UNIVERSITY OF CENTRAL ASIA
GRADUATE SCHOOL OF DEVELOPMENT
Mountain Societies Research Institute

CRITICAL ECOSYSTEM PARTNERSHIP FUND

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This document reports on research conducted within "Conservation and Research of Wild Fruit Species in Western Tian Shan, Kyrgyz Republic" (CEPF-110679) project kindly supported by the Critical Ecosystem Partnership Fund, however, data collected within this project will be further analyzed and more publications are being developed with proper acknowledgements; authors declare no conflict of interests.

Cover photo: Maksim Kulikov

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The Mountain Societies Research Institute (MSRI) was established in 2010 to conduct research for development with the goal to improve the well-being of mountain societies in Central Asia. MSRI is part of the Graduate School of Development, University of Central Asia. The University of Central Asia (UCA) was founded in 2000. The University of Central Asia (UCA) was founded in 2000. The Presidents of Kazakhstan, the Kyrgyz Republic, and Tajikistan, and His Highness the Aga Khan signed the International Treaty and Charter establishing this secular and private university, ratified by the respective parliaments, and registered with the United Nations.

CONTENTS

Introduction

Kyrgyzstan occupies only 0.13% of Earth's land surface but has about 2% of the global floral and 3% of the faunal diversity (SAEPF et al., 2006). The walnut-fruit forests in the south of Kyrgyzstan represent a unique ecosystem with *Juglans regia* L. being the dominant tree species and an important habitat for *Malus* spp. (Beer et al., 2008). These mainly grow on the western slopes of Fergana range and southern slopes of Chatkal range in the south of Kyrgyzstan. This area is also the home of many wild fruits and flowers with wide ranges of genetic diversity, including many widely cultivated plants like tulips (Botschantzeva & Varekamp, 1982; Zonneveld, 2009) and apples (Cornille et al., 2014).

The western slopes of Fergana ridge and southern slopes of Chatkal range in the south of Kyrgyzstan are covered with unique walnut-fruit forests. They represent semi-wild forests consisting largely of common walnut *Juglans regia* L. trees with patches of native apple *Malus sieversii* (Ledeb.) M. Roem., *M. niedzwetzkyana* Dieck and *Pyrus korshinskyi* Litv.*,* which are globally threatened. Many other tree species also grow in these forests, but do not develop in patches and are distributed sporadically within the walnut and apple forests. These species include *Acer turkestanicum* Pax, *Pyrus turcomanica* Maleev, *Prunus Sogdiana* Vassilcz., *Crataegus spp.*, *Betula spp.*, *Juniperus spp.*, *Populus spp.*, *Fraxinus spp.*, *Lonicera spp.*, *Berberis spp.*, *Cotoneaster spp.*, *Rosa spp.,* and other species.

The forests are characterized by great spatial variability in species and density due to complex orography. The apple trees and their patches are sporadically distributed in walnut forests (Wilson et al., 2019), some trees have natural origin, whereas others were planted mainly by forestry units. The non-native trees represent plantations of garden apple varieties or garden varieties grafted on wild rootstock, and their distribution does not appear to follow any pattern. Wild ancestors of domestic apple species represent great value *per se* because of high contents of anthocyanin (van Nocker et al., 2012; Wang, Li, et al., 2015) and as genetic pool for new varieties (Cornille et al., 2014; Yan et al., 2008).

The remarkable feature of *Malus niedzwetzkyana* Dieck is red color of its flesh and skin, a result of high content of anthocyanins (Wang, Li, et al., 2015; Wang, Wei, et al., 2015), which is flavonoid pigment imparting red, blue, or purple pigmentation to fruits, flowers and foliage. These compounds are powerful antioxidants and are widely accepted to benefit human health. Thus, wild fruit forests represent a valuable stock of genes for development of new fruit varieties with beneficial qualities (Forsline et al., 2003).

