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# Field validation of country-wide remote sensing based-land use classification in Kyrgyzstan

## Kırgızistan'da ülke çapında uzaktan algılama tabanlı arazi kullanım sınıflandırmasının saha doğrulaması

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**Abstract**

Observing and monitoring land use, land-use change and forestry (LULUCF) trends has extensively been used remote sensing. Collect Earth, a free remote sensing tool, was used in Kyrgyzstan to assess the historical and present LULUCF trends in 2015 and 2019. However, it is quite difficult for users to classify land cover and determine changes in land use if no satellite images with sufficient temporal and spatial resolution are available. The unavailability of high/very high spatial and temporal resolution satellite images (7.2%) or the availability of low spatial and temporal resolution satellite images (7.8%) was the primary reason for mandatory field verification. A fieldwork was conducted to validate the remote sensing assessment in 2019. In total, 941 sample plots were visited, and 119 misclassified sample plots were detected during the field validation work. Hence, this article reports an updated version of LULUCF assessment in Kyrgyzstan. The database update resulted in the re-classification of 1073 sample plots in Kyrgyzstan. The results of the field validation showed that forestlands occupied 1.81 million ha (9%) of the total land in 2019, with a 5.33% uncertainty in Kyrgyzstan. However, it was 1.36 million ha based on the remote sensing study.

***Keywords:*** Collect Earth, Field validation, Land use, Remote sensing, Kyrgyzstan

**Öz**

Arazi kullanımı, arazi kullanım değişikliği ve ormancılık (AKAKDO) eğilimlerini gözlemlemek ve izlemek için uzaktan algılama yaygın olarak kullanılmaktadır. Ücretsiz bir uzaktan algılama yazılımı olan Collect Earth, Kırgızistan'da 2015 ve 2019 yıllarındaki tarihi ve mevcut AKAKDO eğilimlerini değerlendirmek için kullanılmıştır. Ancak, yeterli zamansal ve mekansal çözünürlüğe sahip uydu görüntüleri mevcut değilse, kullanıcıların arazi örtüsünü sınıflandırması ve arazi kullanımındaki değişiklikleri belirlemesi oldukça zordur. Yüksek/çok yüksek mekansal ve zamansal çözünürlüklü uydu görüntülerinin eksikliği (%7,2) ve düşük mekansal ve zamansal çözünürlüklü uydu görüntülerinin (%7,8) varlığı, zorunlu saha doğrulamasının birincil nedeni olmuştur. 2019 yılında, arazide seçilen örnek sahalar ziyaret edilerek bir saha çalışması yürütülmüştür. Toplamda 941 örnek saha ziyaret edilmiş ve arazi doğrulama çalışması sırasında 119 yanlış sınıflandırılmış örnek saha tespit edilmiştir. Bu nedenle, bu makale Kırgızistan'daki AKAKDO değerlendirmesinin güncellenmiş bir versiyonunu sunmaktadır. Veritabanı güncellemesi, Kırgızistan›daki 1073 örnek alanın yeniden sınıflandırılmasıyla sonuçlanmıştır. Saha doğrulama sonuçları, Kırgızistan'da ormanlık alanların 2019'da toplam arazinin 1,81 milyon hektarını (%9) kapladığını %5,33'lük bir belirsizlik ile göstermiştir. Halbuki, bu alan, uzaktan algılama çalışmasına göre 1,36 milyon ha olarak hesaplanmıştır.

***Anahtar kelimeler:*** Collect Earth, Saha doğrulaması, Arazi kullanımı, Uzaktan algılama, Kırgızistan

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## 1. Introduction

"Land use" describes how land is used for the sum of human activities and arrangements (Lambin, 2006; Arsanjani, 2011; McConnell, 2015). Observing and monitoring land use is crucial for several reasons, spanning environmental, economic, and social dimensions. Understanding how land is utilized and managed can significantly impact sustainable development, resource management, and environmental conservation. The observation and monitoring of land use and land-use change (LULUC) have made extensive use of remote sensing (Olokeogun et al., 2014; Mishra et al., 2016; Rai et al., 2016; Hua, 2017; Liping et al., 2018; Schepaschenko et al., 2019). Remote sensing offers consistent, accurate, reliable, and quick land observations and assessments over time at various temporal and spatial scales at the local, regional, and global levels to support the decision-making process (Reis, 2008; Klein et al., 2012; Srivastava et al., 2013; Pervez et al., 2016).

Using specific techniques, remote sensing images-which can also be a great data source-can be effectively used to gather, evaluate, and simulate current information regarding LULUC (Pradhan et al., 2008; Singh et al., 2017). Accordingly, recent developments in this sector have enabled nations to map and monitor their land resources and environment more efficiently and economically (Martínez and Mollicone, 2012; Hansen et al., 2013; Khadka et al., 2020).

Monitoring LULUC with remote sensing is a common way to generate the data needed to calculate anthropogenic influences on the Earth's system. Using remote sensing data, users can easily evaluate and compute the land area on a wide scale that has been assigned to different land-use categories in the past and present (Bey et al., 2016).

Using remote sensing is time-efficient and economical in countries where the terrain is mountainous. The area of the country is another factor in deciding whether to conduct LULUC monitoring and reporting via remote sensing or field inventory. Remote sensing is increasingly vital in Kyrgyzstan for various applications, particularly environmental monitoring, disaster management, and land resource management. The country's unique geography, characterized by mountainous terrain and significant ecological challenges, makes remote sensing an essential tool for addressing these issues effectively.

Remote sensing allows LULUCF monitoring (Liping et al., 2018; Schepaschenko et al., 2019), mapping tree density (Crowther et al., 2015), conducting forest inventory, and monitoring of forest trends and valuation of ecosystem services (Achard et al., 2010; Potapov et al., 2011; Hansen et al., 2013; Romero-Sanchez and Ponce-Hernandez, 2017; Lister et al., 2019; Schepaschenko et al., 2019).

In addition to worldwide studies, local-level remote sensing research has been carried out in Kyrgyzstan in several studies. Jia et al. (2019) used a hybrid approach to create a forest cover map by merging classifier results, geographical data, and land cover. An estimated 472,369 ha (2.4%) of the nation's land area are covered by forests. In the Mailuu-Suu Valley, Piroton et al. (2020) observed landslides and determined their triggering factors. Their findings demonstrated that small-scale displacement, long-term land degradation, intense rainfall events, and quick snowmelt cause landslides. In a different study, Nazarkulov et al. (2021) analyzed 85,000 sampling units in the Uzgen region to create geohazard maps, identified hazards in 3,500 plots, and carried out a geohazard inventory.

