Land cover change and multiple remotely sensed datasets consistency in China

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Abstract

Introduction: Although numerous land cover datasets can act as references for understanding land cover change in China, the inconsistencies between the datasets can also provide understanding. Previous studies on the consistency between land cover datasets have mostly focused on land cover type consistencies and have ignored data consistencies in land cover change.

Outcomes: Therefore, we aim to analyse the consistencies in land cover changes through likelihood assessment methods. We compared the spatiotemporal changes in forest, grassland, cropland, and bare land in the Climate Change Initiative land cover dataset (CCI-LC), Moderate-resolution Resolution Imaging Spectroradiometer land cover dataset (MCD12Q1), China’s National Land Use and Cover Change (CNLUCC), Globeland30 and Global Land Cover Fine Surface Covering 30 (GLC-FC530) datasets in 2010. The results showed that the percentages and changes in each land cover type in MCD12Q1 were different from those in the other datasets.

Discussion: For example, the proportion of grassland in MCD12Q1 was the highest, reaching 48.04%. The places with high consistency were the places where the land cover types were concentrated, and the bare land had the highest consistency. However, the consistency of China’s land cover change was quite low, and the percentage of low consistency was more than 87% from 2000-2018. Comparison of the data with the global artificial impervious area (GAIA) and Hansen-Global Forest Change (Hansen-GFC) datasets showed that the percentage of high construction gain consistency (38.83%) was higher than the forest change consistency, and the percentage forest loss high consistency (8.85%) was lower than the forest gain high consistency (12.76%).

Conclusion: The results not only provide a basis for the use of land cover datasets but also give a clearer understanding of the pattern of land cover changes.

Introduction

Global climate change and high-intensity human activities have resulted in rapid land cover changes (Foley et al. 2005; Liu et al. 2021; Song et al. 2018). Studies have shown that 60% of land cover changes are related to direct human activities, and 40% are related to indirect driving factors, such as climate change (Song et al. 2018). At the same time, changes in land cover have in turn affected the environment and human well-being (Duveiller, Hooker, and Cescatti 2018; Sulla-Menashe et al. 2019; Yang et al. 2017). For example, more than 19% of the change in greenness in vegetation in the northern temperate zone is mainly driven by land use changes (Piao et al. 2019). In addition, land cover changes affect the available energy and water on the land surface, thereby altering the water cycle by changing the time and amount of evapotranspiration (Sterling, Ducharme, and Polcher 2012). Therefore, understanding global land cover changes has become important for understanding global environmental changes; thus, there is a great need for high-quality land cover data (Stehman and Foody 2019). To date, many high-quality land cover datasets have emerged due to the continuous development of remote sensing technology (Wu et al. 2020; Zhang et al. 2021), such as CCI-LC (Defourny et al. 2017), MCD12Q1 (Friedl et al. 2010), and Globeland30 (Chen et al. 2015). In addition to global-scale datasets, many national-scale datasets have also begun to appear, such as the United States National Land Cover Database (NLCD) (Wickham et al. 2017) and land cover map of Nepal (Uddin et al. 2015). However, different mapping standards and algorithms lead to poor comparability between different datasets (Kaptué Tchuente, Roujean, and De 2011). In particular, differences in land cover change locations have led to an inconsistent understanding of global land cover transformation. Therefore, identifying the characteristics of land cover changes in time and space requires interactive verification between different data sources.
Several studies have evaluated the inconsistencies of different land cover datasets at regional or global scales. Giri, Zhu, and Reed (2005) analyzed the consistency between Global Land Cover 2000 and MODIS and found that when the land cover level was detailed, the inconsistencies increased. Hua et al. (2018) explained that spatial consistency between continents was quite different and that surface conditions had different effects on spatial consistency among the GLC2000, CCI LC, MCD12, GLOBCOVER and GLCNMO datasets. Kapteü Tchuënt, Roujane, and De (2011) showed that the areas in which these four land cover datasets (GLC2000, GLOBCOVER, MODIS and ECOCLIMAP) agreed accounted for 40.9% of the African continent. Pouliot et al. (2014) assessed the MODIS annual land cover of Canada and found that the accuracy was 70% in 19 classes. However, most of these studies focused on the inconsistencies of multiple land cover types in specific years, while there was a lack of analysis on the inconsistencies of land cover changes. In addition, consistency analyses of land cover changes over long time periods are also relatively lacking. In addition, the study of land cover change consistency can inform users in the selection of datasets. Regions with low consistency can also be the focus of future studies in land cover characterization and mapping (Bai et al. 2014).

