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RESEARCH

Using Open Foris Collect Earth in Kyrgyzstan to support greenhouse gas inventory in the land use, land use change, and forestry sector

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Abstract The Kyrgyz Republic (Kyrgyzstan) is one of the countries most vulnerable to the adverse effects of climate change in Central Asia. The land use, land use change, and forestry (LULUCF) sector is critical in climate change mitigation in Kyrgyzstan and is integral to national greenhouse gas (GHG) inventories. However, consistent, complete, and updated activity data is required for the LULUCF sector to develop a transparent GHG inventory. Collect Earth (CE), developed by the Food and Agriculture Organization of the United Nations (FAO), is a free, user-friendly, and open-source tool for collecting activity data for the LULUCF sector. CE assists countries in developing GHG inventories by providing consistent and complete land representation. This article reports an estimate of land use and land-use change dynamics in Kyrgyzstan, based on analyzing 13,414 1-hectare (ha) sampling units through an augmented visual interpretation approach using satellite imagery at the very high spatial and temporal resolution available through the Google Earth platform. The results show that in 2019, forests covered 1.36 million ha or 6.83% of the total land with a 6.23% uncertainty. This estimate was 5 to 16% higher than previous estimates, detecting an additional 63,024 to 188,164 ha of forestland that had not been reported previously. The new estimates suggest an average increase of 10.4% in the current forestlands of Kyrgyzstan.

Keywords Collect Earth · Google Earth · LULUCF · GHG inventory · Climate change · Kyrgyzstan

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Introduction

Kyrgyzstan is one of Central Asia's most vulnerable countries to the adverse effects of climate change due to its arid climate, sensitive environment, and natural ecosystems (Lioubimtseva et al., 2005). The country recognizes the urgency of climate change. Kyrgyzstan is taking necessary measures and actions to achieve sustainable development goals, ensure sustainable forest management (SFM), and tackle climate change according to its national conditions to contribute to the global objectives of the United Nations Framework Convention on Climate Change (UNFCCC) and the Paris Agreement.

Kyrgyzstan reports GHG inventories through national communications and biennial update reports. Base year total GHG emissions from all sectors have decreased from 28,290.68 giga ton carbon dioxide equivalent (Gg tCO_2e) to 17,858.41 Gg tCO_2e between 1990 and 2018.

The LULUCF sector is one of the five key economic sectors and focuses on the reporting and removal of human-induced GHG emissions as set out in the Intergovernmental Panel on Climate Change (IPCC) classification (Tzamtzis et al., 2019). These land-use types in the IPCC report include forestlands, croplands, grasslands, wetlands, settlements, and other lands.

LULUCF is integral to national GHG inventories and mitigation actions and critical to carbon sequestration and storage in Kyrgyzstan. Total GHG removals in forestry and other land-use sectors were 10,273.53 Gg tCO_2e in 1990 and 10,941.37 Gg tCO_2e in 2018 (NIR, 2022). The LULUCF sector is the only sink sector reducing the overall GHG emissions in the country. GHG removals from this sector have increased by 6.5% between 1990 and 2018 thanks to implementing SFM practices, such as afforestation and forest restoration.

As stated in the first Nationally Determined Contributions (NDC), total GHG emissions would reach 46,302 Gg tCO_2e, and GHG removals would be 11,759 Gg tCO_2e in the LULUCF sector by 2050 under the business-as-usual (BAU) scenario. As a developing, lower middle-income country, Kyrgyzstan has set targets to reduce GHG emissions by 15.97% (27,986 Gg tCO_2e; – 12,532 Gg tCO_2e from the LULUCF sector) under the BAU scenario and by 43.62% (17,552 Gg tCO_2e; – 12,159 Gg tCO_2e from the LULUCF sector) if international support is mobilized (NDC, 2021).

The NDC document considered mitigation actions in all relevant sectors in the country, such as energy, agriculture, forestry, and other land-use sectors. The mitigation targets in the forestry and other land-use sectors will be achieved through expanding carbon sinks and planting perennial vegetation, strengthening the national measurement, reporting, and verification (MRV) system, and introducing new technologies for low-carbon development (NDC, 2021).

LULUCF activities can support the achievement of the mitigation goals in NDC, ensure sustainable land and forest management, increase GHG removals from the atmosphere, enhance carbon stocks in carbon pools, contribute to national development goals, and provide economic, social, and environmental co-benefits.

Forest ecosystems have high priority in the LULUCF sector because of their carbon sequestration and storage capacity. Nevertheless, Kyrgyzstan is among the countries that have a low forest cover. Forestlands in Kyrgyzstan covered 1.29 million ha in 2019 (FAO, 2020). However, according to national statistics, the total state forest fund area is over 2.6 million ha (NC3, 2016), of which 1.17 million ha is covered by forests as of 2019 (GoK, 2022). The per capita forest area is 0.2 ha, mostly unevenly distributed across the country. Around 90% of forests are located between 700 and 3600 m in elevation (Jia et al., 2019; SAEPF, 2015). Nevertheless, forests face some issues, such as anthropogenic forest degradation due to overharvesting for logging, fuelwood and buildings, unregulated livestock grazing, an increasing population that puts more pressure on forestlands, and inadequate financial resources. These problems result in the unsustainable use of forest resources and reduce the carbon sequestration and storage capacity by forests.

Continuous monitoring of LULUCF is essential for efficient reporting and verification of carbon stocks and changes to meet the international commitments of Kyrgyzstan in this sector. GHG inventory in the LULUCF sector requires consistent, transparent, complete, and up-to-date activity data. In contrast to pixel-based maps, sample-based area estimation allows the correction of systematic errors and provides confidence intervals based on sampling errors required by the Paris Agreement. Therefore, the countries do not only accurately measure and report GHG emissions but also they assess the uncertainties embedded in their calculations (Sandker et al., 2021). Additionally, periodic monitoring of lands is essential to estimate the total extent and changes over time, support policy and strategy development, facilitate decision-making, improve the planning process (Khadka et al., 2020; Romero-Sanchez & Ponce-Hernandez, 2017), and evaluate human interventions and impact on land resources (Li & Shao, 2014). Moreover, it supports categorizing land-use types and sub-classes and achieves highly accurate land-use change estimates (Maniatis et al., 2021), ensures sustainable land/forest management, and promotes the sustainable provision of ecosystem services in production landscapes.

In this context, Open Foris Collect Earth (CE), developed by FAO, supports countries for efficient, low-cost monitoring of lands and generates relevant data and information for reporting purposes (Bey et al., 2016; Maniatis et al., 2021; Reytar et al., 2021; Tzamtzis et al., 2019).

CE has been widely used in recent studies to develop forest cover maps (Schepaschenko et al., 2015), estimate the global extent of tree cover and forest cover in dryland biomes (Bastin et al., 2017), report land use and land use changes (García-Montero et al., 2021a; Martín-Ortega et al., 2018), and monitor trees outside forests (García-Montero et al., 2021b). CE also supports countries by providing consistent and complete land representation to calculate carbon stocks and changes based on IPCC guidelines (Tzamtzis et al., 2019).

Several studies have been conducted in Kyrgyzstan using remote sensing techniques or CE at local levels. For example, Jia et al. (2019) prepared a forest cover map with a hybrid approach, combining land cover, geographical features, and classifier products. The forest cover was estimated as 472,369 ha or 2.4% of the country's land area. Piroton et al. (2020) monitored landslides and identified triggering factors in the Mailuu-Suu Valley, showing that long-term land degradation and small-scale displacement, heavy rainfall events, and rapid snow melt trigger landslides. In another study, Nazarkulov et al. (2021) conducted a geohazard inventory, detected hazards in 3500 plots, and developed geohazard maps by interpreting 85,000 sample plots in the Uzgen region.

On the other hand, De Simone et al. (2021) detected 41,400 ha of forest cover loss in mountainous areas by monitoring Mountain Green Cover Index between 2015 and 2018. Finally, Isaev et al. (2023) monitored walnut forests in the western Tien Shan using the normalized difference vegetation index (NDVI) and vegetation condition index (VCI) calculated based on the Sentinel-2 satellite and drone images.