Conversely, De Simone et al. (2021) conducted a study to track the Mountain Green Cover Index. They found 41,400 ha of forestland had been lost in mountainous regions between 2015 and 2018. Isaev et al. (2022) finally tracked walnut forests using the normalized difference vegetation index (NDVI) and vegetation condition index (VCI) in western Tien Shan. The research addressed challenges in obtaining field data due to difficult access and aims to enhance ecological monitoring through remote sensing. The study highlights the potential of using remote sensing to monitor ecological parameters over large areas, particularly in mountainous regions where traditional data collection is challenging. The study also found a strong correlation between the drought index derived from Sentinel-2's VCI and ground-based precipitation data, indicating that remote sensing can effectively monitor drought conditions. The study demonstrates that combining high-resolution unmanned aerial vehicle (UAV) data with satellite imagery can significantly improve ecological monitoring capabilities in complex terrains like Kyrgyzstan, ultimately contributing to better forest management practices and conservation strategies.

Regular, useful, and quick land observations and evaluations at various geographical and temporal scales at the global, regional, and local levels are possible with remote sensing open-access software tools (Wulder and Coops, 2014; Turner et al., 2015; Klein et al., 2017).

Collect Earth, developed by the Food and Agriculture Organization of the United Nations (FAO), among other software, is a thorough and easy-to-use instrument for monitoring land. It may be applied to evaluate natural disasters, land-use changes, sustainable resource management, and ecosystem health. Bey et al. (2016) provided more technical information regarding Collect Earth.

Recently, Collect Earth has been extensively employed in various research projects, such as creating forest cover maps (Schepaschenko et al., 2015), estimating global tree coverage and forests in drylands (Bastin et al., 2017), determining LULUC (Martín-Ortega et al., 2018; García-Montero et al., 2021a; Bassullu and Martín-Ortega, 2023), and monitoring trees in non-forestlands (García-Montero et al., 2021b).

However, Collect Earth has certain drawbacks. Applying a suitable sampling design and sampling intensity to sufficiently capture the land parameters' variability is critical for precision and accuracy assessment. Also, the point-sampling methodology limits the entire variability of the land that can be identified and measured because it is a non-exhaustive spatial cover (Bey et al., 2016).

Additionally, even though remote sensing techniques allow users to analyze satellite images in high and very high resolution, there are still no satellite images with sufficient temporal and spatial resolution in some areas. The majority of these images are taken in isolated, mountainous regions that receive a lot of snowfall all year round. Since Google Earth is the primary source of the images used in this research, there is most likely not much interest to discover more regarding these locations. Missing or low/medium resolution remote sensing images make classification harder. For example, monitoring diverse forests, mapping forest types, and documenting LULUC may require higher-resolution images than those obtained from medium-resolution satellites (i.e., Sentinel 2A (i.e., 10 m) and Landsat (30 m) (García-Montero, 2021a). Thus, it is quite difficult for users to classify land cover and determine changes in land use. There are also controversial sample plots with a hard-to-define type of land use categories without a field survey.

Validation and calibration are crucial elements in almost every remote sensing study. The models' findings or the observations from remote sensing are compared to the ground measurements in both situations. The sensor's field of view and the scale at which in-situ measurements are taken are frequently out of sync, especially in studies using medium-resolution remote sensing (Baccini et al., 2007).

Field data are necessary for calibrating models based on remote sensing and validating model outcomes (Franklin, 1986; Ardo, 1992; Cohen and Spies, 1992; Danson and Curran, 1993; Gemmell, 1995; Wulder, 1998; Puhr and Donoghue, 2000; Cohen et al., 2001; Cohen et al., 2003). However, for pragmatic reasons, the quantity of data collected and the geographic region visited during fieldwork are typically minimal. Indeed, the necessity to keep fieldwork expenses within reasonable bounds over wide swaths of land frequently leads to sampling relatively tiny regions with field plots smaller than one ha. Therefore, a major challenge when using field data in remote sensing-based studies is making sure that the in-situ measurements provide a sufficient and representative sample supporting the study or mapping goals (Baccini et al., 2007).

Thanks to ground-based data collected during the time-consuming validation work, users can comprehend land characteristics and variability across the land-use categories in greater detail. The data from both the remote sensing and the field validation work provide more detailed land characteristics from a small number of field sites to the landscape level by drawing from the much larger number of sites evaluated in remote sensing studies. The data from the field validation can be used to estimate uncertainties within the spatial extent and area estimation of land-use categories (Bey et al., 2016).

The necessity of remote sensing validation in the field hasn't gotten much attention despite its significance. But recently, it has been noted in several articles as a significant issue, especially in relation to validation work (Milne and Cohen, 1999; Tian et al., 2002).

Kyrgyzstan is a mountainous country with low resolution and no satellite images. This results in incorrect land use classifications. The unavailability of high/very high spatial and temporal resolution satellite images (7.2%) and the availability of low spatial and temporal resolution satellite images (7.8%) were the primary reasons for mandatory field verification. Hence, we conducted field validation work to verify the land-use, land-use change, and forestry (LULUCF) assessment in 2019. Field validation also supported the reassessment of inconsistent plots due to operator bias. The research reported in this paper extends the combination of remote sensing and field validation efforts. It demonstrates the necessity of field validation work in remote sensing studies.

## 2. Materials and Methods

### 2.1. Study site

The study site covers Kyrgyzstan's territory (Figure 1), located within the Tien Shan and Pamir-Alai Mountains. The country covers an area of 19.99 million ha. State Forest Fund occupies 2.66 million ha (GoK, 2022). While forestlands cover 1.36 million ha (6.8%) of the total land, croplands cover 1.72 million ha (8.6%) (Bassullu and Martín-Ortega, 2023).


Figure 1. Map of the study site (UN, 2011)
Şekil 1. Araştırma sahası haritası (UN, 2011)

### 2.2. Land use classes

This study used land use classes defined in Chapter 3 of the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Volume 4 Agriculture, Forestry and Other Land Use (IPCC, 2006).

### 2.3. Data source and land use representation

Through a Collect Earth study, we used the sample plots and the first results of the LULUCF assessment performed by Bassullu and Martín-Ortega (2023). This research analyzed 13.414 1-ha sample plots via an augmented visual interpretation approach using very high spatial and temporal resolution satellite imagery on the Google Earth platform. The data generated through Collect Earth corresponds to Approach 3 in Chapter 3 of the 2006 IPCC Guidelines.

The activity data is annually spatially explicit land-use conversion data where the position of each sampling unit is known, and therefore, auxiliary data -maps- can be used to stratify the information by regions, climatic zones, conservation areas, and forest concessions. Likewise, through Collect Earth, data can be extracted from areas by category and by changes between land use categories. This allows a very detailed analysis of land use dynamics and enables the use of specific emission factors for the subdivision combinations of land use (forest type) and conservation area.