In recent decades, China’s land cover has undergone rapid changes as a result of fast economic and social development (Bryan et al. 2018; Song and Deng 2017). To alleviate the various impacts of land cover changes and promote the sustainable development of land, China has issued a series of land management policies (Fu 2020; Hua et al. 2016). With the implementation of these policies, China has become an important area for global land cover changes, such as urbanization, forest change and, dominantly, global greening (Chen et al. 2019; Li et al. 2020; Wang et al. 2021). The rapid development of China’s economy has promoted urbanization. Due to urban expansion, 32,153 km² of cropland has been lost in China, and urban expansion invaded 11,925 km² of high-quality cropland, resulting in the permanent loss of 1.06% of the total high-quality cropland from 2003 to 2016 (Qiu et al. 2020). In addition, China has also experienced large-scale deforestation and afforestation activities, resulting in great changes in forest cover, which in turn have caused climate and environmental changes (Brandt et al. 2012; Peng et al. 2014). In particular, China implemented the Grain to Green Program in 1999, which has resulted in a 25% increase in vegetation coverage on the Loess Plateau in the past ten years (Feng et al. 2016). Under the influence of human activities, land cover in China is changing rapidly and is characterized by high fragmentation and diversity, making the analysis of land cover change consistency very challenging (Yu et al. 2018). Therefore, it is crucial to explore the differences in land cover change in multiple datasets, especially urban change and forest change. It will help to form more rational judgments on China’s important process of land cover change. In order to increase the comparison of the data, in addition to the global data set, we also use the data set CNLUCC for China.

Generally, the quality of land cover data can be determined by referring to the data measured in specific areas or from another land cover reference map (Bai et al. 2014). For example, Yang et al. (2017) collected five sets of sample units for verification to quantify the accuracy of seven land cover datasets and found that the highest overall spatial consistency was between GLC2000 and CCI-LC 2000 (53.8%). Bai et al. (2014) used GLCD-2005 as reference data to analyze the consistency of GLCC, UMD, GLC2000, MODIS LC, and GLOBCOVER and concluded that GLC2000 has the highest consistency with GLCD-2005. However, these methods have difficulty obtaining data and cannot show the consistency of locations between different land cover products. In addition, a confusion matrix is also a common method to assess the consistency of land cover datasets (Wei et al. 2020). Wang et al. (2021) used a confusion matrix to evaluate the overall accuracy and category accuracy of different land cover datasets, and the results showed that the overall accuracy between Globeland30 and CCI-LC was the highest. However, the confusion matrix can only assess the consistency of land cover data in a single year and cannot show the consistency of land cover change data. In addition, the likelihood assessment method can not only show the consistency between each pixel but also show the change in the consistency of the land cover time series (Li et al. 2017). Therefore, we adopt the likelihood assessment method to assess the consistency of land cover changes.

The differences between multi-source land cover data also make these data unable to show the definite trend of the land cover change in China. Since China’s land cover has undergone rapid and obvious changes, the research hypothesis of this article is to evaluate the consistency of multi-source land cover changes. To evaluate the regional consistency of multi-source data, we design four research steps: (1) analyze the spatiotemporal change in land cover in China; (2) evaluate the consistency of the proportions of various land cover types from different data sources; (3) analyze the consistency of the changing trends of various land types from different data sources; and (4) identify the differences between construction expansion and forest changes in different datasets.

Materials and methods

Study area

The study area includes all of China, the most populous country in the world Figure 1. There are many different types of land cover in China, including forest,
grassland, cropland, and bare land. In recent decades, due to rapid economic growth and the implementation of land use policies, China’s land cover changes have become complicated (Song and Deng 2017). Moreover, land cover changes have obvious regional differences due to China’s large area.

**Data source and pre-processing**

We used five land cover datasets and two single land cover type datasets for consistency analysis (Table 1). We divided the dataset into three parts: continuous time series land cover datasets, multi-period land cover datasets and single land cover type datasets.

1. Continuous time series land cover datasets include CCI-LC and MCD12Q1. CCI-LC is a 300 m resolution land cover dataset produced by the European Space Agency (ESA). It uses the United Nations (UN) Land Cover Classification System (LCCS) classification system, including 22 types of land cover, and its greatest advantage is that it has a continuous time series from 1992 to 2018 (Defourny et al. 2017). MCD12Q1 is a dataset created by the United States Geological Survey and has a resolution of 500 meters. It contains six classification systems, and we have adopted the International Geosphere-Biosphere Programme (IGBP) classification (Friedl et al. 2010). In addition to having a different classification system, MCD12Q1 has a long time series from 2001 to 2019.