While each of the studies focused on different aspects of land monitoring at different levels, an updated national dataset for the LULUCF is lacking in Kyrgyzstan to monitor land use and land use change trends and to support developing a comprehensive GHG inventory. A scientifically sound assessment is needed to provide an updated LULUCF sector report and reveal the spatiotemporal change in Kyrgyzstan. To this end, the present study aims to systematically monitor land use dynamics in Kyrgyzstan using a state-of-the-art remote sensing tool (i.e., CE) based on the national grid system.

Materials and methods

Study area

The study area is Kyrgyzstan at the national level (Fig. 1). With its seven regions, Kyrgyzstan is located within the Tien Shan and Pamir-Alai Mountain ranges, where less than 20% of this territory has comfortable living conditions due to the mountainous topography. The country has a continental and mainly arid climate, divided into four climate zones based on elevation above sea level (NC3, 2016).

The country has an area of 19.90 million ha[1] with 2.66 million ha of state forest land (GoK, 2022). According to the FAO, the country's total land area is 19.18 million ha,[2] and forestlands cover almost 1.29 million ha. The area of forestlands has increased by 14.14% between 1990 and 2019 (FAO, 2020).

Collect Earth software

CE, a free and publicly accessible software, collects current and historical data on forestlands, croplands, grasslands, wetlands, settlements, and other lands using the Google Earth platform and a Java- and HTML-based data entry form (Makinta et al., 2015). Users can visually interpret moderate to very high spatial and temporal resolution satellite images, archives, and databases in Google Earth, Bing Maps, Yandex, Google Earth Engine, Google Earth Engine Code Editor, DigitalGlobe, SPOT, Sentinel-2, Landsat, MODIS, and Planet data (Bey et al., 2016; Maniatis et al., 2021). Moreover, Google Earth Engine automatically generates NDVI data and graphics for selected sample plots using MODIS data since 2000 and Landsat and Sentinel data at all available dates without cloud cover (Schepaschenko et al., 2019).

[1] The total area (19,905,183 ha) of Kyrgyzstan is created by CE (extracted from areas_per_attribute.csv) and could differ from the official statistics (19,995,100 ha).

[2] The total area (19,180,000 ha) of Kyrgyzstan by FAO and could differ from the official statistics (19,995,100 ha).

Fig. 1 Map of the study area (UN, 2011)

The data entry forms in CE contain IPCC and national-consistent land use categories, sub-categories, and sub-divisions. The data entry forms may be customized in CE, as was done in this study for Kyrgyzstan-specific classification schemes consistent with the guidelines of the IPCC and FAO.

Users can collect information for each sample plot, including the latest satellite images, vegetation types, vegetation density, infrastructure elements and cover, water bodies, disturbances such as floods, landslides, overgrazing, fires, and year of land conversion. The "Collect" database automatically saves the data entered in CE, and Saiku Server uses this data for analyses. Users can analyze and assess historical and current data through the publicly available web-based Saiku software. Saiku provides the outputs in tabular or graphic formats that can be exported as XLS, CSV, PDF, PNG, or JPG files (CE, 2023; Makinta et al., 2015).

Sampling design

Grid design

The sampling design for the 2019 LULUCF assessment was based on the 2015 LULUCF assessment. A regular, systematic grid measuring 0.04°×0.04° was established nationwide with 13,414 sample plots. The grid from 2015 was reproduced from the*.csv* file used in that assessment to maintain the same ID for comparison. It was transformed into a vector file (*.shp*) and uploaded to Google Earth Engine to add new variables due to the requirements of the updated survey. These attributes were later used in the final grid.

Due to a decrease in longitude values towards the north direction, longitude distances between sampling points in the grid are greater in the south than in the north. Because latitude is not affected by this effect, the distance in latitude between plots remains equal.

- Maximum longitude and latitude distances between sampling points in the northernmost part of the grid: Long: 3.25 km; Lat: 4.44 km.
- Minimum longitude and latitude distances between sampling points in the southernmost part of the grid: Long: 3.45 km; Lat: 4.44 km (Fig. 2).

Sampling design

Square sample plots with an area of 1 ha (100 m × 100 m) were systematically distributed to the entire study area (Fig. 3). However, this sampling size (i.e., 1 ha) contrasts with the national definition of forest in Kyrgyzstan, which was recently adopted right after the 2015 LULUCF assessment. In Kyrgyzstan, a "forest" is defined as land spanning at least 0.2 ha with trees and shrubs higher than 1.9 m and 0.5 m, respectively, and a canopy cover of more than 10%, minimum width of 25 m, and minimum stand density of 0.1 (GoK, 2015). Following the national forest definition, a forest was considered the land covering a minimum of 10% of the sample plot with trees or shrubs, with a minimum 25 m distance between the trees (GoK, 2015) in this study.

Area calculation (expansion factors)

CE automatically calculates the expansion factors, the area representing a plot using the IPCC guidelines (IPCC, 2006). We calculated the expansion factor with the extent of 7 regions in Kyrgyzstan. In this regard, the expansion factor (F) was calculated through Eq. 1 for all plots across the country.

$$Fc = Ac/Nc \tag{1}$$

where Fc is the expansion factor of a plot in the country, Ac is the country's total area (extracted from areas_per_attribute.csv), and Nc is the number of plots within the country.

Table 1 shows the equivalence of area per plot after applying the expansion factors.

The areas of the country and provinces (*.shp format*) were extracted using a Google Earth Engine (GEE) script developed by FAO. According to this dataset, the country's total area is 19.90 million ha, extracted from areas_per_attribute.csv. Province areas were extracted from the Global Administrative Unit Layers (GAUL) dataset and correspond to areas shown in Table 1.