The rural economy relies heavily on walnut-fruit forests, which serve as primary sources of income for many villagers. Among the vast regions of these forests in Central Asia, those near Arkyt (Figure 1), Arslanbob (Figure 2), Padysha-Ata (Figure 3) and Kara-Alma (Figure 4) villages are among the most significant. Locals harvest walnuts as the main crop on a yearly basis, while wild apples also contribute to the income of rural families.

In Kyrgyzstan, agricultural production is typically practiced on family-based smallholder peasant farms. Because the much of the country is covered by high mountains, most of these smallholder family farms are in highland areas. Mountain farming has many diverse features due to rugged topography, climate regimes, and landscapes that support highly variable ecosystems and, consequently, farming systems. For example, while agropastoral farming predominates in vast high mountain pastures, southwestern Kyrgyzstan has the largest natural walnut-fruit forests where silvopastoral farming communities exist. These mountain pastoralists face environmental and socio-economic sustainability challenges.

On one hand, mountain lands are very vulnerable to climate change and hazards and they are also marginalized due to poor infrastructure and limited access to markets and technologies (Rawat & Schickhoff, 2022). In addition to these stresses, most agropastoral and silvopastoral smallholder farms face further challenges such as degradation of pastures and forests and loss of biodiversity, mainly due to overgrazing (Crewett, 2012; Kerven et al., 2011; Undeland, 2015). To prevent unsustainable use of pastures and forests, and biodiversity loss, the government established several protected areas in walnut-fruit forests, e.g. Dashman nature reserve, Sary-Chelek biosphere reserve and Aflatun-Padyshata (Decree No 405 “On the Establishment of the Padysh-Ata State Reserve,” 2003). However, despite their protected status these areas of biodiversity conservation are still under immense anthropogenic pressure. This occurs because the main focus in the past was to prohibit certain human activities to protect areas while neglecting the dependence of local communities on these forest recourses. This indicates that the suitability of these measures, their consequences on local livelihoods, and response strategies by farmers have not been well understood. In general, knowledge about these silvopastoral farming systems and their socio-economic situation remains limited.

Figure 1. Sary-Chelek biosphere reserve.

Most vegetation biodiversity studies in walnut-fruit forests assess the current (i.e., static) spatial distribution of species in the forests (Borchardt et al., 2010; Cantarello et al., 2014; Orozumbekov et al., 2014; Wilson et al., 2019). These studies outline the contemporary use of forests, species distribution, and their covariates. Pollen and stomata studies (Beer et al., 2007, 2008; Beer & Tinner, 2008) look deeper into forest history trying to reveal the past species compositions and aid reconstruction of climate history. Other studies examine tree-ring patterns and their relation to climatic factors and mass movement events (Isaev, Ermanova, et al., 2022; Kang et al., 2022; Winter et al., 2009; Zaginaev et al., 2016, 2019) confirming that tree rings are good covariates for restoration of missing climate data. Broader studies on Central Asian vegetation phenology (Gessner et al., 2013; Kariyeva et al., 2012; Propastin et al., 2007, 2008) utilized metrics like the beginning, end, and peak of season, derived from remotely sensed vegetation data with accumulated precipitation and temperature indices for liner regression analysis to identify interrelations between vegetation and climatic variables. These investigations also revealed significant covariation of climatic and vegetation metrics with different temporal lags in various types of vegetation. However, these studies did not use the plethora of time-series decomposition and analysis methods, which could reveal more interactions and patterns (Kulikov & Schickhoff, 2017).

Vegetation phenology indicates the annual development of plants and is a good variable to understand vegetation dependencies on climatic factors, with possible implications for climate change. There have been several phenological studies in Kyrgyzstan and the region (Henebry et al., 2017; Kulikov & Schickhoff, 2017; C. Li et al., 2021; Tomaszewska et al., 2020; Tomaszewska & Henebry, 2020), mostly dealing with grassland vegetation.