2. Multi-period land cover datasets include China’s National Land Use and Cover Change (CNLUCC), Globeland30 and Global Land Cover Fine Surface Covering 30 (GLC-FCS30). CNLUCC is mapped by the Data Center for Resources and Environmental Sciences (RESDC), Chinese Academy of Sciences, with a spatial resolution of 30 m for the years 2000, 2005, 2010, 2015 and 2018. It includes 6 first-level land types and 25 second-level land types, and the overall accuracy of these datasets has been reported to be higher than 90% (Xu et al. 2018). Globeland30 was developed by

![Figure 1](https://example.com/figure1.png)  
**Figure 1.** The main land cover types in China (Globeland30 products of 2020). Note: This map is based on the standard map GS (2019)1822 downloaded from the Standard Mapping Service website of the Natural Resource of the People’s Republic of China. The base map has no modification.

| Dataset       | Resolution (m) | Time               | Classification Method                        | Source                                      |
|---------------|----------------|--------------------|----------------------------------------------|---------------------------------------------|
| CCI-LC        | 300            | 2001–2018          | Unsupervised classification                  | https://www.esa-landcover-cci.org/         |
| CNLUCC        | 30             | 2000/2005/2010/2015/2018 | Visual interpretation                         | http://www.resdc.cn                        |
| GAIA          | 30             | 2001–2018          | Exclusion-inclusion framework                 | http://data.ess.tsinghua.edu.cn/           |
| GLC-FCS30     | 30             | 2005/2010/2015/2020 | Operational SPECILib-Based                  | http://data.earthenginepartners.appspot.com/science-2013-global-forest |
| Hansen-GFC    | 30             | 2000/2010/2020     | Pixel-Object-Knowledge                       | http://data.earthenginepartners.appspot.com/science-2013-global-forest |
| MCD12Q1       | 500            | 2001–2018          | Decision tree                                | https://ladweb.modaps.eosdis.nasa.gov/      |

Note: For datasets with spatial resolution greater than 30 m, they are downsampled to 30 m before analysis.

For datasets with single land cover type classification systems, we further divided them into multiple classes. For example, forest, grassland, shrubland and water were divided into several types, including forest, grassland, shrubland, bare land, construction, wetland, construction, permanent snow and ice, and water.
the National Geomatics Center of China and has a 30 m spatial resolution. It includes the three phases, 2000, 2010 and 2020, and there are ten land cover classes. It uses a pixel-object-knowledge (POK) classification method, and the third-party evaluation accuracy is 83.5% (Chen et al. 2015). GLC-FCS 30, with a 30 m resolution, was generated by the Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences for 2015 and 2020. It was generated using the reflectance spectrum of the spatial-temporal spectrum library, including 9 first-level land types and 19 second-level land types (Zhang et al. 2019). Although these multi-period datasets do not have continuous time series, their spatial resolution is higher than that of continuous time series datasets.

(3) Single land cover type datasets include global artificial impervious area (GAIA) and Hansen-Global Forest Change (Hansen-GFC). GAIA is an impervious surface map from 1985 to 2018 drawn by Tsinghua University on the Google Earth Engine platform using all files with a resolution of 30 meters (Gong et al. 2020). The mean overall accuracy of GAIA is greater than 90%, and cross-product comparison shows that GAIA data are the only data that span 30 years. The Hansen-GFC data are produced by the University of Maryland and include the loss and gain of global forests from 2001 to 2020. The accuracy assessment shows that the overall accuracy of forest loss is 99.6%, and the overall accuracy of forest gain is 99.7% (Hansen et al. 2013). These land cover type datasets provide a relatively accurate reference for the consistency analysis of land cover data changes.

Table 1 shows that these land cover products have different resolutions and classification systems. Therefore, we pre-process these data in two steps. First, since the resolution of the dataset varies from 30 m to 500 m, we resample the spatial resolution to 1 km through the nearest neighbor method. In addition, because the datasets have different classification systems, for example, Globelands30 has 10 categories, while MCD12Q1 has 17 categories, we have unified the categories. We reclassified all datasets into 9 categories: forest, grassland, shrubland, cropland, wetland, water, construction land, bare land and permanent ice and snow (Table 2).

### Likelihood assessment method

We used the likelihood assessment method to analyze the consistency of the land cover datasets. The likelihood assessment method can be understood as the voting process of the datasets, and Jung et al. used the similarity score method to explore the synergies between land cover products (Jung et al. 2006). The principle of the likelihood assessment method is to evaluate the consistency of each pixel in different land cover datasets by measuring the certainty and uncertainty of each land cover dataset, and this method is usually used when it is difficult to determine the credibility of more than one existing dataset (Fang et al. 2020). This voting process can be accomplished by overlay analysis. For example, if all datasets show a certain pixel as a forest, the voting score for that pixel as a forest is high, and the consistency of the datasets is high.