### 2.4. Fieldwork for the validation

Bassullu and Martín-Ortega (2023) conducted the remote sensing study in 2019. Hence, the research, including available satellite images, covers 2000 and 2019.

Fieldwork for the validation process was planned after the LULUCF assessment in 2019. The objective of the fieldwork was to confirm the accuracy of the LULUCF assessment, validate selected sample plots from Collect Earth, and obtain additional data, if possible. Hence three groups were created with the national experts to conduct the field work. After consultation about the previous field inventories in Kyrgyzstan, some concepts were extracted to help national experts carry out this task. Previous field works were conducted following Scheuber's (1999) study. Thus, we also used this study as a guide.

### 2.4.1. Accessibility information

Scheuber (1999) decided not to visit sample plots in lake basins (e.g., Issyk-Kul, Son-Kul) and any territory above 3.500 m due to accessibility problems. The remaining sample plots were sorted by accessibility. We defined the following criteria; slope, the distance between sample plots and highways, and availability of forest plantations, when deciding the accessibility of a sample plot. Hence, we established four categories regarding the accessibility of the sample plots.

- Category 1: Slope up to 5º, the existence of forests, residence area (orchards, outdoor and by-the-road plants), the distance between the sample plot and highway is 1-3 km.
- Category 2: Slope between 6º -15º, forest cover up to 33%, the distance between the sample plot and highway is 3.1-5.0 km.
- Category 3: Slope between 16º -30º, forest cover from 34% to 66%, the distance between the sample plot and highway is 5.1-8 km.
- Category 4: Slope over 31º, forest coverage over 67%, the distance between the sample plot and highway is over 8.1 km (Chyngojoev et al., 2010).

### 2.4.2. Time consumption in the field

Table 1 shows that in all forest types, except broadleaved forests, about one day is needed to assess the information of one sample plot. The experience of the field teams reveals that in broadleaved forests, 3 sample plots can be assessed in 2 days. Here, either a half day is typically needed for the fieldwork of one sample plot or a whole day (Scheuber, 1999).

The total time needed for one sample plot (about 100 m) varied from 7.4 hours (h) to 9.6 h in a walnut (*Juglans*) forest, from 1.7 h to 7.4 h in a broadleaved forest, from 4.4 h to 12.6 h in a spruce (*Picea*) forest, and from 8.0 h to 12.1 h in a juniper (*Juniperus*) forest. Besides, the structure of the walnut and juniper forests is very homogeneous. Most variation can be found in spruce forests.

Table 1. The time needed for traveling and measurement of plots during the fieldwork (Scheuber, 1999)
Tablo 1. Saha çalışması sırasında seyahat ve örnek noktaların ölçümü için gereken süre

| Time | Walnut forest | | Broad-leaved forest | | Spruce forest | | Juniper forest | | All sample plots | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Min | % | Min | % | Min | % | Min | % | Min | % |
| Measurement | 323 | 61 | 82 | 33 | 94 | 21 | 310 | 54 | 165 | 41 |
| Travel | 203 | 39 | 167 | 67 | 359 | 79 | 262 | 46 | 240 | 59 |
| Total | 526 | 100 | 249 | 100 | 453 | 100 | 572 | 100 | 405 | 100 |

The relation between measurement time and traveling time varies greatly depending on the forest type (Table 1). For example, the worst relation is found in spruce forests, where 79% of the time is spent traveling, and only 21% is dedicated to work.

### 2.4.3. Stratification by accessibility and selection of plots for field validation

Accessing the sampling units in regions with challenging topography or inadequate road systems can become exceedingly costly and time-consuming. A compromise to lower travel costs while maintaining the probability sampling strategy is to stratify based on accessibility zones (i.e., distance to roads) and choose a larger percentage of samples from the "easy to access" zones. It is advised to omit inaccessible locations for data gathering if the necessary information or data is available. These can include no-access locations such as national parks, military installations, and hilly or steep terrain. Since the samples dropping in these regions were not observed from the ground, these regions are not included in the accuracy assessment (Haub et al., 2015).

In this regard, the following criteria were applied to select sample plots for field validation.

- Select only roads in good condition to conduct the fieldwork, or at least rank them in order of importance.
- Create a buffer of 5 km around the selected roads where plots within this buffer are candidates for visiting.
- Within this buffer, select those plots with low slope values.
- Check for consistency of selected plots, similar % of land use compared with the total number, and cover all elevation ranges to represent different ecological conditions.
- Calculate the number of plots to select based on the number of workers and days dedicated to fieldwork.

Only roads showing the maximum speed limit were selected using the layer from open street maps (OSM). Roads classified with this property seem to correspond to the main communication roads and visually connect all the different regions in the country. A 5 km buffer was applied, and all plots falling within this buffer were selected, with a total of 280 plots. To check the representativity of the plots chosen, they were compared with the whole population in two ways: First, in representativity of IPCC land use categories (Figure 2) and second, in their variability in altitude as a proxy of ecological conditions (Figure 3).

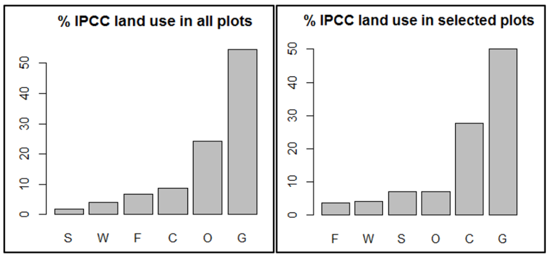


Figure 2. Share of each IPCC land use in all plots (left) and selected plots (right)
S: Settlement, W: Wetland, F: Forest, C: Cropland, O: Other land, G: Grassland
Şekil 2. Tüm örnek noktalarda (solda) ve seçilen örnek noktalarda (sağda), her bir IPCC arazi kullanım oranı
S: Yerleşim, W: Sulak alan, F: Orman, C: Tarım arazisi, O: Diğer alan, G: Mera

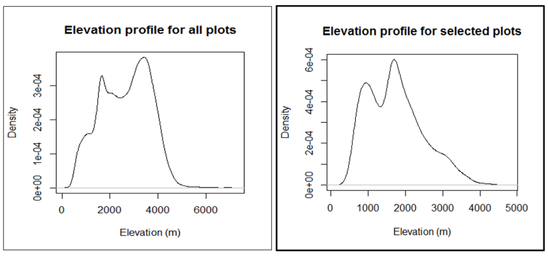


Figure 3. Elevation profile for all plots (left) and the selected plots for field validation (right)
Şekil 3. Tüm örnek noktalarda (solda) ve saha doğrulaması için seçilen örnek noktalarda (sağda) yükseklik profili

Based on the selection criteria, we planned to visit 673 sample plots due to limited time, human resources, and the project budget. Hence, Table 2 presents the number of selected sample plots for field validation by regions and land use categories. Figure 4 provides the distribution of selected sample plots across the country.