Figure 2. Dashman nature reserve

Tomaszewska et al. (2020) found significant correlations between snow seasonality and vegetation peaks (NDVI) with warmer spring temperatures and less snow leading to lower pasture productivity in Naryn province of Kyrgyzstan. Tomaszewska & Henebry (2020) noted that 55 to 70% of the variation in vegetation phenological metric (the quantity of accumulated growing degree-days) can be explained by elevation and snow cover metrics, making precipitation and terrain factors the main covariates for vegetation phenology in Naryn and Alai regions of Kyrgyzstan. Li et al. (2021) discriminated between different vegetation types and found distinct spatial heterogeneity for different vegetation indicating that they should be approached differently, and that spatial discretization is important to avoid mixing of different meaningful phenological signals. They also showed a significant relation of vegetation phenology with temperature in Xinjiang, China. Kulikov & Schickhoff (2017) conducted spatial discretization of the entire area of Kyrgyzstan based on temporal behavior of remotely sensed vegetation indices and climatic factors, which also indicated great spatial heterogeneity depending on the vegetation classes and orography (Kulikov & Schickhoff, 2017).

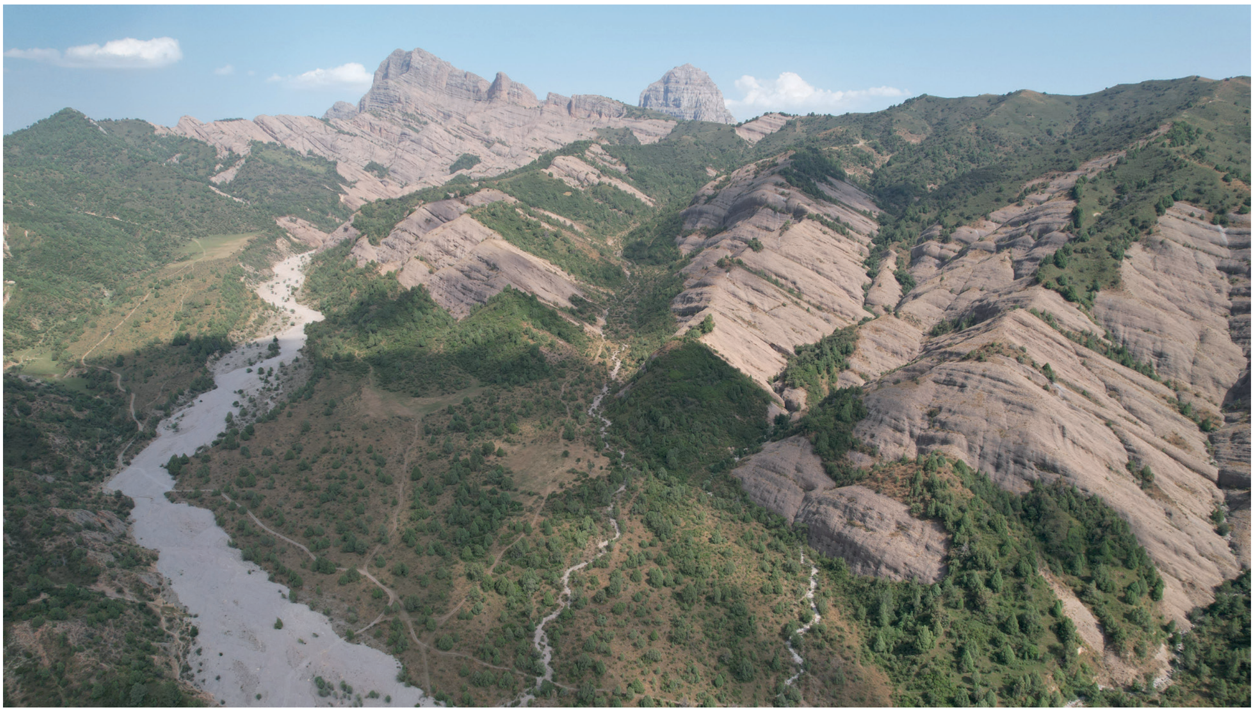


Figure 3. Padysha-Ata nature reserve

Central Asian grasslands contribute significantly to carbon sequestration, a major control on climate change, including increases in CO_2, temperature, and precipitation (Fang et al., 2019; C. Li et al., 2013; Zhu et al., 2019). Forests, which are far less abundant than grasslands in Central Asia, are also important carbon sinks and should be studied and managed to derive benefits related to their carbon sequestration capacity (C. Li et al., 2013). However, few studies on forest vegetation phenology and phenology of different forest types have been conducted in Kyrgyzstan. Similarly, little attention has been paid to quantifying the impact of climate on trees and modelling these interactions. It is important to address this research gap by identifying phenological patterns of different forest types and tree species and their temporal relation with climatic factors like land surface temperature and precipitation. It is also important to quantify these relations by developing regression models, which could be used in future simulations of forest behavior.