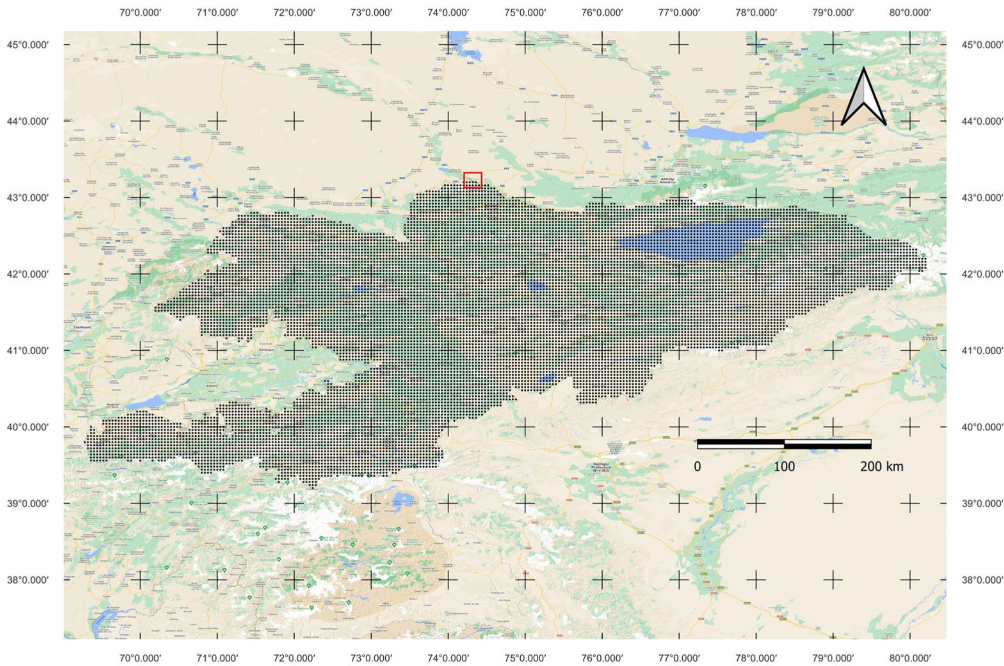
Survey design

Use of Open Foris Collect for survey design

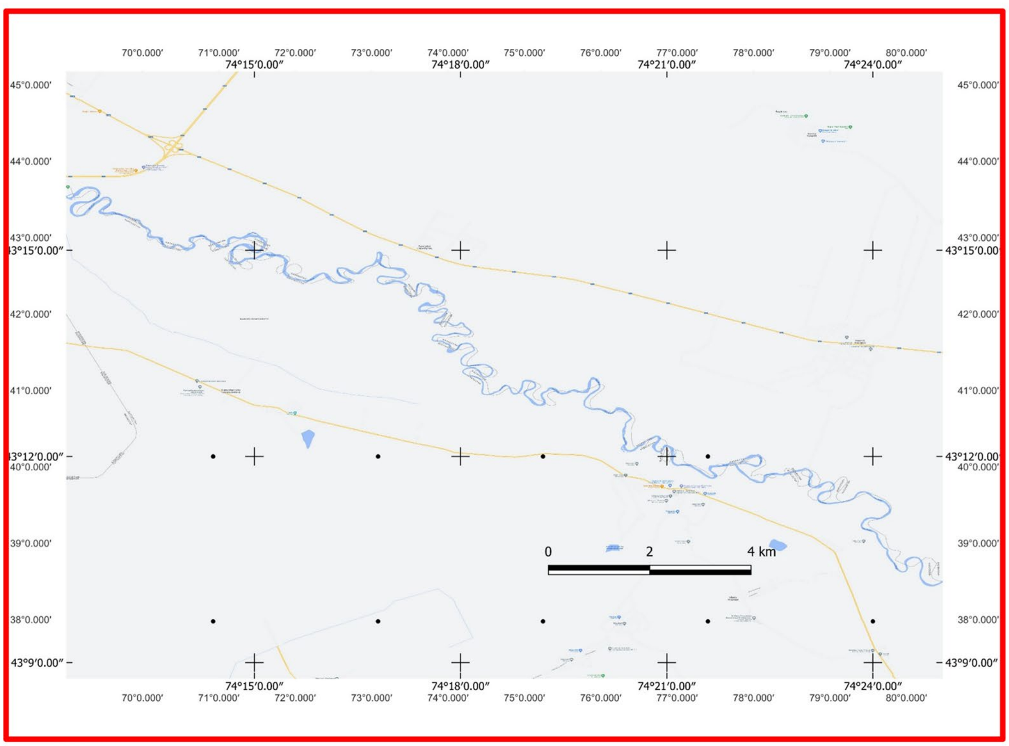
The survey used in Kyrgyzstan's Mapathon focused on collecting LULUCF data. The survey was designed using Open Foris Collect. It was cloned from a recent survey designed to conduct assessments in several African countries (Africa DEAL 2019 v.3.2.cep). Africa DEAL 2019 v.3.2 resulted from many years of improvement following feedback from several assessments carried out worldwide. It incorporates internal calculations and rules of validation to avoid mistakes in assessing sample plots. Finally, it was intended to be a standard survey used for the whole African continent and, therefore, a comparable survey for Africa and worldwide to carry out LULUCF assessments.

The main changes in the original survey were related to national classifications (land use sub-categories and sub-divisions) and the addition of elements commonly observed in high-resolution images, such as glaciers. An additional tab was designed to evaluate erosion, a significant driver and threat of land degradation, and a barrier to sustainable land management and development in the country (Khan et al., 2018; Wang et al., 2020). The final survey, which was available in English, has a total of 7 tabs (Fig. 4).

The first four tabs, "Imagery," "Erosion," "Description," and "Attributes," are descriptive tabs where the interpreter has to choose between different options (imagery and erosion) and count which elements are present inside the plot (description, attributes). In the description and attributes tabs, the user must count the number of dots (the plot has 49 dots, and the central one is painted red) that fall on top of each element. Each dot represents a 2% cover. The tabs "LU2019" and "LULUC" describe the land use observed in the plot following IPCC rules and also temporal changes, if any. Finally, the "Comments" tab allows operators to provide any additional comments which could not be reflected in the survey.



(A)



(B)

Fig. 2 The systematic, regular grid for Kyrgyzstan with 13,414 sample plots. **A** Distance between points in longitude distances is lower in high latitudes than in lower latitudes. **B** A zoomed square in red is shown in the northern part

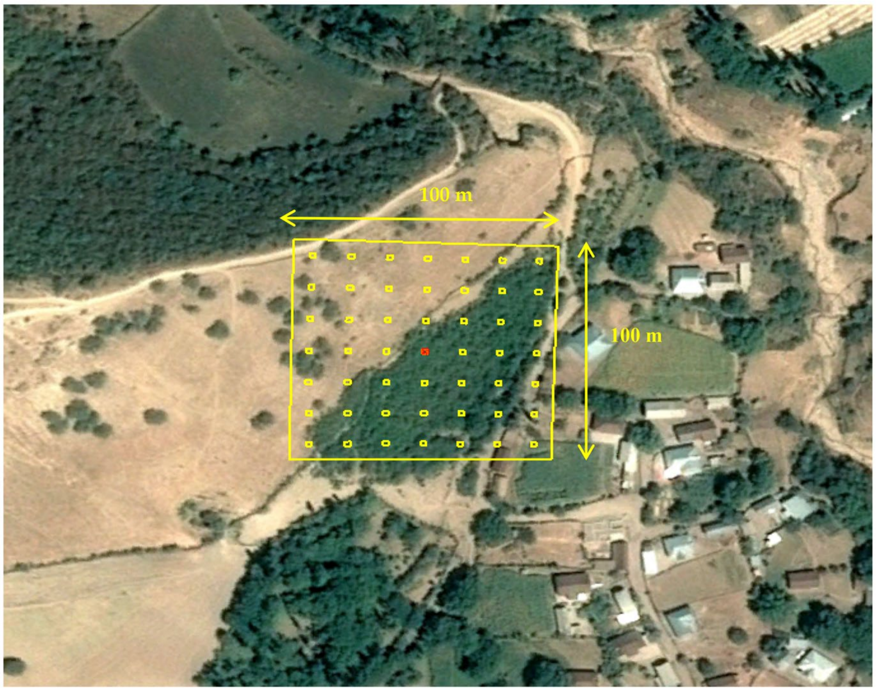


Fig. 3 An example of a 1-ha sampling unit

Reference labeling protocol

The six main land-use categories used in this study were proposed by Chapter 3 of the 2006 IPCC Guidelines for National GHG Inventories: forestlands, croplands, grasslands, wetlands, settlements, and other lands (IPCC, 2006). Each sample plot was assigned to one of the six main land-use categories. In addition, land-use sub-categories and national sub-divisions were used (Fig. 5).

Table 1 The number of plots, area of the different regions, and equivalent area of each plot

Province	Area of the region (ha)	Equivalent area per plot (ha)
Batken	1,669,178	1,529.95
Chuy	1,999,006	1,484.04
Jalal-Abad	3,341,600	1,481.86
Naryn	4,529,919	1,487.16
Osh	2,932,652	1,510.89
Talas	1,140,848	1,455.16
Ysyk-Kol	4,291,980	1,468.34

Hierarchy for the classification of land use in the plot

Martínez and Mollicone (2012) developed hierarchical rules to classify land use categories based on land cover and forest definition of FAO. Table 2 provides hierarchical rules and thresholds for all land categories. A plot with 30% of tree/shrub cover is classified as forestland unless it has more than 20% of settlements or croplands. Once the primary land use was determined, the operators classified the land for sub-categories and sub-divisions using the land representation scheme described in Fig. 5. This hierarchy allows classifying a plot with a single-use class in case there is a mixture of different land uses within the plot.