After the preliminary selection of sample plots, we developed a schedule and approved the preliminary routes for fieldwork. We also prepared the field verification forms for the sample plots.

Even though Collect Earth, combined with Google Earth, Bing Maps, and Google Earth Engine, allows users to analyze satellite images, there are still no satellite images with sufficient temporal and spatial resolution for some areas. It is quite difficult for users to classify land cover and determine changes in land use. For example, in 2010 satellite images, one of the sample plot was a pasture. However, today, this territory is used as cropland. Over the past year, it has been changed to a settlement. There are also controversial sample plots with a hard-to-define type of land use categories without a field survey, and these sample plots were included in a field survey.

The analysis showed that no images with high spatial resolution exist for 961 sample plots (7.2%). Certain regions of Kyrgyzstan, particularly those with mountains, do not have 1- meter or sub-meter pixel resolution images for the year 2016 and some years beyond. There, Landsat images are accessible. While Google Earth imagery offers a combination of Airbus and Maxar products with resolutions between 0.15 and 1.5 meters and 0.15 to 5 meters, respectively, Bing Maps imagery offers products with pixel resolutions up to 0.30 meters. In addition, in 1.045 plots (7.8%), images were taken between 2001 and 2010. Suppose, in one case, it is rather challenging to define land cover types accurately; in other cases, it is difficult. In that case, there is no opportunity to determine land-use changes more precisely. In such cases, the Google Earth Engine service was actively used to show the vegetation index. However, despite this, in some cases, it was challenging to determine the subtypes of land use accurately. Thus, no the low spatial and temporal resolution of satellite images served as one of the reasons for mandatory verification in the field.

The field visit ended with verifying 941 sample plots (268 sample plots more than planned) since some were close to roads and easy to validate, particularly the croplands, settlements, and wetlands (Table 3). As suggested in previous fieldwork (Scheuber, 1999), forest plots took a whole working day because there were many necessary measures. In contrast, croplands, settlements, and wetlands took less time.

We also compared the slope with land use categories in selected plots. Figure 5 shows the distribution of slopes by IPCC land use in selected plots. Because plots were located close to the main roads, so slopes generally have low values.

Table 2. The number of selected plots for field validation in the regions
Tablo 2. Bölgelerde saha doğrulaması için seçilen örnek nokta sayıları

| Region | Planned number of sample plots | Land use categories | | | | | |
|---|---|---|---|---|---|---|---|
| | | Forestland | Cropland | Grassland | Wetland | Settlement | Otherland |
| Chui | 105 | 5 | 39 | 39 | 1 | 14 | 7 |
| Issyk-Kul | 86 | 9 | 19 | 38 | 2 | 7 | 11 |
| Naryn | 93 | 4 | 18 | 59 | 1 | 6 | 5 |
| Talas | 57 | 6 | 30 | 21 | 0 | 0 | 0 |
| Jalal-Abad | 153 | 43 | 28 | 82 | 0 | 0 | 0 |
| Batken | 77 | 13 | 24 | 40 | 0 | 0 | 0 |
| Osh | 102 | 11 | 51 | 40 | 0 | 0 | 0 |
| Total | 673 | 91 | 209 | 319 | 4 | 27 | 23 |

Table 3. Summary table of the surveyed field plots of the regions
Tablo 3. Bölgelere ait araştırma yapılan örnek noktaların özet tablosu

| District name | Planned sample plots | Number of verified sample plots | Difference |
|---|---|---|---|
| Chui | 105 | 155 | 50 |
| Issyk-Kul | 86 | 111 | 25 |
| Naryn | 93 | 115 | 22 |
| Talas | 57 | 67 | 10 |
| Jalal-Abad | 153 | 196 | 43 |
| Batken | 77 | 164 | 87 |
| Osh | 102 | 133 | 31 |
| Total | 673 | 941 | 268 |

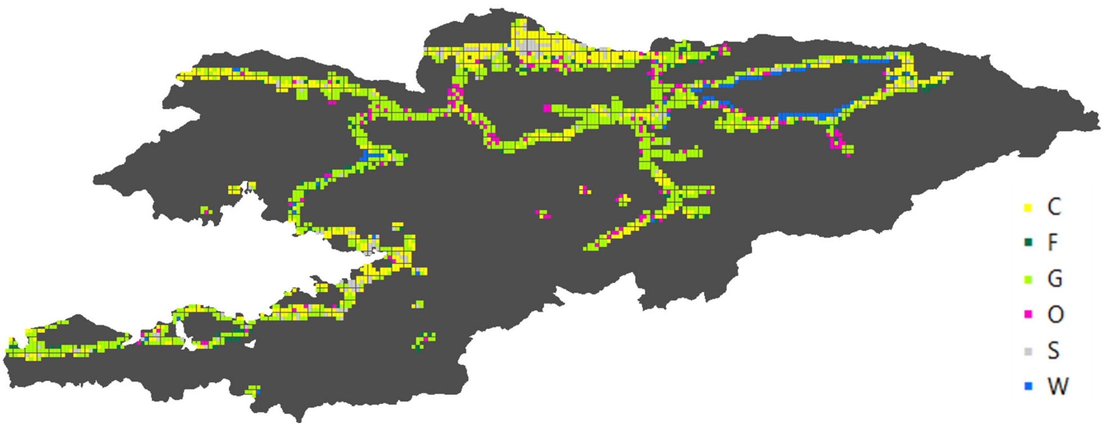


Figure 4. Map of selected plots for field validation (within 5 km from the main road) by land use categories
S: Settlement, W: Wetland, F: Forest, C: Cropland, O: Other land, G: Grassland
Şekil 4. Arazi kullanım kategorilerine göre saha doğrulaması için seçilen örnek noktalar (ana yola 5 km)
S: Yerleşim, W: Sulak alan, F: Orman, C: Tarım arazisi, O: Diğer alan, G: Mera

### 2.5. Fieldwork

We established three teams of national experts to conduct field validation work. The first team visited Chui, Issyk-Kul, and Naryn regions, the second team visited the Talas and Jalal-Abad regions, and the last team conducted field validation work in the Osh and Batken regions. The region maps are presented in Figures 6 to 10.