To assess the consistency of land cover data in China, we used the likelihood assessment method for four widely used land cover datasets. The consistency evaluation requires datasets of the same year, but GLC-FCS30 has only two periods, namely, 2015 and 2020, we only used the GLC-FCS30 dataset in our spatial and temporal land cover change analysis. Since GLC-FCS30 does not include 2010, only four datasets CCI-LC, MCD12Q1, Globelands30, and CNLUC for 2010 were included in our land cover consistency analysis. GLC-FCS30 does not have a longer time series, it was also not included in the land cover change consistency analysis, and the first and last years of the remaining four datasets were used, i.e., including 2000–2018. As forests, grassland, cropland and bare land are the four largest land cover types in China, we chose these four for our analysis. We used the Map Algebra tool in ArcGIS 10.2 to spatially superimpose the pre-processed dataset to

| Type        | CCI-LC                     | MCD12Q1 (GBP) | CNLUC     | GLC-FCS30 | Globelands30 |
|-------------|----------------------------|---------------|-----------|-----------|--------------|
| 1 Forest    | 40/50/60/61/62 /70/71/72 /80/81/82/90 /100/160/170 | 1/2/3/4/5     | 21/22/23/24 | 12/50/60/61/62 /70/71/72 /80/81/82/90 | 20            |
| 2 Grassland | 110/130                    | 8/9/10        | 31/32/33  | 11/130    | 30           |
| 3 Shrubland | 120/121/122                | 6/7           | -         | 120/121/122 | 40           |
| 4 Cropland  | 10/11/12/20/30             | 12/14         | 11/12     | 10/20     | 10           |
| 5 Wetland   | 180                        | 11            | 45/46     | 180       | 50           |
| 6 Water     | 210                        | 17            | 41/42/43  | 210       | 60           |
| 7 Construction | 190                    | 13            | 51/52/53  | 190       | 80           |
| 8 Bare land | 140/150/151/152/153/200/201/202 | 16 | 61/62/63/64/65/66/67 | 140/150/152/153/200/201/202 | 90           |
| 9 Permanent snow and ice | 220 | 15 | 44 | 220 | 100 |
vote on the four land cover datasets with a consistency in the range of 0–4. For example, for forest, a value of “0” means that the pixel is not a forest in the four datasets, and a value of “4” means that the pixel is a forest in the four datasets. The higher the pixel value is, the higher the probability that the pixel is a forest, that is, the higher the consistency of the datasets. In addition to the analysis for China as a whole, we also analyzed in each province in order to represent the regional variation in the consistency of land cover data in China.

We used the same method for the change consistency analysis. Firstly, the first and last years of the four datasets were used to obtain the pixels where the land cover changed. Then, the pixels of land cover change shown in the four datasets are voted according to the likelihood assessment method. For example, if two of the four datasets show that an pixel has changed from cropland to forest, then it is scored as “2.” Finally, the consistency of the dataset is evaluated based on the score. However, because there were few pixels in which the land cover changed, and to better show the results, we classified the pixel values, setting 1 as low consistency and 2–4 as high consistency. In addition, a single land cover type dataset may have a higher credibility and a better representation of land cover change than the land cover datasets. Moreover, due to urbanization and ecological conservation policies, forest and urban changes are the more obvious parts of China’s land cover change. We added the GAIA and Hansen-GFC datasets to compare the consistency of the datasets, including the gain and loss of forest and gain of construction.

Results

Spatiotemporal change in land cover

In terms of temporal change, we calculated the percentage of each land cover type in the first and last years of five datasets to observe the differences in land cover changes in China in different datasets (Figure 2). Forest, grassland, cropland and bare land account for a high proportion, covering more than 90% of China’s area. The proportion of grassland in MCD12Q1 was the highest, reaching 48.04%. From the perspective of land cover change, the forest showed an increasing trend in all five datasets, and the growth rate of forest percentage in MCD12Q1 was the highest (0.18). For grassland, except in Globeland30, the remaining four datasets all showed a trend of grassland reduction, and CNLUC had the highest grassland percentage reduction rate, which was 0.12. For cropland, except for MCD12Q1, all the datasets had the phenomenon of decreased cropland, and GLC-FCS30 had the highest cropland reduction (0.16%). For bare land, CNLUC and GLC-FCS30 showed a trend of increased bare land, while CCI-LC, MCD12Q1 and Globeland30 showed a trend of decreased bare land. Globeland30 had the highest rate of decrease in the percentage of bare land, which was 0.29, while the rate of increase in the percentage of bare land in CNLUC was the highest (0.11). The remaining land cover types accounted for a small proportion of China, and the shrubs had obvious changing trends. The MCD12Q1 shrubs increased by 0.17, while the shrubs in CCI-LC, Globeland30 and GLC-FCS30 decreased by 0.24, 0.28 and 0.26, respectively. In terms of percentage, MCD12Q1 was obviously different from other datasets, especially the percentage of grassland. From the perspective of change, there are

