 countries with low HSA-8 & low GFISI, biodiversity conservation and food securities with low HSA-8 & low GFISI, biodiversity conservation and food securities with low HSA-8 & low GFISI, biodiversity conservation should be the policy priority and for the 9 countries with low HSA-8 & low GFISI, biodiversity conservation and food securities with low HSA-8 & low GFISI, biodiversity conservation and food securities with low HSA-8 & low GFISI, biodiversity conservation and food securities with low HSA-8 & low GFISI, biodiversity conservation and food securities with low HSA-8 & low GFISI, biodiversity conservation and food securities with low HSA-8 & low GFISI, biodiversity conservation and food securities with low HSA-8 & low GFISI, biodiversity conservation and food security are facing less threats than the other countries.

4.3. Limitations and future research

The data used in this study (including Global LULC, biodiversity datasets of different taxa, GFSI) has uncertainties which may cause the uncertainties in the results. Although we conduct scenario analysis to reduce the uncertainties, better data should be used to validate and improve the results in this study.

Besides, global-scale analysis provides a whole picture of balancing biodiversity conservation and food security. Based on the findings, further research at national, regional and local scales could be conducted, to monitor the actual landscape change, and to find out context-specific solutions to reduce the conflicts between biodiversity conservation and food security.

5. Conclusion

To achieve sustainable development in the 21st century, it is critical to identify conflict risk hotspots between biodiversity conservation and food security at global level. By applying methods including LISA and combining Global LUCC, species richness of birds, mammals, amphibians, and GFSI, we identified 10 countries (Congo (Kinshasa), Sierra Leone, Malawi, Togo, Zambia, Angola, Guinea, Nigeria, Laos, Cambodia) and 7 BHs (Eastern Afromontane, Guinean Forests of West Africa, Horn of Africa, Indo-Burma, Mediterranean Basin, Maputaland-Pondoland-Albany and Tropical Andes) as conflict risk hotspots between biodiversity conservation and food security at the global scale. These regions are mainly located in developing countries, which require urgent attention. Optimizing agricultural structure and layout, improving yield by technological innovation, mechanization and breeding, providing food subsidies could contribute to mitigating the conflicts. We call for international cooperation and mechanisms of assistance to support these conflict risk hotspots to balance biodiversity conservation and food security.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Global LUCC is available at http://www.geosimulation.cn/Global-SSP-RCP-LUCC-Product.html, Species richness dataset is available at https://biodiversitymapping.org/, BH dataset is available at https://zenodo.org/record/3261807#. X_QoYDPAiAf, GFSI is available at https://foodsecurityindex.eiu.com/

Acknowledgements

This research was funded by the National Key R&D Program of China (grant number: 2017YFA0604401; 2019YFA0606601), Tsinghua University Initiative Scientific Research Program (grant number: 2021Z11GHX002) and the National Key Scientific and Technological Infrastructure project "Earth System Science Numerical Simulator Facility" (EarthLab).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gecco.2022.e02036.

References

Anselin, L., 1995. Local indicators of spatial association-LISA. Geogr. Anal. 27, 93-115.

Butchart, S.H.M., et al., 2010. Global biodiversity: indicators of recent declines. Science 328, 1164.

Chen, G., et al., 2020. Global projections of future urban land expansion under shared socioeconomic pathways. Nat. Commun. 11, 537.

Delzeit, R., Zabel, F., Meyer, C., Václavík, T., 2017. Addressing future trade-offs between biodiversity and cropland expansion to improve food security. Reg. Environ. Change. 17, 1429–1441.

Foley, J.A., et al., 2005. Global consequences of land use. Science 309, 570.

Godfray, H.C.J., et al., 2010. Food security: the challenge of feeding 9 billion people. Science 327, 812.

Hoffman, M., Koenig, K., Bunting, G., Costanza, J. & Williams, K.J. Biodiversity Hotspots (version 2016.1). 2016.1 ed: Zenodo; 2016.