Data collection

A 10-day "Capacity Development Training on LULUCF Assessment Training" was conducted in Bishkek/Kyrgyzstan between 15 and 25 April 2019 to undertake LULUCF assessment through CE. During the first 3 days, the operators were trained to perform CE and interpret high-resolution images to assess land use trends and land use change in Kyrgyzstan. During the remaining

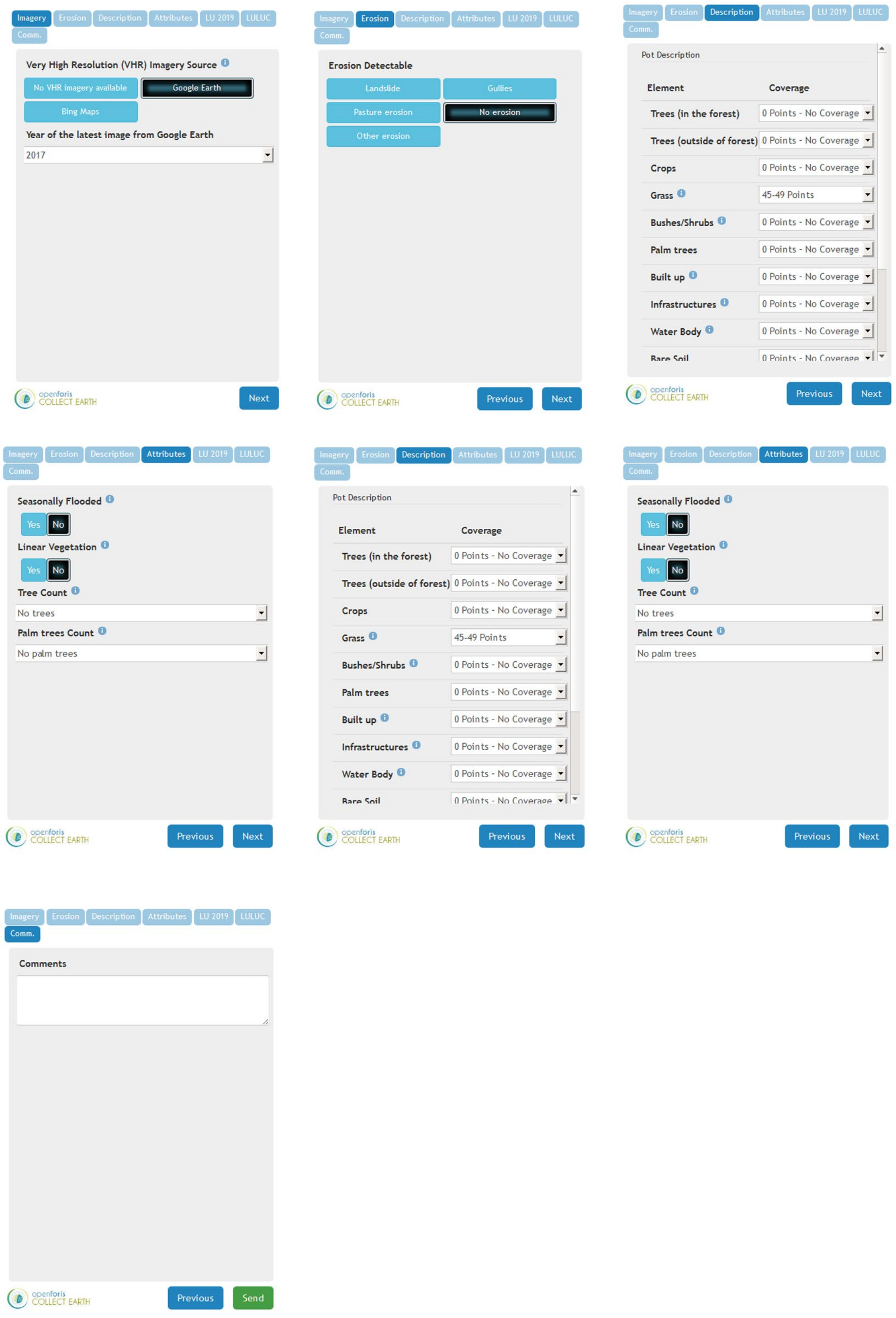


Fig. 4 An example of data collection forms

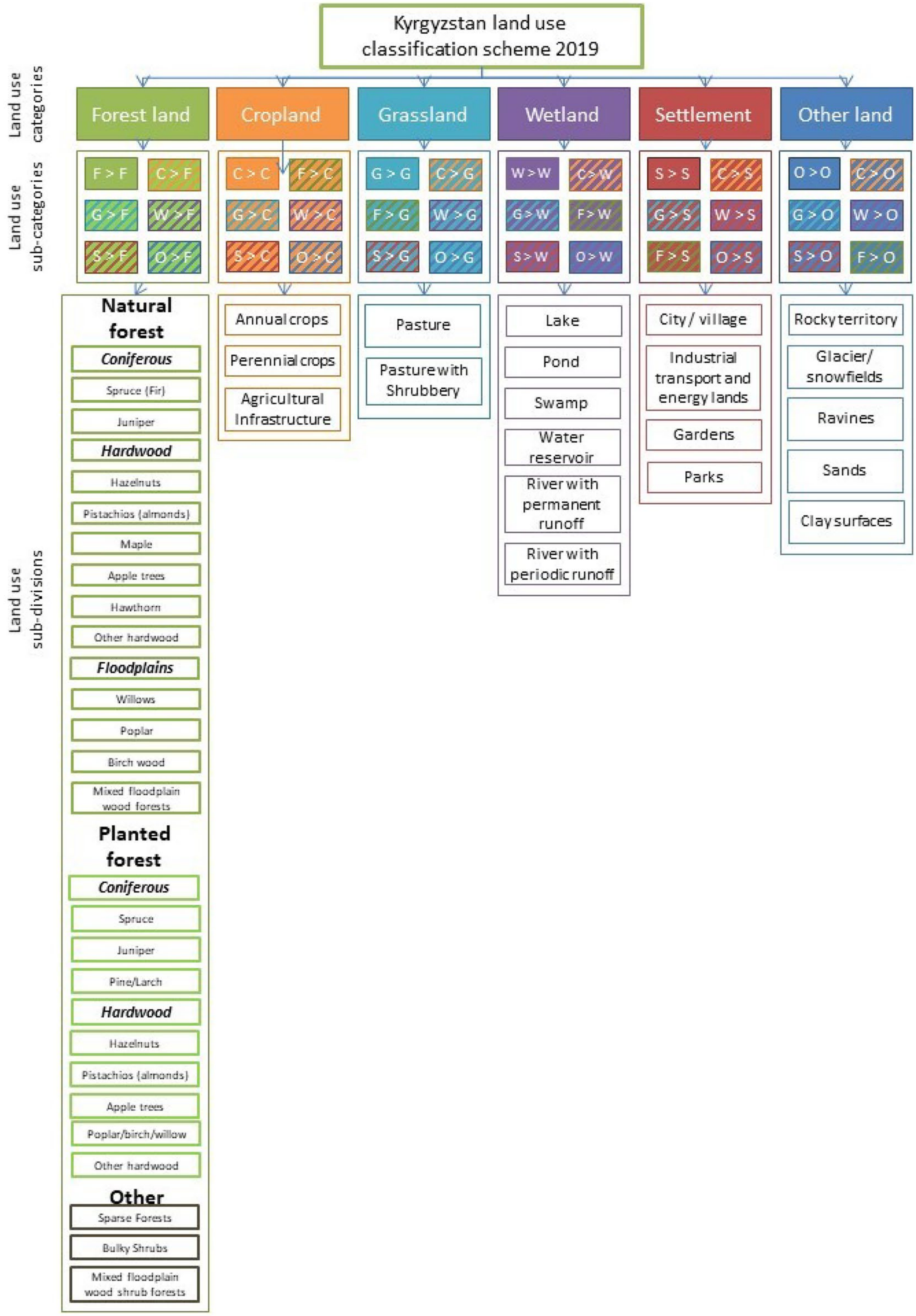


Fig. 5 IPCC's land representation scheme

Table 2 Hierarchy to classify IPCC land use classes

Category	Minimum land cover
Settlements	20%
Croplands	20%
Forestlands	30%
Grasslands	20%
Wetlands	20%
Other lands	> 20%

days of the Mapathon, the operators assessed LULUCF information visually on individually assigned batches of sample plots through CE.

The sampling design for the LULUCF assessment was conducted using free, open-source, high-resolution image repositories and optical datasets available on Google Earth, Bing Maps, Google Earth Engine Explorer, and Code Editor (i.e., Annual Greenest-Pixel, 32-Day, and 8-Day Top of Atmosphere Reflectance Composites from Landsat 7 and 8). Google Earth Engine also enabled visualization of false color composites using bands 4, 5, and 3 of Landsat 7 images and bands 5, 6, and 4 of Landsat 8 images.