![Figure 2. Percentage of land cover types in different datasets (E: CCI-LC, M: MCD12Q1, C: CNLUC, G: Globeland30, F: GLC-FCS30; the numbers indicate the years).](image-url)
large differences, and even opposite trends, between datasets. Nevertheless, China’s land cover was relatively stable overall, especially in the CCI-LC dataset.

In terms of spatial change, we calculated the percentage of the four main land cover types in each province for the four datasets in 2010 (Figure 3). The differences between provinces were obvious. In Northeast China and East China, such as Heilongjiang and Shandong, the percentage of cropland was relatively high; in Northwest China, such as Xinjiang, bare land was dominant; in North China, such as Inner Mongolia, grassland accounted for a relatively large percentage; and in South China, such as Guangdong, it was dominated by forest (Figure A1). Hong Kong and Taiwan were also dominated by forest. The differences between land cover datasets were also obvious. For example, in the CCI-LC, Globeland30 and CNLUC datasets, the percentage of forest in Beijing was 50.56%, 52.39% and 59.83%, while it was only 13.95% in MCD12Q1. In addition, the percentage of grassland in Guizhou in MCD12Q1 was 75.17%, while in CCI-LC, Globeland30 and CNLUC, it was 2.58%, 18.80% and 16.94%, respectively. The differences in the resolution and the classification standard of the datasets caused the difference in the results, and the difference between MCD12Q1 with the lowest resolution and the rest of the products was the most obvious. Moreover, the different spectral information of the ground features also affects the consistency of datasets. The average percentages of bare land in the four datasets were 5.12%, 6.46%, 5.90% and 7.12%, while the average percentages of cropland were 44.93%, 28.42%, 39.44% and 36.35%, respectively. Therefore, among the four types of land cover, the consistency of bare land was higher than that of the other three types. In summary, there were obvious differences between the datasets, especially MCD12Q1, so the consistency analysis of the datasets is critical.

**Consistency of land cover**

We used the likelihood assessment method to evaluate the consistency of datasets for the four main types of land cover in China in 2010 (Figure 4). Different consistency scores of the same land cover types were evenly distributed. The percentage of the forest with a consistency score of “1” was 30.45%, while the percentages with scores of “2,” “3,” and “4” were 21.19%, 25.21%, and 22.85%, respectively. Similarly, the percentages of consistency scores of “1,” “2,” “3,” and “4” in bare land were 28.22%, 16.12%, 16.92%, and 38.74%, respectively. In addition, areas with low or high consistency are visible in Figure 4. The areas with high forest consistency (“4”) were mainly distributed in eastern Northeast China, the Hanzhong Basin, the southern Himalayas and eastern Taiwan, while the areas with low forest consistency (“1”) were more scattered. The areas with high grassland consistency were the Qinghai-Tibet Plateau and Inner Mongolia.

![Figure 3](image_url). The percentage of different land cover types by province in 2010 (from left to right are CCI-LC, MCD12Q1, Globeland30 and CNLUC).
sensing
Therefore, so bare for Sichuan and of topographical may be consistent. This consistency is high. The areas with low grassland consistency were mainly distributed in the Hanzhong Basin and its southern area. The areas with high consistency of cropland were the North China Plain, the middle and lower reaches of the Yangtze River, and the Sichuan Basin, where the terrain is flat and suitable for agriculture. The areas with high consistency of bare land were more concentrated, mainly in the Tarim and Turpan Basins and the Hexi Corridor. Therefore, the areas where different types of land cover are concentrated are easy to identify in remote sensing images, so they have a high consistency.