We considered locality and transport availability and used GIS tools in sample plot selection. Some parts of selected sample plots may be inaccessible due to various circumstances (poor road conditi-

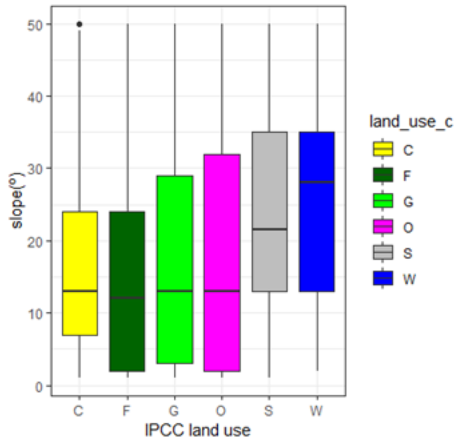


Figure 5. Distribution of slopes by IPCC land use categories in selected plots
S: Settlement, W: Wetland, F: Forest, C: Cropland, O: Other land, G: Grassland
Şekil 5. Seçilen örnek noktalardaki eğimlerin IPCC arazi kullanım kategorilerine göre dağılımı
S: Yerleşim, W: Sulak alan, F: Orman, C: Tarım arazisi, O: Diğer alan, G: Mera

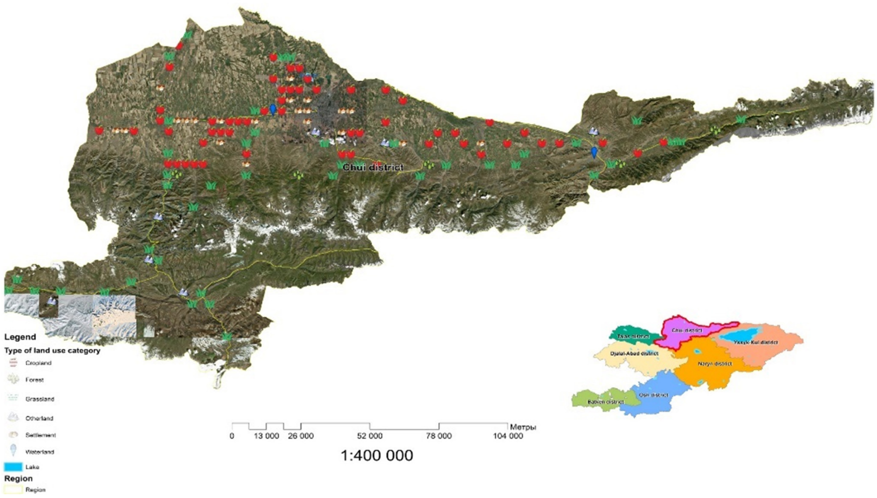


Figure 6. Map of Chui Region
Şekil 6. Chui Bölgesi haritası

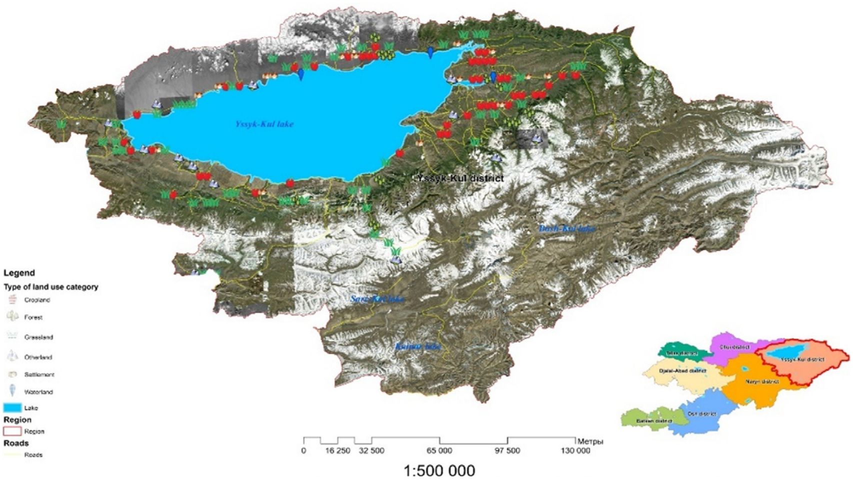


Figure 7. Map of Issyk-Kul Region
Şekil 7. Issyk-Kul Bölgesi haritası

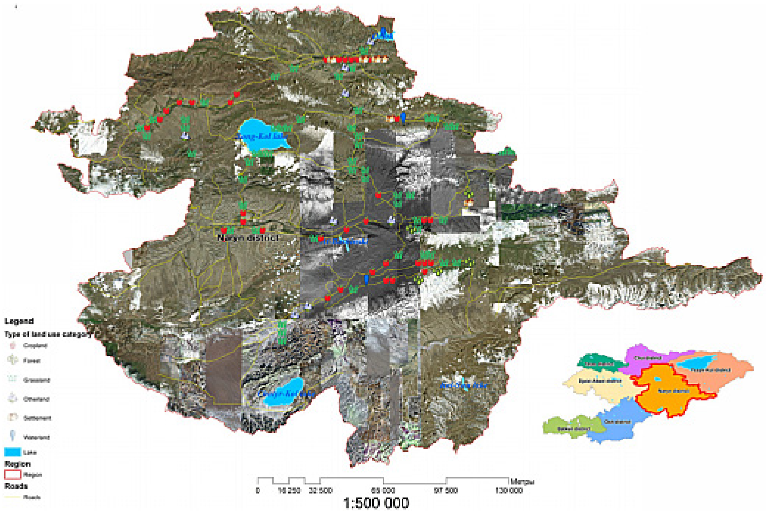


Figure 8. Map of Naryn Region
Şekil 8. Naryn Bölgesi haritası

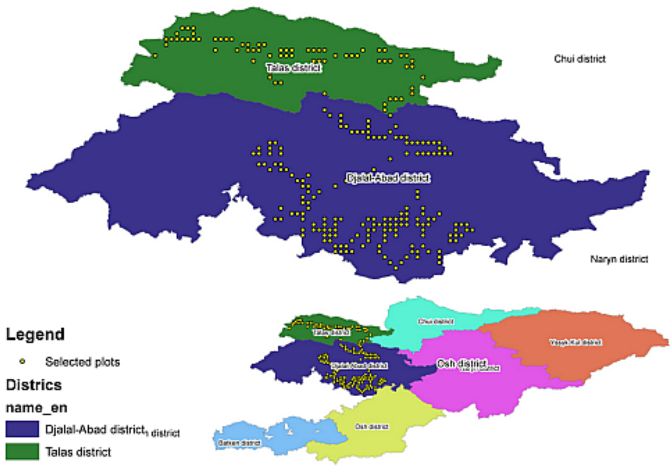


Figure 9. Map of Talas and Jalal-Abad regions
Şekil 9. Talas and Jalal-Abad Bölgeleri haritası