Data check and validation

Plots assessed during the training were checked and validated for consistency. Not all plots could be validated or reviewed due to time and resource constraints. For those plots that could not be entirely reviewed, descriptive interpretations in the form of tables and figures were provided. Other plots, due to their importance for the assessment (forestland and plots with observed changes), were reviewed more thoroughly:

- All plots classified as forestlands were consistently reviewed one by one. This decision was made due to the significant role of trees and shrubs as carbon stocks. The number of forest plots was initially 956; however, it decreased to 911 after revision.
- All plots classified with observed changes were also checked for consistency because of the nature of the LULUCF assessment. The number of plots with observed changes was initially 56, but it decreased to 22 after revision.

Results and discussion

Comparison between LULUCF 2015 and LULUCF 2019

The study updated the previous LULUCF assessment by correcting overestimations. The comparison between LULUCF assessments 2015 and 2019 is presented in Table 3. The main differences were in grassland, at 9.21%, and other lands, at −4.72%. These differences may be related to misclassifications of land use classes between the periods. Another significant difference was found in the forest class with a −2.37%, probably due to an overestimation in the 2015 assessment.

The new results showed that forestlands in Kyrgyzstan cover 1.36 million ha or 6.83% of the total land with a 6.23% sampling error. According to Jia et al. (2019), forestlands covered 472,369 ha in 2010, approximately 2.4% of the country. However, the forest definition could explain the low estimation of forest area since a 40% tree cover threshold value was used in the study. Yin et al. (2017) reported that forests covered 3.3% of the total land in Kyrgyzstan from 2009 to 2011. Tomaszewska and Henebry (2021) estimated that croplands covered less than 10% of and forests covered around 5% from 2001 to 2017 in Kyrgyzstan. The differences in forest area can be explained by distinct reporting periods and the varying forest definitions authors used.

In our study, the forest area estimate is 5 to 16% higher than previous estimates (FAO, 2020; GoK, 2022), equal to 63,024 to 188,164 ha of forest that has never been reported. The new estimate increases current forestlands by 10.4% on average in Kyrgyzstan.

Table 3 Differences between LULUCF 2015 and LULUCF 2019

	Settlements	Forests	Wetlands	Croplands	Other lands	Grasslands
% Area IPCC 2019	1.77	6.83	4.05	8.64	24.19	54.51
% Area IPCC 2015	1.48	9.20	4.38	10.20	28.91	45.30
The difference in % 2019–2015	0.29	−2.37	−0.33	−1.56	−4.72	9.21

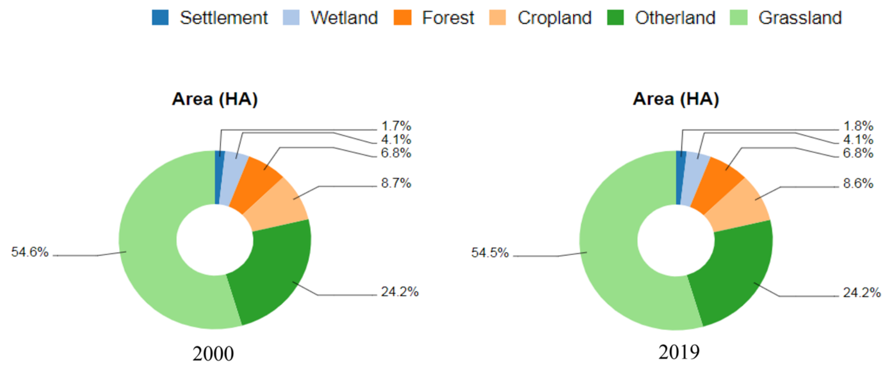


Fig. 6 IPCC land proportions for 2000 and 2019

However, according to the first national forest inventory (2008–2010), forests have decreased from 1.42 to 1.39 million ha between 1990 and 2010 (NC3, 2016). Ann inconsistency is apparent between NC3 (2016) and GoK (2022).

Land use and land use change

The assessment shows that land use change has been minimum from 2000 to 2019 in Kyrgyzstan (Fig. 6). The total land use change produced across all land types is 1.44% (assessed plots with detected changes are 22/13,414 = 0.16%).

Similarly, Klein et al. (2012) developed land use change maps for Central Asia using MODIS time series from 2001 to 2009. Chen et al. (2013) also developed land cover/land use change maps for Central Asia between 1990 and 2009 with three different datasets. Both studies detected land use changes (i.e., deforestation, a decrease of croplands) over time at the regional level and provided some insights at the country level. However, they either used different land use classifications or provided quantitative data at the regional level. Likewise, Hu and Hu (2019) reported that grasslands and bare lands (other lands) covered 71.7% and 7.1% in 2017, which is compatible with our findings. The difference between the estimates could be explained by the reporting period and the difficulty distinguishing between the grasslands and other lands.

Regarding the changes among six land use types, Kyrgyzstan experienced land use change and area increase mainly in settlements and grasslands. An area increase follows this in other lands and forestlands. On the other hand, the area of croplands and wetlands has decreased considerably (Tables 4 and 5).

The greatest loss discovered for 2000 was due to the conversion of croplands, followed by wetlands. Croplands were converted mainly into settlements (−0.43%) and some into grasslands (−0.17%). Grasslands (−0.12%), forestlands (−0.11%), and other lands (−0.06%) were lost to a lesser extent. Higher gains in 2019 correspond to settlements (+0.47%) which have only gains from other land use types and can be interpreted as urban expansion. Grasslands also showed an increase (+0.46%). Forestlands experienced an increase of 0.21%, followed by other lands (0.20%) and croplands (0.09%) to a lesser extent.

Table 4 Land use change matrix for 2000–2019 (the units are in ha)

Land use (2019)	**Land use 2000**					
	Forest	**Cropland**	**Grassland**	**Wetland**	**Settlement**	**Other lands**
Forest	1,355,660.61	0.00	3,017.12	1,487.17	0.00	0.00
Cropland	0.00	1,712,958.42	2,950.21	0.00	0.00	3,040.85
Grassland	1,454.88	2,963.73	10,845,141.04	1,481.86	0.00	0.00
Wetland	0.00	0.00	0.00	807,075.22	0.00	0.00
Settlement	0.00	7,445.71	4,391.62	0.00	341,104.33	0.00
Otherland	0.00	0.00	2,963.73	1,455.16	0.00	4,810,591.02

Table 5 Land use change matrix showing the percentage of different land use classes

Land use (2019)	Land use 2000						
	Forest	Cropland	Grassland	Wetland	Settlement	Other lands	Gain 2000–2019
Forest	99.89	0.00	0.03	0.18	0.00	0.00	+0.21
Cropland	0.00	99.40	0.03	0.00	0.00	0.06	+0.09
Grassland	0.11	0.17	99.88	0.18	0.00	0.00	+0.46
Wetland	0.00	0.00	0.00	99.45	0.00	0.00	+0.00
Settlement	0.00	0.43	0.04	0.00	100.00	0.00	+0.47
Otherland	0.00	0.00	0.03	0.18	0.00	99.94	+0.20
Loss 2000–2019	−0.11	−0.60	−0.12	−0.55	0.00	−0.06	

Net changes in land use are shown in Fig. 7. Between 2000 and 2019, net losses were found in wetlands and croplands, whereas forestlands, other lands, grasslands, and settlements increased in ascending order.

The results of this study support the decline of croplands in the country with a decrease of − 0.51%. This trend has a direct impact not only on forest conservation but also on the increase of forestlands (0.10%) and grasslands (0.34%). Most forests are naturally protected because of the insignificant agricultural pressure and because they are located in areas with low accessibility due to high altitudes and slopes with poor roads and railway networks. Moreover, forests in the country are also protected as natural areas. Describing trends in the amount of land allocated to agricultural use is vital to understanding land use change, primarily because agriculture has been viewed as the primary driver of deforestation worldwide (Khan et al., 2018).