Remotely sensed data provide a great potential for analyzing earth surface dynamics at various spatiotemporal scales, particularly in areas that are challenging to access (Walcker et al., 2021). Knowledge of spatial variability among and within forest parcels is a key factor for the users of walnut-fruit forests to estimate yield and quality (Khaliq et al., 2019). In this context, remote sensing (RS) has already shown its potential and effectiveness in spatiotemporal vegetation monitoring (Bollas et al., 2021; Botvich et al., 2021; Mancini et al., 2019; Vicente et al., 2022). Additionally, many satellite platforms (e.g., Landsat, MODIS, Aster, SPOT, Sentinel-1, Sentinel-2) are now providing free datasets, thus promoting satellite imagery for many agricultural applications (Bayle et al., 2021; Bobrowski et al., 2018; Bollas et al., 2021; Botvich et al., 2021; Park et al., 2021; Yang et al., 2017), including those with multi-sensor data fusion approaches (Semmens et al., 2016). For example, remotely sensed images from Sentinel-2 used in our research, offer decametric resolution in space and time, with a ground sample distance (GSD) of up to 10 m and a revisit time of six days. Misregistration of Sentinel-2 imageries was addressed in the Processing

Baseline (version 02.04) (Khaliq et al., 2019) and deployed by European Space Agency (ESA) on June 15, 2016.

Figure 4. Kara-Alma forestry unit.

However, when considering vegetation in complex terrain, such as mountainous Kyrgyzstan with 94% of the land above 1000 m a.s.l. (Isaev, Ajikeev, et al., 2022), remote sensing becomes more challenging. Indeed, steep and complex orography causes varying illumination and may deeply affect the computation of the overall spectral indices leading to biased vegetation status assessments. Therefore, novel approaches and algorithms using Unmanned Aerial Vehicles (UAV) have been developed for satellite-based multispectral vegetation pixel (MVP) calibration across mountainous regions. Low altitude platforms, such as UAV and airborne sensors provide imagery with high spatial resolution (up to a few cm) and flexible flight scheduling (Jay et al., 2019) facilitating vegetation monitoring at high resolution in complex terrain.

At the same time the socio-economic dimension deserves great attention to make forest conservation sustainable. Previous research has documented the importance of non-timber forest products (NTFPs) for rural livelihoods and highlighted the role of livestock and off-farm income in mitigation of fluctuating NTFP income (Dörre & Schütte, 2014; K. Schmidt, 2007; M. Schmidt, 2005, 2013) . However, detailed quantitative analyses of these economic activities are largely lacking, thus limiting the effectiveness of policy actions aimed at sustainable land management in the walnut forest areas – e.g., bans on NTFP collection and nature protection status. A comprehensive analysis of the farmers' livelihoods (i.e., the role of NTFPs, resource capacities, animal production systems and off-farm activities) will help identify constraints and opportunities of smallholder farms. Furthermore, such detailed analysis enables the development of agricultural interventions and policies aimed at improving animal husbandry while simultaneously reducing the negative effects of forest grazing, thus contributing to conservation of these unique ecosystems.