Through regional statistics, we obtained the consistency score percentage for each province (Figure 5). The consistency scores of forests and bare land in each province were relatively even, while the consistency scores of grasslands and bare land were unevenly distributed in most provinces, and the low consistency percentage was relatively high (Figure A2). For forests, regions with low consistency in Xinjiang, Ningxia, Qinghai, Shandong, and Shanghai accounted for a relatively high percentage, especially in Shanghai and Qinghai, which accounted for more than 90%. This may be related to the lower forest area in these provinces. For grassland, Xinjiang, Qinghai, Ningxia, Inner Mongolia, and Sichuan provinces had a high percentage of high grassland consistency, while other provinces had low consistency, accounting for the majority. For China as a whole, although the percentage of low consistency was relatively high, the proportion of each consistency score was fairly even. The percentage of cropland with high consistency was higher than that of forest, grassland and bare land. The eight provinces of Tianjin, Hebei, Jilin, Heilongjiang, Jiangsu, Anhui, Shandong, and Henan had a high consistency ratio of greater than 40%. However, in Inner Mongolia, Fujian, Guangdong, Hainan, Tibet, Qinghai, and Hong Kong, the proportion of low consistency of cropland exceeded 40%. Bare land had obvious low consistency in most provinces. Except for Inner Mongolia, Gansu, and Xinjiang, where the high grassland consistency exceeded 35%, the rest of the provinces all had low grassland consistency. Hong Kong and Qinghai are worth noting. Multi-source datasets showed that there is no distribution of bare land in Hong Kong, and the proportion of each consistency score in Qinghai is average. There are regional differences in the consistency of datasets due to the distribution of land types, especially cultivated land, which has obvious north-south differences.

Figure 4. Consistency of (a) forest; (b) grassland; (c) cropland; (d) bare land in 2010. Note: This map is based on the standard map GS(2019)1822 downloaded from the Standard Mapping Service website of the Natural Resource of the People’s Republic of China. The base map has no modification.
Consistency of land cover change

In addition to the land cover consistency, we also analyzed the change in the land cover consistency of the four datasets. Similarly, the analysis of the change in consistency was based on the mutual transformation of the four main land cover types. We counted the converted areas of four land types in the four land cover datasets and compared them with land cover; the difference in the land cover change between datasets was more obvious (Figure 6). The areas of forest, cropland converted to bare land, bare land converted to forest, and cropland were small. The changes in the conversion of grassland into the other types were obvious and had large areas. Different datasets had great differences.

Figure 5. Consistency of (a) forest; (b) grassland; (c) cropland; (d) bare land in 2010.

Figure 6. Area of land cover change in different land cover datasets (F: forest, G: grassland, C: cropland, B: bare land).
in the identification of land cover changes. For example, except for the mutual conversion of grassland and cropland and the conversion of bare land to grassland, the areas of land cover change identified by CNLUCCE were higher than those identified by the other datasets. In addition, the area converted from forest to cropland in MOD12Q1 was significantly smaller than that in the other datasets. The area of grassland converted to bare land identified by CNLUCCE and the area of bare land converted to grassland in Globeland30 were also significantly higher than other datasets. Due to the impact of the environment and human activities, land cover changes have complex characteristics. Therefore, the determination of land cover changes was much more uncertain than the determination of land cover types.

We also used the likelihood assessment method to analyze the consistency of land cover changes in multi-source datasets. We calculated the percentages of the consistency scores from “1” to “4” for different types of land cover changes (Figure 7). Unlike the trend of more average scores for land cover consistency, the consistency of land cover changes was lower. The percentage of each land cover change with a consistency score of “1” was greater than 87%. The low consistency ratio of grassland to forest, cultivated land to bare land, and bare land to forest reached more than 99%. Among all land cover changes, the conversion of bare land to cultivated land had a relatively high consistency, and the high consistency score was 12.88%. In addition, the percentage of land cover change consistency with a score of “4” was very low, and the highest was only 0.16%. To show the spatial distribution of land cover change consistency, we took the conversion between grassland and bare land as an example to create a land cover change consistency distribution map (Figure 8). The consistency of the conversion of bare land to grassland was obviously higher than the consistency of the conversion of grassland to bare land. In addition, the areas where bare land was transformed into grassland with high consistency were relatively concentrated, mainly in northern Xinjiang and the northern part of the Qinghai-Tibet Plateau. However, the high-consistency areas where grassland was transformed into bare land were scattered in the middle of the Qinghai-Tibet Plateau. This may be due to China’s planting of trees and grasses in recent years.