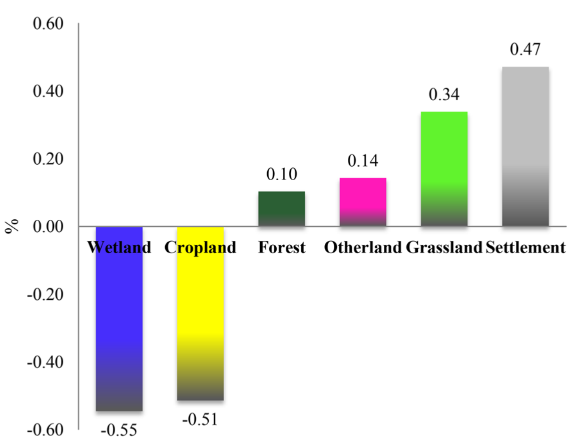


Fig. 7 Net gains and losses in land use categories from 2000 to 2019

Forest loss from 2000 to 2019 represents only 1454.88 ha due to transformations from hardwood plantations into grasslands for grazing, the leading driver for forest disturbance. Most of the area gained (4504.29 ha) corresponds to newly established spruce and pistachio plantations and recurrently flooded floodplains colonized by willow species. This net increase in forest area was 0.22% (Fig. 8).

Although our study showed a total net forest increase of 3049.4 ha, FAO (2020) provided a total net forest increase of 116,240 ha from 2000 to 2019. Likewise, national statistics (GoK, 2022) show a total net forest increase of 10,900 ha from 2011 to 2019. The methodology and forest definition could explain the most remarkable difference between the findings. However, a more detailed

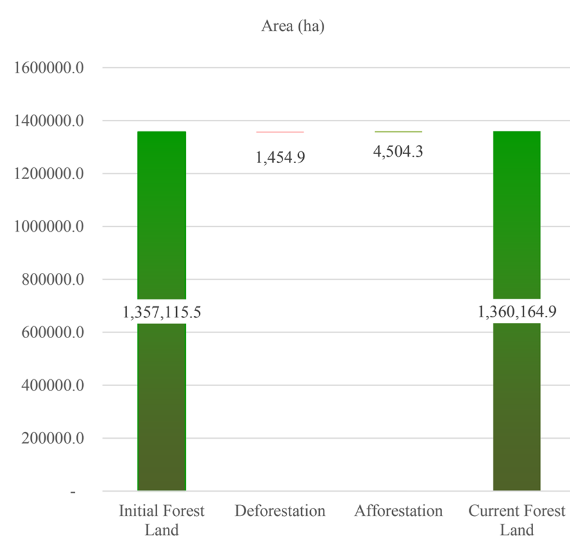


Fig. 8 The total area gained and lost owing to deforestation or afforestation practices from 2000 to 2019 (ha)

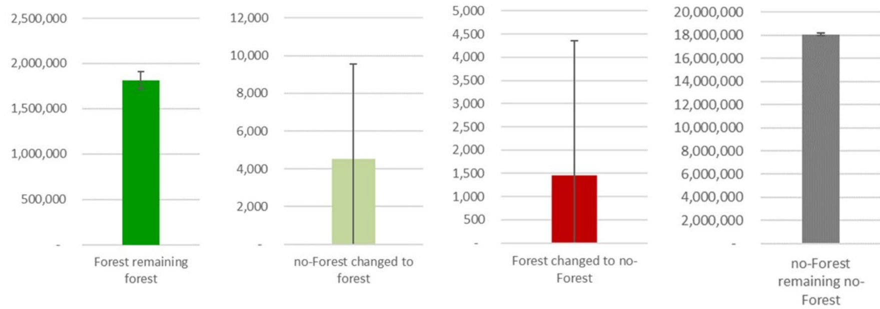


Fig. 9 Uncertainties associated with changes in forest and non-forest lands

LULUCF assessment can be conducted to improve the quality of the work. On the other hand, Hansen et al. (2013) reported 30,000 ha of tree cover loss for Kyrgyzstan based on the results from a time-series analysis with Landsat imagery by characterizing global tree cover extent and change. Similarly, De Simone et al. (2021) detected 41,400 ha of forest cover loss in mountain areas by monitoring Mountain Green Cover Index between 2015 and 2018. The difference in this study could be explained by the reporting years, forest definition, or the methodology applied.

Based on the uncertainty analyses, there may not be an actual change in forest area in Kyrgyzstan because the difference in forest area from 2000 to 2019 is within the confidence interval. In other words, the change in the forest area is smaller than the confidence interval; hence, we found that no significant change occurred in Kyrgyzstan (Fig. 9) for these 19 years.

Current land use sub-divisions and their changes were detailed in Tables 6, 7, 8, and 9. The tables describe the current land subdivision in 2019 in rows, and the previous land use sub-division in 2000 in columns, allowing tracking the conversion more effectively.

Table 6 Forestland sub-division categories, ha

Forest	Land use subdivision 2000	
Land use subdivision 2019	**Pasture**	**River with permanent runoff**
Natural Floodplains-Willows	–	1,487.17
Planted Forest Coniferous-Spruce	1,487.17	–
Planted Forest Hardwood-Pistachios (almonds)	1,529.95	–

Changes in land use occur evenly spaced in time with no particular event associated with them except for settlements which seem to be centered from 2011 to 2016.

The reasons behind the small land use changes observed in Kyrgyzstan between 2000 and 2019 are complex and seem to combine numerous factors. Some of the reasons directly related to land use and physical peculiarities have been investigated in the country. All these should be interpreted together along with socioeconomic and political factors.

This study developed a land use map for Kyrgyzstan to show the distribution of different land use categories across the country (Fig. 10).

Sampling uncertainties in Kyrgyzstan

Confidence intervals were calculated for the collected data. Confidence intervals reflect the robustness of the sample design adopted in Kyrgyzstan, indicating whether the sample is sufficiently representative of the land uses. The standard error (ha) of an area estimate was obtained from IPCC (2006). The following equation calculates the standard error of an area estimate:

$$A\sqrt{(p_i * (1 - p_i))/(n - 1)}, \quad (2)$$

Table 7 Cropland sub-division categories, ha

Cropland	Land use subdivision 2000			
Land use subdivision 2019	**Annual crops**	**Perennial crops**	**Pasture**	**Rocky territory**
Annual crops	–	1,454.88	1,481.86	1,529.95
Perennial crops	2,984.83	–	1,468.35	1,510.90

Table 8 Settlement sub-division categories, ha

Settlement	Land use subdivision 2000				
Land use subdivision 2019	**Annual crops**	**Perennial crops**	**Pasture**	**Gardens/orchards**	**Pasture with shrubbery**
City/village	5,958.54	–	–	1,454.88	
Industrial/transport/energy lands	–	–	1,454.88		1,481.86
Gardens/orchards	–	1,487.17	1,454.88	–	–

Table 9 Other land sub-division categories, ha

Otherland	Land use subdivision 2000		
Land use subdivision 2019	**Pasture**	**Sands**	**Pond**
Rocky territory	–	1,510.90	–
Sands	1,481.86	–	–
Ravines	1,481.86	–	–
Clay surfaces	–	–	1,455.16

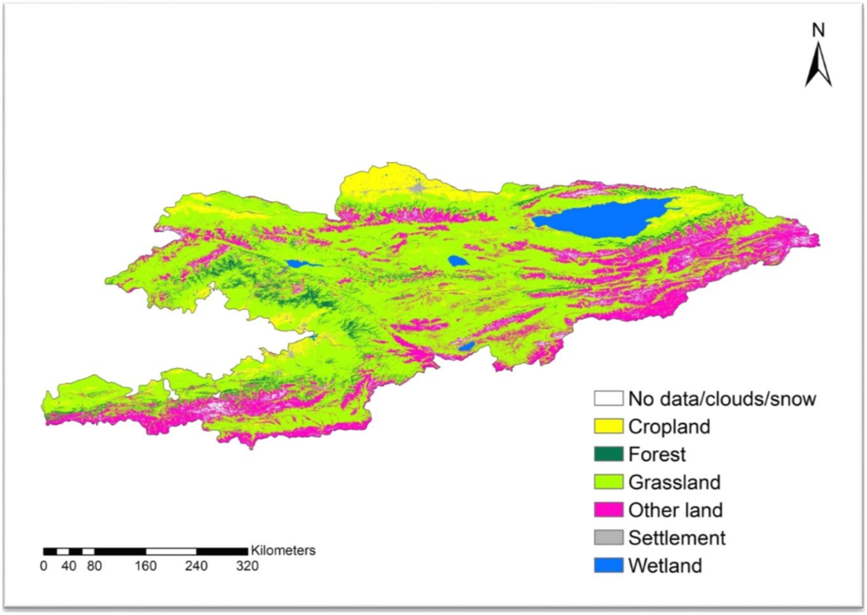


Fig. 10 Land use distribution in Kyrgyzstan at 30-m resolution

Table 10 Uncertainty estimates for Kyrgyzstan for 2019

Current land use 2019	Sample size	Area	Confidence intervals (ha)	Uncertainty %
Forest	911	1,360,165	±84,755.4	±6.23%
Cropland	1,163	1,718,949	±94,793.1	±5.51%
Grassland	7,307	10,851,042	±167,758.5	±1.55%
Otherland	3,247	4,815,010	±144,290.8	±3.00%
Wetland	548	807,075	±66,682.7	±8.26%
Settlement	238	352,942	±44,471.4	±12.60%
Total	13,414	19,905,183		