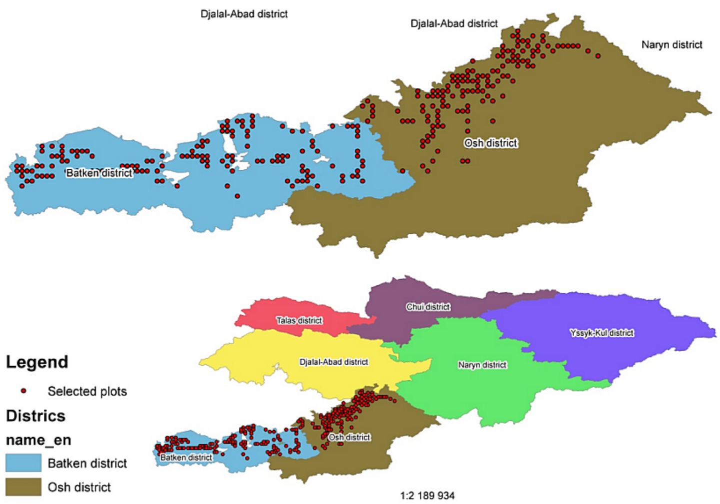


Figure 10. Map of Osh and Batken regions
Şekil 10. Osh and Batken bölgeleri haritası

ons or lack of roads, enclaves, border sections),. Therefore, field trips were carried out by a flexible route. For example, some remote and inaccessible mountain areas of the Jalal-Abad region (Chatkal and Ala-Buka) and Osh region (Alai, Chon-Alai, and Kara-Kulzha) were excluded.

Due to the discrepancies between the types of land categories detected during the field survey, we decided to re-inventory all sample plots to improve the reliability and update the Collect Earth database, considering the results obtained from the field validation.

According to the results, a significant change occurred in the grassland category since vegetation in satellite imagery is visually difficult to recognize. In such cases, NDVI is needed - this is a well-known index showing vegetation's presence and condition. We used multispectral images Landsat 8 OLI, Landsat 7ETM +, Sentinel 2, and Modis to determine the presence of vegetation.

For example, Plot hi14517 was qualified as other land (bare soil). Based on the NDVI value, the plot contains vegetation, and its land use category is grassland.

Besides, other lands, such as sandy, clay, and rocky surfaces, were classified as grasslands due to the lack of high-resolution satellite images. In this case, the NDVI was also used to determine the presence of vegetation. Many forestlands (i.e., juniper, hawthorn (*Crataegus*)) are qualified as pastured shrubs. Slight deviations were detected in the remaining areas, mainly caused by the reasons above.

### 3. Findings

After the field validation work, we reviewed all sample plots based on Bassullu and Martín-Ortega (2023) assessed. First, we corrected misclassified plots. Based on the field validation work, 119 sample plots from 941 were reclassified into other land use types, which is 12.6% (Annex).

Later, we checked the whole database and applied the knowledge acquired during the fieldwork. In total, 1073 plots were reclassified after reviewing the entire dataset. The updated data was saved in the "Collect" database. We used the Saiku Server to update the LULUCF assessment based on the reclassified sample plots. Table 4 presents a confusion matrix comparing sample plots through the remote sensing assessment and field validation work.

Table 4. Confusion matrix comparing land use in the sample plots
Tablo 4. Örnek noktalarda arazi kullanım matrisi

| C | | Remote sensing assessment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | F | G | O | S | W | Total | UA** | |
| Field validation work | Cropland | 1105 | 0 | 34 | 2 | 1 | 1 | 1143 | 0.97 |
| | Forest | 5 | 891 | 293 | 20 | 6 | 1 | 1216 | 0.73 |
| | Grassland | 40 | 16 | 6838 | 105 | 4 | 4 | 7007 | 0.98 |
| | Other land | 0 | 3 | 136 | 3116 | 0 | 1 | 3256 | 0.96 |
| | Settlement | 13 | 1 | 2 | 1 | 227 | 1 | 245 | 0.93 |
| | Wetland | 0 | 0 | 4 | 3 | 0 | 540 | 547 | 0.99 |
| | Total | 1163 | 911 | 7307 | 3247 | 238 | 548 | 13414 | |
| | PA* | 0.95 | 0.98 | 0.94 | 0.96 | 0.95 | 0.99 | 0.95 | OA*** |

*Producer's accuracy (PA): Probability that a value predicted to be in a certain class is that class.
**User's accuracy (UA): Probability that a value in a given class was classified correctly.
***Overall accuracy (OA): Percentage of correctly classified plots from known reference plots.

The overall agreement of comparing both assessments in 2019 was 95 If we consider the last assessment after the fieldwork, the wetland and grassland categories were the most accurate, with misclassification values of around 1% and 2%, respectively; the main error in classifying grassland was classifying it as forest, cropland, and other land. Another important misclassification was with the forest class, previously classified as grassland, probably due to the vast open woodlands in the country or the abundance of shrubs that could be confounded with trees using high-resolution imagery. The rest of the classes were all represented with accuracy values equal to or higher than 93%.

Table 5 shows a comparison between remote sensing assessment and field validation work. Differences in number of plots and uncertainties between assessments and years are also shown. The largest variation was detected in the forest category, with a difference in uncertainty of around (0.90%). The rest of the classes showed differences equal to or below 0.18% in uncertainty.

Once we reassessed all sample plots, we rerun the

LULUCF analysis to update the size of all land use categories. Table 6 presents the land-use change matrix for 2000 and 2019.

Table 7 shows the land-use change matrix showing the percentage of different land-use classes.

The highest area loss between 2000 and 2019 was in cropland (-1.05%), followed by wetland (-0.37%). Cropland is transformed mainly into settlement (-0.53%) and grassland (-0.52%). Grassland (-0.17%), forest (-0.08%), and other land (-0.06%) are lost to a lesser extent.

Table 5. The number of sample plots and uncertainties between remote sensing assessment and field validation work
Tablo 5. Örnek noktaların sayıları ve uzaktan algılama değerlendirmesi ile saha doğrulama çalışması arasındaki belirsizlikler

| Field validation work | | | Remote sensing assessment | | | | |
|---|---|---|---|---|---|---|---|
| Land use in 2000 | Sample size | Uncertainty % | Land use in 2000 | Sample size | Uncertainty % | Difference in sample number | Difference in uncertainty |
| Forest | 1214 | 5.34% | Forest | 909 | 6.24% | 305 | -0.90% |
| Cropland | 1150 | 5.55% | Cropland | 1166 | 5.51% | -16 | 0.04% |
| Grassland | 7010 | 1.62% | Grassland | 7312 | 1.54% | -302 | 0.08% |
| Otherland | 3255 | 2.99% | Otherland | 3246 | 3.00% | 9 | -0.01% |
| Wetland | 549 | 8.25% | Wetland | 551 | 8.24% | -2 | 0.01% |
| Settlement | 236 | 12.66% | Settlement | 230 | 12.82% | 6 | -0.16% |
| Field validation work | | | Remote sensing assessment | | | | |
| Land use in 2019 | Sample size | Uncertainty % | Land use in 2019 | Sample size | Uncertainty % | Difference in sample number | Difference in uncertainty |
| Forest | 1216 | 5.33% | Forest | 911 | 6.23% | 305 | -0.90% |
| Cropland | 1143 | 5.57% | Cropland | 1163 | 5.51% | -20 | 0.06% |
| Grassland | 7007 | 1.62% | Grassland | 7307 | 1.55% | -300 | 0.07% |
| Otherland | 3256 | 2.99% | Otherland | 3247 | 3.00% | 9 | -0.01% |
| Wetland | 547 | 8.27% | Wetland | 548 | 8.26% | -1 | 0.01% |
| Settlement | 245 | 12.42% | Settlement | 238 | 12.60% | 7 | -0.18% |