**Comparison with high-resolution dataset**

For construction gain, CNLUCCE and MCD12Q1 identified the largest and smallest areas of construction gain, respectively (Figure 9a). CCI-LC and GAIA showed little difference in the increased area of construction. For forest gain, CNLUCCE and Hansen-GFC showed the largest and least increased forest areas, respectively. In addition, the largest area of forest gain (CNLUCCE) was more than 24 times the smallest area (Hansen-GFC), and the difference was very obvious. The loss of forest had a similar phenomenon. CNLUCCE and Hansen-GFC showed the largest and least decreased forest areas, respectively. The difference between CNLUCCE and Hansen-GFC reached 63 times. Therefore, the consistency of land cover change between Hansen-GFC and the rest of the datasets was significantly greater than

![Figure 7. Percentage of consistency scores for different land cover changes (F: forest, G: grassland, C: cropland, B: bare land).](image-url)
that of GAIA. We suggest that the definition of forest is more complicated than that of city and may be a contributing factor. There are many different types of forests, such as coniferous broad-leaved forests and mixed forests, which make the interpretation of remote sensing images more difficult and thus increase uncertainty. In addition, the difference in the scope of the dataset is also an important reason. For example, CNLUCC is a dataset for China, so the identified area of land cover change identified is higher than that in other datasets.

We counted the consistency score percentages of six datasets, including GAIA and Hansen-GFC (Figure 9b). First, for the gain in construction, the percentages of consistency scores “1,” “2,” “3,” “4,” and “5” were 68.17%, 19.67%, 8.07%, 3.35% and 0.74%, respectively. The consistency for the gain in construction was relatively high, and the percentage of high consistency (score for 2–5) was 38.83%. Then, for the gain in forest, the percentages of consistency scores “1,” “2,” “3,” “4,” and “5” were 87.24%, 11.91%, 0.83%, 0.02% and 0.001%, respectively. That is, the percentage of forest gain with high data consistency (2–5) was 12.76%.

Finally, for forest loss, the consistency of the forest loss was lower than that of the forest gain. The percentages of consistency scores “1,” “2,” “3,” “4,” and “5” were 91.15%, 8.47%, 0.37%, 0.01% and 0.00%, respectively. There was no pixel with the highest consistency score (5) for forest loss. In general, the consistency of construction increase was higher than that of forest gain and loss. That is, the increasing trend of Chinese cities is more obvious than the trend of forest change, and it can be more easily identified by datasets. In addition, land use policies in different regions of China have also led to unstable trends in forest changes, which in turn lead to low data consistency.

Discussion

Differences between different measurement methods

In addition to the likelihood assessment method, we also evaluated the consistency between datasets by the method of land cover fraction changes. We analyze the effect of different analysis methods on the results.
by comparing different methods, and also thus prove the reliability of the neighborhood analysis results. First, we calculated the fraction of construction and forest in each dataset for the first and last years at a 1 km resolution. For example, for CCI-LC and MCD12Q1, the first and last years were 2001 and 2018, respectively, while for Globeland30, the first and last years were 2000 and 2020. Then, by subtracting the fraction of the last year from the fraction of the first year, we obtained the changes in the fraction of construction (gain) and forest (gain and loss) in different datasets. Finally, we randomly selected 50,000 points to calculate the coefficient of determination ($R^2$) and root mean square error (RMSE) between GAIA or Hansen-GFC and the other four datasets through formulas (1) and (2) (Figure 10). $R^2$ and RMSE are common methods for comparing correlations and consistency between data. We evaluated the consistency GAIA and Hansen-GFC through $R^2$ or RMSE and compared them with the results of the likelihood assessment method. Datasets with higher $R^2$ or lower RMSE values had better consistency.

$$R^2 = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} (Y_i - \bar{Y})^2}}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (X_i - Y_i)^2}$$

where $n$ is the number of random points (50,000); $i$ is the land cover change type (construction gain, forest gain or forest loss); $X_i$ is the fraction of CCI-LC, MCD12Q1, Globeland30 and CNLUC under different land cover changes; $Y_i$ is the fraction of GAIA and Hansen-GFC under different land cover changes; $\bar{X}$ is the average fraction of CCI-LC, MCD12Q1, Globeland30 and CNLUC; and $\bar{Y}$ refers to the average fraction of GAIA and Hansen-GFC.

For the gain in construction, the $R^2$ between GAIA and Globeland30 was the highest (0.38), and the $R^2$ between GAIA and MCD12Q1 was the lowest (0.13). Similarly, the lowest RMSE was between GAIA and Globeland30 (0.16), and the highest RMSE was between GAIA and MCD12Q1 (0.20). For the gain in forest, the $R^2$ between Hansen-GFC and other datasets was low, and the $R^2$ between Hansen-GFC and MCD12Q1 was the highest (0.03). The RMSEs between Hansen-GFC and CCI-LC, MCD12Q1, Globeland30 and CNLUC for forest gain were 0.16, 0.29, 0.11, and 0.12, respectively. The $R^2$ of the forest loss between Hansen-GFC and other datasets was smaller than the forest gain, and all were less than 0.001. The RMSEs between Hansen-GFC and CCI-LC, MCD12Q1, Globeland30 and CNLUC for forest loss were 0.15, 0.15, 0.12, and 0.12, respectively. Therefore, GAIA was more consistent with other datasets than Hansen-GFC. In addition, consistent with the results of the likelihood assessment method, the order of the consistency of land cover change was construction gain > forest gain > forest loss. Although the evaluation methods have different results, they have no influence on the final conclusion.