Table 11 Uncertainty estimates for Kyrgyzstan for 2000

Initial land use 2000	Sample size	Area	Confidence intervals (ha)	Uncertainty %
Forest	909	1,357,115	± 84,669.1	± 6.24%
Cropland	1,166	1,723,368	± 94,903.6	± 5.51%
Grassland	7,312	10,858,464	± 167,747.2	± 1.54%
Otherland	3,246	4,813,632	± 144,275.6	± 3.00%
Wetland	551	811,499	± 66,857.2	± 8.24%
Settlement	230	341,104	± 43,730.9	± 12.82%
Total	13,414	19,905,183		

where p_i is the proportion of sampling units in the particular land-use category i; A is the known total area, and n is the total number of sampling units. The 95% confidence interval for Ai, the estimated area of land-use category i, was given approximately ± 2 times the standard error (Tables 10 and 11).

Table 10 shows lower uncertainties in 2019, with ± 1.55% and ± 3.00% for grasslands and other lands, followed by croplands (± 5.51%), forestlands (± 6.24%), and wetlands (± 8.26%). The settlements show the highest value of uncertainty (± 12.60%), which indicates that an increase in sample size will result in a decrease in uncertainty. Because land use change was minimal, uncertainties for the initial year 2000 show minimum changes (Table 11).

Conclusions

The primary goal of the LULUCF assessment was to update the current and historical activity data in the LULUCF sector, monitor land use and land use change trends, and support national GHG inventory.

We used CE to demonstrate its efficiency in monitoring land use change, allowing Kyrgyzstan to update the land use activity data in the LULUCF sector to develop a robust and transparent national GHG inventory and reporting under the UNFCCC.

Open source, free use of very high-resolution imagery supported Kyrgyzstan to monitor the trends in all land-use categories where available data is outdated, overestimated, and field accessibility is limited.

The LULUCF assessment indicated that the total land use change is 1.44%. When comparing the 2000 and 2019 land use and land use change dynamics, Kyrgyzstan has experienced relatively minor land use changes in all land use types. There were minor increases observed in forests (0.10%), other lands (0.14%), grasslands (0.34%), and settlements (0.47%). On the contrary, minor decreases were observed in wetlands (0.55%) and croplands (0.51%). The primary drivers of land conversion in croplands were urbanization and grassland transformation. The settlement class experienced the most significant relative gain with 11,837 ha or a 3.4% increase from 2000 to 2019.

Forestlands in Kyrgyzstan covered 1.36 million ha or 6.83% of the total land, with a 6.23% uncertainty in 2019. The new forest area estimation was 5 to 16% higher than previous estimates, corresponding to an additional 63,024 to 188,164 ha of forestland that was not reported previously. The new LULUCF assessment increases the forest area by 10.4% in Kyrgyzstan. This study acknowledges the different forest extent estimates by other studies since the forest definition, country area, methodology, or reporting period could differ from our study.

Our study showed that CE is a time and cost-efficient software to generate accurate and consistent LULUCF data at various levels within a short period, particularly in lands where access is limited and the land-use information is outdated or non-existent. In light of the fact that spatially explicit LULUCF assessment previously overestimated the land extent, particularly forestlands, the new LULUCF data developed in this study provided reliable, accurate, and up-to-date activity data to support GHG inventory under the UNFCCC.

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Author contribution Pablo Martín-Ortega established the CE methodology and survey (area of attributes file, national grids, and Azerbaijan Mapathon (pilot CSV file)). Caglar Bassullu and Pablo Martín-Ortega designed and delivered capacity-building training. Caglar Bassullu and Pablo Martín-Ortega collected and coordinated the data collection by other operators through CE. Pablo Martín-Ortega conducted the quality control, data cleansing procedure, and reassessment of inconsistent sampling units. Pablo Martín-Ortega performed the statistical analyses. Caglar Bassullu conceived, designed, and wrote the paper. Caglar Bassullu and Pablo Martín-Ortega edited the manuscript. All authors contributed to the manuscript revision and read and approved the submitted version. The authors declare no competing financial interest.

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Data availability The data supporting this study's findings are available on request from the corresponding author, Caglar Bassullu.

Declarations

All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

Conflict of interest The authors declare no competing interests.

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References

Bastin, J. F., Berrahmouni, N., Grainger, A., Maniatis, D., Mollicone, D., Moore, R., et al. (2017). The extent of forest in dryland biomes. *Science, 356*(6338), 635–638.

Bey, A., Diaz, A. S., Maniatis, D., Marchi, G., Mollicone, D., Ricci, S., et al. (2016). Collect Earth: Land use and land cover assessment through augmented visual interpretation. *Remote Sensing, 8*, 807. https://doi.org/10.3390/rs8100807

CE. (2023). Open Foris Collect Earth Web Site. https://openforis.org/tools/collect-earth/. Accessed 27 Feb 2023.

Chen, X., Bai, J., Li, X., Luo, G., Li, J., & Li, B. L. (2013). Changes in land use/land cover and ecosystem services in Central Asia during 1990–2009. *Current Opinion in Environmental Sustainability., 5*, 116–127.

De Simone, L., Navarro, D., Gennari, P., Pekkarinen, A., & de Lamo, J. (2021). Using standardized time series land cover maps to monitor the SDG indicator "Mountain Green Cover Index" and assess its sensitivity to vegetation dynamics. *ISPRS International Journal of Geo-Information, 10*, 427. https://doi.org/10.3390/ijgi10070427

FAO. (2020). Extent of forest and other wooded land in Azerbaijan. *Global Forest Resource Assessment.* https://fra-data.fao.org/assessments/fra/2020/KGZ/sections/extentOfForest. Accessed 27 Feb 2023.

García-Montero, L. G., Pascual, C., Martín-Fernández, S., Sanchez-Paus Díaz, A., Patriarca, C., Martín-Ortega, P., et al. (2021a). Medium- (MR) and very-high-resolution (VHR) image integration through Collect Earth for monitoring forests and land-use changes: Global forest survey (GFS) in the temperate FAO Ecozone in Europe (2000–2015). *Remote Sensing, 13*, 4344. https://doi.org/10.3390/rs13214344

García-Montero, L. G., Pascual, C., Sanchez-Paus Díaz, A., Martín-Fernández, S., Martín-Ortega, P., García-Robredo, F., et al. (2021b). Land use sustainability monitoring: "Trees outside forests" in temperate FAO-Ecozone (oceanic, continental, and Mediterranean) in Europe (2000–2015). *Sustainability., 13*, 10175.

GoK. (2015). Order of the Government of the Kyrgyz Republic No. 706 about Approval of the Procedure for Carrying Out Forest Management in the Kyrgyz Republic (October 13, 2015). https://cis-legislation.com/document.fwx?rgn=81228. Accessed 7 June 2023.