Table 6. Land-use change matrix
Tablo 6. Arazi kullanımı değişim matrisi

| | Forest | Land use 2000 (ha) | | | | | |
|---|---|---|---|---|---|---|---|
| | | Cropland | Grassland | Wetland | Settlement | Otherland | |
| Land use 2019 (ha) | Forest | 1,809,741.07 | | 3,017.12 | 1,487.17 | | |
| | Cropland | | 1,680,173.85 | 5,935.04 | | | 3,040.85 |
| | Grassland | 1,454.88 | 8,815.54 | 10,387,747.94 | 1,481.86 | | |
| | Wetland | | | | 805,719.42 | | |
| | Settlement | | 8,975.66 | 4,391.62 | | 349,930.31 | |
| | Otherland | | | 4,445.59 | | | 4,828,824.76 |

Table 7. Land-use change matrix (%)
Tablo 7. Arazi kullanımı değişim matrisi (%)

| | Land use 2000 (%) | | | | | | |
|---|---|---|---|---|---|---|---|
| Land use 2019 (%) | Forest | Cropland | Grassland | Wetland | Settlement | Otherland | Gain 2000-2019 |
| Forest | 99.92 | | 0.03 | 0.18 | | | +0.21 |
| Cropland | | 98.95 | 0.06 | | | 0.06 | +0.12 |
| Grassland | 0.08 | 0.52 | 99.83 | 0.18 | | | +0.78 |
| Wetland | | | | 99.63 | | | +0.00 |
| Settlement | | 0.53 | 0.04 | | 100.00 | | +0.57 |
| Otherland | | | 0.04 | | | 99.94 | +0.04 |
| Loss 2000-2019 | -0.08 | -1.05 | -0.17 | -0.37 | -0.00 | -0.06 | |

The highest gains in 2019 correspond to grassland (+0.78%) followed by settlements (+0.57%), which have only been gained from other land-use types due to urban expansion. Forests show an increase (+0.21%), followed by cropland (+0.12) and otherland (+0.04) to a lesser extent.

Net changes in land use, i.e., gains-losses, are shown in Figure 14**.** Net losses between 2000 and 2019 correspond to cropland, wetland, and other land, whereas forest, settlement, and grassland increase in ascending order (Figure 11).

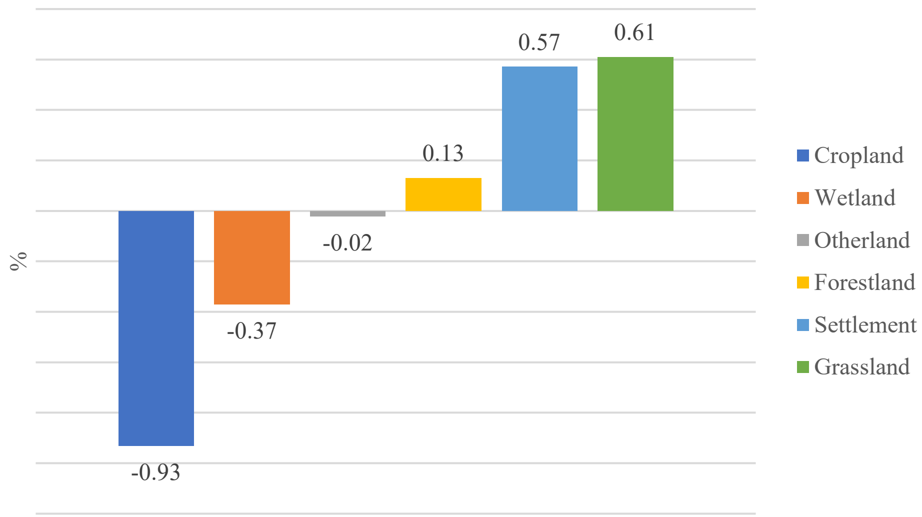


Figure 11. Net gains and losses of the area in the different IPCC land use classes between 2000 and 2019
Şekil 11. 2000 ile 2019 yılları arasında farklı IPCC arazi kullanım sınıflarında alansal net kazançlar ve kayıplar

## 4. Discussion and Conclusions

The primary objective of this research was to validate the remote sensing LULUCF assessment conducted by Bassullu and Martín-Ortega (2023) by visiting selected sample plots in the field, updating the database for the current and historical LULUCF data, and verifying or revising inconsistent or incorrect sample plots based on the field data.

Fieldwork was conducted by three teams consisting of Kyrgyz national experts. We determined 673 sample plots for field validation. However, national experts visited 941 sample plots across the country. Based on the fieldwork, we detected incorrect assessments in 119 sample plots where the land use category was misclassified. Hence, we decided to update the Collect Earth database based on the feedback from the field validation work. We reassessed all 13,414 sample plots. The results of the surveyed sample plots became the basis for revising 1.073 sample plots by updating the database in Collect Earth and reanalyzing land use categories for all sample plots in the country.

The overall agreement of comparing both assessments in 2019 was 95%. If we consider the last assessment after the fieldwork as the most accurate one, wetlands and grasslands had lower values of misclassification of about 1 and 2%, respectively. This was due to the main error for classifying grasslands that they were classified as forests, croplands, and other lands.

A notable misclassification occurred with the forest class, which had previously been classified as grassland. This confusion likely arose from the open structure of the woodlands in the country, as well as the abundance of shrubs that could be mistaken for trees when using high-resolution imagery. However, by visiting the plots in the field, we were able to accurately differentiate this feature. All other classes had representation values equal to or greater than 93%.

The update of the Collect Earth database yielded a new LULUCF assessment. Based on the updated LULUCF assessment, forest cover is 1.81 million ha in Kyrgyzstan, 9% of the country's land area, with a 5.33% uncertainty in 2019. Besides, minor increases were observed in forests (0.13%), settlements (0.57%), and grasslands (0.61%). On the contrary, minor decreases were observed in otherlands (0.02%), wetlands (0.37%), and croplands (0.93%).