![Figure 10](image_url) Comparison of $R^2$ and RMSE between different land cover changes among datasets.
Research perspectives

Our results showed that the consistency between multi-source land cover datasets was not high. Therefore, to better provide a theoretical basis for land management in land cover datasets, we proposed some future research prospects. First, due to the different classification criteria of multi-source datasets, a unified classification conversion table is needed in the future. Previous studies have also analyzed the consistency of land cover datasets from the perspective of classification standards (Fisher 2010; Pérez-Hoyos, García-Haro, and San-Miguel-Ayanz 2012). For example, Pérez-Hoyos, García-Haro, and San-Miguel-Ayanz (2012) used the flexible Boolean comparison method to evaluate four land cover datasets in Europe and found that this method can minimize the uncertainty caused by the ambiguity of the legend, thereby increasing the consistency by approximately 10%. In this study, we reclassified all datasets, which may result in some loss of information. Therefore, a unified classification conversion table can help to unify different datasets and reduce uncertainty. Second, inconsistencies result from differences in the time resolution of the datasets, such as CCI-LC having a continuous time series and Globeland30 having a 10-year period. For example, due to the non-uniformity of the dataset time series, only four datasets can be selected for the consistency analysis. With the development of remote sensing technology and the increase in remote sensing images, continuous time series of land cover mapping has become an important topic. For example, Wang et al. (2021) used multi-source remote sensing products and Bi-LSTM deep learning methods to map China’s land cover classification from 1982 to 2015. Third, the different spatial resolutions of the datasets lead to inconsistencies, such as the resolution of MCD12Q1 being 300 m and the resolution of CNLUC being 30 m. It is also clear from the results that MCD12Q1, which has the lowest spatial resolution, has the greatest variation from the other datasets and the lowest consistency. The emergence of high-resolution remote sensing images has made fine land cover mapping possible, such as FROM-GLC10 (Gong et al. 2019). Fourth, most of the current land cover datasets focus on the types of land cover and ignore the importance of the fraction of land cover. The fraction of land cover can better reflect the land cover, and it is also easier to reconcile data. Our results found low data consistency for land cover change in China, which may be related to the different classification thresholds used for mapping. For example, CCI-LC classifies mosaic land with more than 50% cropland and less than 50% natural vegetation as mosaic cropland, while MCD12Q1 classifies cropland with more than 60% cover as cropland (Defourny et al. 2017; Friedl et al. 2010). Finally, a unified validation dataset is also crucial for the land cover products. At present, most of the global land cover verification datasets are collected through visual interpretation, which consumes considerable manpower and material resources, and since most of the existing verification datasets are generated to verify a land cover map, their effectiveness in verifying land cover data is limited (Tsendbazar et al. 2018; Xiong et al. 2017). In summary, the future production of land cover datasets needs to pay more attention to the unification of classification standards and resolutions, as well as fraction of land cover and verification datasets. Due to the low consistency of land cover change in China, there is an urgent need for high quality and high precision land cover datasets that can provide a scientific theoretical basis for land management and sustainable development.

Conclusion

The consistency assessment between datasets can provide a basis for improving the accuracy of the dataset. In this study, we analyzed the consistency and change in the consistency of multi-source land cover products in China through the likelihood assessment method and compared them with a high-resolution dataset. For the spatiotemporal changes in land cover, the difference between MCD12Q1 and other datasets was greater, and the consistency of bare land was greater than that of forest, grassland, and cropland. Therefore, we suggest that datasets with high spatial resolution should be selected as much as possible when conducting land cover studies. The results showed that although the data consistency scores were relatively average, there were no obvious spatial differences in land cover consistency. The consistency of land cover changes between the datasets was low, and the percentage of all land cover changes with low consistency was more than 87%. The comparison with high-resolution data showed that changes in forests were more difficult to identify and less consistent than changes in construction. Globeland30 may have higher accuracy when the study involves construction. However, due to the limitation of datasets, the first and last years of the land cover change analysis were not uniform. More long time series and high spatial resolution land cover datasets are needed in the future for consistency assessment.

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Appendix

Figure A1. The percentage of different land cover types by province in 2010.

Figure A2. Consistency of (a) forest; (b) grassland; (c) cropland; (d) bare land in 2010.