GoK. (2022). Kyrgyzstan brief statistical handbook. National Statistical Committee of the Kyrgyz Republic. http://www.stat.kg/media/publicationarchive/672efdec-dda1-400c-96b4-f0508d24d220.pdf. Accessed 27 Feb 2023.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., et al. (2013). High-resolution Global Maps of 21st-century forest cover change. *Science*, *342*, 850–853. Data available online from: https://glad.earthengine.app/view/global-forest-change. Accessed 27 Feb 2023.

Hu, Y., & Hu, Y. (2019). Land cover changes and their driving mechanisms in Central Asia from 2001 to 2017 supported by Google Earth Engine. *Remote Sensing., 11*, 554. https://doi.org/10.3390/rs11050554

IPCC. (2006). IPCC Guidelines for National Greenhouse Gas Inventories. https://www.ipcc.ch/report/2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/. Accessed 27 Feb 2023.

Isaev, E., Kulikov, M., Shibkov, E., & Sidle, R. C. (2023). Bias correction of Sentinel-2 with unmanned aerial vehicle multispectral data for use in monitoring walnut fruit forest in western Tien Shan, Kyrgyzstan. *Journal of Applied Remote Sensing, 17*(2), 022204–1.

Jia, T., Li, Y., Shi, W., & Zhu, L. (2019). Deriving a forest cover map in Kyrgyzstan using a hybrid fusion strategy. *Remote Sensing, 11*, 2325. https://doi.org/10.3390/rs11192325

Khadka, A., Dhungana, M., Khanal, S., & Kharal, D. K. (2020). Forest and other land cover assessment in Nepal

using Collect Earth. *Banko Janakari, 30*(1), 3–11. https://doi.org/10.3126/banko.v30i1.29176
Khan, F., Sohail, Z., Khan, T., Fatima, B., Malik, F., Bukhari, S. F. H., et al. (2018). Deforestation: A continuous battle—A case study from Central Asia and other countries. D. Egamberdieva, M. Öztürk (Eds.), *Vegetation of Central Asia and Environs.* pp. 73–117. https://doi.org/10.1007/978-3-319-99728-5_4
Klein, I., Gessner, U., & Kuenzer, C. (2012). Regional land cover mapping and change detection in Central Asia using MODIS time-series. *Applied Geography, 35*, 219e234. https://doi.org/10.1016/j.apgeog.2012.06.016
Li, X., & Shao, G. (2014). Object-based land-cover mapping with high-resolution aerial photography at a county scale in Midwestern USA. *Remote Sensing, 6*(11), 11372–11390. https://doi.org/10.3390/rs61111372
Lioubimtseva, E., Cole, R., Adams, J. M., & Kapustin, G. (2005). Impacts of climate and land-cover changes in arid lands of Central Asia. *Journal of Arid Environments, 62*, 285–308.
Makinta J., Mbandezi S., Mollicone D., Marchi G., Bey A., & SanchezPaus Diaz, A. (2015). Monitoring forests and land use change in South Africa with free and open source software and free satellite imagery. *XIV World Forestry Congress*, 7–11 September 2015, Durban, South Africa.
Maniatis, D., Dionisio, D., Guarnieri, L., Marchi, G., Mollicone, D., Morales, C., et al. (2021). Toward a more representative monitoring of land-use and land-cover dynamics: The use of a sample-based assessment through augmented visual interpretation using Open Foris Collect Earth. *Remote Sensing, 13*, 4197. https://doi.org/10.3390/rs13214197
Martín-Ortega, P., Picard, N., García-Montero, L. G., del Río, S., Penas, A., Marchetti, M., et al. (2018). Importance of Mediterranean forests. In State of Mediterranean Forests 2018, 1st ed., Food and Agriculture Organization of the United Nations, Plan Bleu, Eds.; Food and Agriculture Organization of the United Nations: Rome, Italy; Plan Bleu: Marseille, France, pp. 31–50.
Martínez, S., & Mollicone, D. (2012). From land cover to land use: A methodology to assess land use from remote sensing data. *Remote Sensing, 4*, 1024–1045. https://doi.org/10.3390/rs4041024
Nazarkulov, K., Koshoev, M., Toktomametova, J., & Sakyev, D. (2021). Geohazards inventory in Central Asia using the geohazard mapping module of the FAO Collect Earth and Earth Map Tools. *International Journal of Geoinformatics*, *17*(1), Online ISSN 2673-0014.
NC3. (2016). Third National Communication of the Kyrgyz Republic under the UN Framework Convention on Climate Change. https://unfccc.int/sites/default/files/resource/NC3_Kyrgyzstan_English_24Jan2017_0.pdf. Accessed 27 Feb 2023.
NDC. (2021). Updated Nationally Determined Contribution 2021. https://unfccc.int/sites/default/files/NDC/2022-06/%D0%9E%D0%9D%D0%A3%D0%92%20ENG%20%D0%BE%D1%82%2008102021.pdf. Accessed 27 Feb 2023.
NIR. (2022). National inventory report on GHG emissions and removals in the Kyrgyz Republic for the period 1990–2018. https://unfccc.int/sites/default/files/resource/NIR%201990_2018_en.pdf. Accessed 27 Feb 2023.
Piroton, V., Schlögel, R., Barbier, C., & Havenith, H. B. (2020). Monitoring the recent activity of landslides in the Mailuu-Suu Valley (Kyrgyzstan) using radar and optical remote sensing techniques. *Geosciences, 10*, 164. https://doi.org/10.3390/geosciences10050164
Reytar, K., Martin, D., Landsberg, F., Ray, S., Granizo, C. G., Cristales, R. Z., et al. (2021). Mapping Together: A guide to monitoring forest and landscape restoration using Collect Earth mapathons. *World Research Institute*, Washington, DC, USA.
Romero-Sanchez, M. E., & Ponce-Hernandez, R. (2017). Assessing and monitoring forest degradation in a deciduous tropical forest in Mexico via remote sensing indicators. *Forests, 8*, 302. https://doi.org/10.3390/f8090302
SAEPF. (2015). Climate Change Adaptation Programme and Action Plan for 2015–2017 for the Forest and Biodiversity Sector. State Agency on Environment Protection and Forestry under the Government of The Kyrgyz Republic, ISBN 978-9967-27-830-1, 56p, Bishkek.
Sandker, M., Carrillo, O., Leng, C., Lee, D., d'Annunzio, R., & Fox, J. (2021). The importance of high–quality data for REDD+ monitoring and reporting. *Forests, 12*, 99. https://doi.org/10.3390/f12010099
Schepaschenko, D., See, L., Lesiv, M., Bastin, J. F., Mollicone, D., Tsendbazar, N. E., et al. (2019). Recent advances in forest observation with visual interpretation of very high-resolution imagery. *Surveys in Geophysics, 40*, 839–862. https://doi.org/10.1007/s10712-019-09533-z
Schepaschenko, D., See, L., Lesiv, M., McCallum, I., Fritz, S., Salk, C., et al. (2015). Development of a global hybrid forest mask through the synergy of remote sensing, crowdsourcing and FAO statistics. *Remote Sensing of Environment, 162*, 208–220.
Tomaszewska, M. A., & Henebry, G. M. (2021). Remote sensing of pasture degradation in the highlands of the Kyrgyz Republic: Finer-scale analysis reveals complicating factors. *Remote Sensing, 13*, 3449. https://doi.org/10.3390/rs13173449
Tzamtzis, I., Federici, S., & Hanle, L. (2019). A methodological approach for a consistent and accurate land representation using the FAO Open Foris Collect Earth tool for GHG inventories. *Carbon Management, 10*, 437–450.
UN. (2011). Map of Kyrgyzstan. https://www.un.org/geospatial/content/kyrgyzstan. Accessed 27 Feb 2023.
Wang, W., Samat, A., Ge, Y., Ma, L., Tuheti, A., Zou, S., & Abuduwaili, J. (2020). Quantitative soil wind erosion potential mapping for Central Asia using the Google Earth Engine platform. *Remote Sensing, 12*, 3430. https://doi.org/10.3390/rs12203430
Yin, H., Khamzina, A., Pflugmacher, D., & Martius, C. (2017). Forest cover mapping in post-Soviet Central Asia using multiresolution remote sensing imagery. *Scientific Reports, 7*, 1375. https://doi.org/10.1038/s41598-017-01582-x