This research recognizes the different forest and other land use extent estimates by other studies and, thus, advises further remote sensing studies with different techniques supported by extended field validation work.

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**Author Contributions**

Ç. Başsüllü designed the field validation work. P. Martín-Ortega selected the methodology and determined the field sample plots. Ç. Başsüllü designed and wrote the manuscript. Ç. Başsüllü and P. Martín-Ortega edited the text. All authors contributed to the manuscript revision and read and approved the updated version.

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Annex. List of inconsistent land use categories of the sample plots

Ek. Örnek sahalarda yanlış sınıflandırılan arazi kullanım kategorilerinin listesi

| № | District Name | Misclassification | Land use classes | |
|---|---|---|---|---|
| | | | Remote sensing data | Field data |
| 1 | Alamedin | 6 | Cropland | Grassland |
| | | | Cropland | Settlement |
| | | | Grassland | Cropland |
| | | | Cropland | Grassland |
| | | | Otherland | Grassland |
| | | | Grassland | Settlement |
| 2 | Issyk-Ata | 1 | Cropland | Settlement |
| 3 | Kemin | 2 | Wetland | Otherland |
| | | | Cropland | Forest |
| 4 | Sokuluk | 5 | Cropland | Settlement |
| | | | Cropland | Grassland |
| | | | Cropland | Grassland |
| | | | Cropland | Grassland |
| | | | Settlement | Forest |
| 5 | Zhaiyl | 7 | Grassland | Forest |
| | | | Cropland | Grassland |
| | | | Otherland | Grassland |
| | | | Otherland | Grassland |
| | | | Grassland | Cropland |
| | | | Cropland | Forest |
| | | | Cropland | Grassland |
| 6 | Panfilov | 3 | Otherland | Grassland |
| | | | Otherland | Grassland |
| | | | Cropland | Settlement |
| Total Chui Region | | 24 | | |
| 7 | Ton | 2 | Cropland | Grassland |
| | | | Otherland | Grassland |
| 8 | Seven-Oguz | 4 | Grassland | Forest |
| | | | Forest | Grassland |
| | | | Otherland | Grassland |
| | | | Grassland | Forest |
| 9 | White Water | 2 | Cropland | Grassland |
| | | | Grassland | Cropland |
| 10 | Tup | 2 | Wetland | Grassland |
| | | | Otherland | Settlement |
| 11 | Issyk-Kul | 7 | Cropland | Settlement |
| | | | Cropland | Grassland |
| | | | Grassland | Cropland |
| | | | Grassland | Otherland |
| | | | Grassland | Otherland |
| | | | Grassland | Otherland |
| | | | Grassland | Otherland |

Annex. List of inconsistent land use categories of the sample plots (Continued)

Ek. Örnek sahalarda yanlış sınıflandırılan arazi kullanım kategorilerinin listesi (Devam)

| | | | | |
|---|---|---|---|---|
| Total Issyk-Kul Region | | 17 | | |
| 1 | Kochkor | 4 | Settlement | Forest |
| | | | Otherland | Grassland |
| | | | Settlement | Grassland |
| | | | Wetland | Grassland |
| 2 | Jumgal | 3 | Cropland | Grassland |
| | | | Cropland | Grassland |
| | | | Cropland | Settlement |
| 3 | Naryn | 5 | Grassland | Forest |
| | | | Cropland | Grassland |
| | | | Cropland | Grassland |
| | | | Cropland | Grassland |
| | | | Cropland | Grassland |
| 4 | At-Bashy | 3 | Cropland | Grassland |
| | | | Cropland | Grassland |
| | | | Otherland | Grassland |
| 5 | Ak-Talaa | 2 | Cropland | Grassland |
| | | | Grassland | Otherland |
| Total Naryn Region | | 17 | | |
| 1 | Talas | 2 | Grassland | Forest |
| | | | Grassland | Forest |
| 2 | Kara-Buura | 2 | Cropland | Grassland |
| | | | Otherland | Grassland |
| Total Talas Region | | 4 | | |
| 1 | Suzak | 4 | Forest | Settlement |
| | | | Grassland | Cropland |
| | | | Grassland | Cropland |
| | | | Grassland | Cropland |
| 2 | Bazar-Korgon | 3 | Grassland | Cropland |
| | | | Grassland | Forest |
| | | | Grassland | Forest |
| 3 | Nooken | 8 | Grassland | Forest |
| | | | Forest | Grassland |
| | | | Grassland | Forest |
| | | | Cropland | Grassland |
| | | | Cropland | Grassland |
| | | | Grassland | Cropland |
| | | | Grassland | Forest |
| | | | Grassland | Forest |

Annex. List of inconsistent land use categories of the sample plots (Continued)

Ek. Örnek sahalarda yanlış sınıflandırılan arazi kullanım kategorilerinin listesi(Devam)

| | | | | |
|---|---|---|---|---|
| 4 | Aksy | 10 | Grassland | Forest |
| | | | Grassland | Forest |
| | | | Grassland | Forest |
| | | | Cropland | Grassland |
| | | | Grassland | Forest |
| | | | Grassland | Otherland |
| | | | Grassland | Forest |
| | | | Grassland | Forest |
| | | | Grassland | Forest |
| | | | Grassland | Forest |
| 5 | Toktogul | 4 | Grassland | Otherland |
| | | | Cropland | Grassland |
| | | | Grassland | Otherland |
| | | | Grassland | Otherland |
| Total Jalal-Abad Region | | 29 | | |
| 1 | Ozgon | 10 | Cropland | Forest |
| | | | Cropland | Settlement |
| | | | Cropland | Grassland |
| | | | Cropland | Grassland |
| | | | Grassland | Forest |
| | | | Cropland | Forest |
| | | | Settlement | Forest |
| | | | Cropland | Settlement |
| | | | Grassland | Cropland |
| | | | Grassland | Forest |
| 2 | Kara-Suu | 3 | Grassland | Otherland |
| | | | Cropland | Grassland |
| | | | Cropland | Forest |
| | Aravan | 1 | Grassland | Cropland |
| | Nookat | 5 | Grassland | Forest |
| | | | Grassland | Forest |
| | | | Grassland | Otherland |
| | | | Forest | Grassland |
| | | | Cropland | Grassland |
| Total Osh Region | | 19 | | |
| 1 | Kadamjai | 5 | Grassland | Otherland |
| | | | Grassland | Otherland |
| | | | Grassland | Otherland |
| | | | Grassland | Otherland |
| | | | Cropland | Grassland |
| 2 | Leilek | 4 | Wetland | Settlement |
| | | | Grassland | Otherland |
| | | | Grassland | Otherland |
| | | | Grassland | Otherland |
| Total Batken Region | | 9 | | |
| Grand total | | 119 | | |