IPBES, 2019. In: Brondizio, E.S., Settele, J., Díaz, S., Ngo, H.T. (Eds.), Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. IPBES secretariat, Bonn, Germany.

Jiang, L., Yu, L., 2019. Analyzing land use intensity changes within and outside protected areas using ESA CCI-LC datasets. Glob. Ecol. Conserv. 20, e789.

Jenkins, C.N., Pimm, S.L., Joppa, L.N., 2013. Global patterns of terrestrial vertebrate diversity and conservation. Proc. Natl. Acad. Sci. 110, E2602.

Jones, K.R., et al., 2018. One-third of global protected land is under intense human pressure. Science 360, 788–791.

Kehoe, L., et al., 2017. Biodiversity at risk under future cropland expansion and intensification. Nat. Ecol. Evol. 1, 1129-1135.

Mcdonald, R.I., Kareiva, P., Forman, R.T.T., 2008. The implications of current and future urbanization for global protected areas and biodiversity conservation. Biol. Conserv. 141, 1695–1703.

Molotoks, A., Kuhnert, M., Dawson, T., Smith, P., 2017. Global hotspots of conflict risk between food security and biodiversity conservation. Land 6, 67.

Newbold, T., et al., 2015. Global effects of land use on local terrestrial biodiversity. Nature 520, 45–50. Neill, O., B, C., et al., 2017. The roads ahead: narratives for shared socioeconomic pathways describing world futures in the 21st century. Glob. Environ. Change 42, 169–180.

Neill, O., B, C., et al., 2016. The scenario model intercomparison project (ScenarioMIP) for CMIP6. Geosci. Model Dev. 9, 3461-3482.

Olson, D.M., et al., 2001. Terrestrial ecoregions of the world: a new map of life on earth: a new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. BioScience 51, 933–938.

Peng, J., Zhao, S., Liu, Y., Tian, L., 2016. Identifying the urban-rural fringe using wavelet transform and kernel density estimation: a case study in Beijing City, China. Environ. Modell. Softw. 83, 286–302.

Pereira, H.M., et al., 2010. Scenarios for global biodiversity in the 21st century. Science 330, 1496.

Phalan, B., et al., 2016. How can higher-yield farming help to spare nature? Science 351, 450.

Pimm, S., et al., 2014. The biodiversity of species and their rates of extinction, distribution, and protection. Science 344, 1246752.

Secretariat of the Convention on Biological Diversity. First draft of the Post-2020 Global Biodiversity Framework. (https://www.cbd.int/article/draft-1-global-biodiversity-framework). Retrieved November 22, 2021, (2021).

Shackelford, G.E., Steward, P.R., German, R.N., Sait, S.M., Benton, T.G., 2015. Conservation planning in agricultural landscapes: hotspots of conflict between agriculture and nature. Divers. Distrib. 21, 357–367.

Sonter, LJ., Dade, M.C., Watson, J.E.M., Valenta, R.K., 2020. Renewable energy production will exacerbate mining threats to biodiversity. Nat. Commun. 11, 4174. Zabel, F., et al., 2019. Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity. Nat. Commun. 10, 2844.

Tester, M., Langridge, P., 2010. Breeding technologies to increase crop production in a changing world. Science 327, 818.

The Economist Intelligence Unit. Global Food Security Index 2019. Available online: (http://foodsecurityindex.eiu.com/) (accessed on 5 August 2020): The Economist Intelligence Unit; 2019.

Tilman, D., et al., 2017. Future threats to biodiversity and pathways to their prevention. Nature 546, 73-81.

Tilman, D., et al., 2001. Forecasting agriculturally driven global environmental change. Science 292, 281.

Tscharntke, T., et al., 2012. Global food security, biodiversity conservation and the future of agricultural intensification. Biol. Conserv. 151, 53–59.

Van Vuuren, D.P., et al., 2011. The representative concentration pathways: an overview. Clim. Change 109, 5.