Project area

The project area includes walnut-fruit forests on the western slopes of Fergana range and southern slopes of Chatkal range (Figure 5). These are located in Padysha-Ata nature reserve, Sary-Chelek biosphere reserve, Dashman nature reserve, and Kara-Alma forestry unit in Jalal-Abad province in southern Kyrgyzstan (Table 1). Notably, these areas have some of the highest population densities in Kyrgyzstan, and many people depend on natural resources for their livelihood. In fact, numerous sizable villages are situated nearby or within these protected areas, such as Kara-Alma village, which is located proximate to Kara-Alma forestry unit. Here, the primary sources of income are the collection of walnuts, animal husbandry, and wild apple collection (Azarov et al., 2022). Villages of Arslanbob, Gumkhana, and Kyzyl-Unkur are located around Dashman nature reserve where the main forest pressures are walnut collection, animal husbandry, and tourism. The village of Arkyt is in the middle of Sary-Chelek biosphere reserve, with walnut collection, animal husbandry, unsustainable tourism and beekeeping as the main sources of income. And Kashka-Suu village is very close to Padysha-Ata nature reserve with animal husbandry, tourism, walnut collection, and bee-keeping as the main sources of income (Azarov et al., 2022). These areas are popular for pilgrimage and ecological tourism, which includes hiking, horse and bicycle riding in the forest.

Table 1. Description of the study sites.

Name	Coordinates	Area km^2	Description
Sary-Chelek biosphere reserve	E71.933132° N41.868115°	237.96	Is a UNESCO biosphere reserve on the south slope of Chatkal range in the south of Kyrgyzstan
Padysha-Ata nature reserve	E71.683163° N41.717878°	680.55	Padysha-Ata nature reserve on the south slope of Chatkal range
Dashman nature reserve	E73.02838° N41.37059°	79.36	Dashman nature reserve is one of the biggest walnut populations in Kyrgyzstan on the western slope of Fergana range
Kara-Alma forestry unit	E73.341518° N41.249517°	267.6	Kara-Alma forestry unit has the largest population of wild apple trees, on the western slope of Fergana range

These areas were selected for the project because they represent the main forest ecosystems in the region, significant habitat for *Juglans regia* L. and *Malus* spp., and encompass their greatest population in the country. The forests occupy foothills of Fergana and Chatkal ranges at elevations from 1000 to 2000 m a.s.l. The terrain consists of gentle rolling hills and mountains with exposed rock; sandstone and limestone are the dominant parent materials for soil development (Adyshev et al., 1987). Soils are represented by Cambisols, Umbrisols, and Leptosols on rocky slopes (IUSS Working Group WRB, 2006) composed mainly of silt and fine sand (Kulikov et al., 2017) with high potential for water erosion. These areas receive high amounts of annual precipitation reaching 1000 mm (Adyshev et al., 1987). The long-term mean January air temperature ranges between -8°C and -14°C; mean July air temperature is between 20°C and 26°C (Adyshev et al., 1987).

The forests consist largely of *Juglans regia* L. trees with *Malus sieversii* (Ledeb.) M. Roem., *M. niedzwetzkyana* Dieck, *Pyrus korshinskyi* Litv., *Acer turkestanicum* Pax, *Pyrus turcomanica* Maleev, *Prunus Sogdiana* Vassilcz., *Picea schrenkiana* Fisch. & C.A. Mey., *Crataegus spp.*, *Betula spp.*, *Juniperus spp.*, *Populus spp.*, *Fraxinus spp.*, *Lonicera spp.*, *Berberis spp.*, *Cotoneaster spp.*, *Rosa spp.*, and other species (Lazkov & Sultanova, 2011). The grass vegetation is mainly represented by *Festuca rupicola* Heuff., *Dactylis glomerata* L., *Bromus tectorum* L., *Trifolium repens* L., *Trifolium pratense* L., *Poa pratensis* L., *Koenigia coriaria* (Grig.) T.M.Schust & Reveal, *Malva neglecta* Wallr, *Eremurus fuscus* (O. Fedtsch.) Vved., *Taraxacum officinale* F.H. Wigg., *Geum urbanum* L., *Impatiens parviflora* DC., *Brachypodium sylvaticum* (Huds.) P. Beauv., *Ligularia thomsonii* (C.B. Clarke) Pojark., *Ranunculus polyanthemos* L., *Vicia tenuifolia* Roth, and *Hypericum perforatum* L. (Borchardt et al., 2010; Lazkov & Sultanova, 2011).

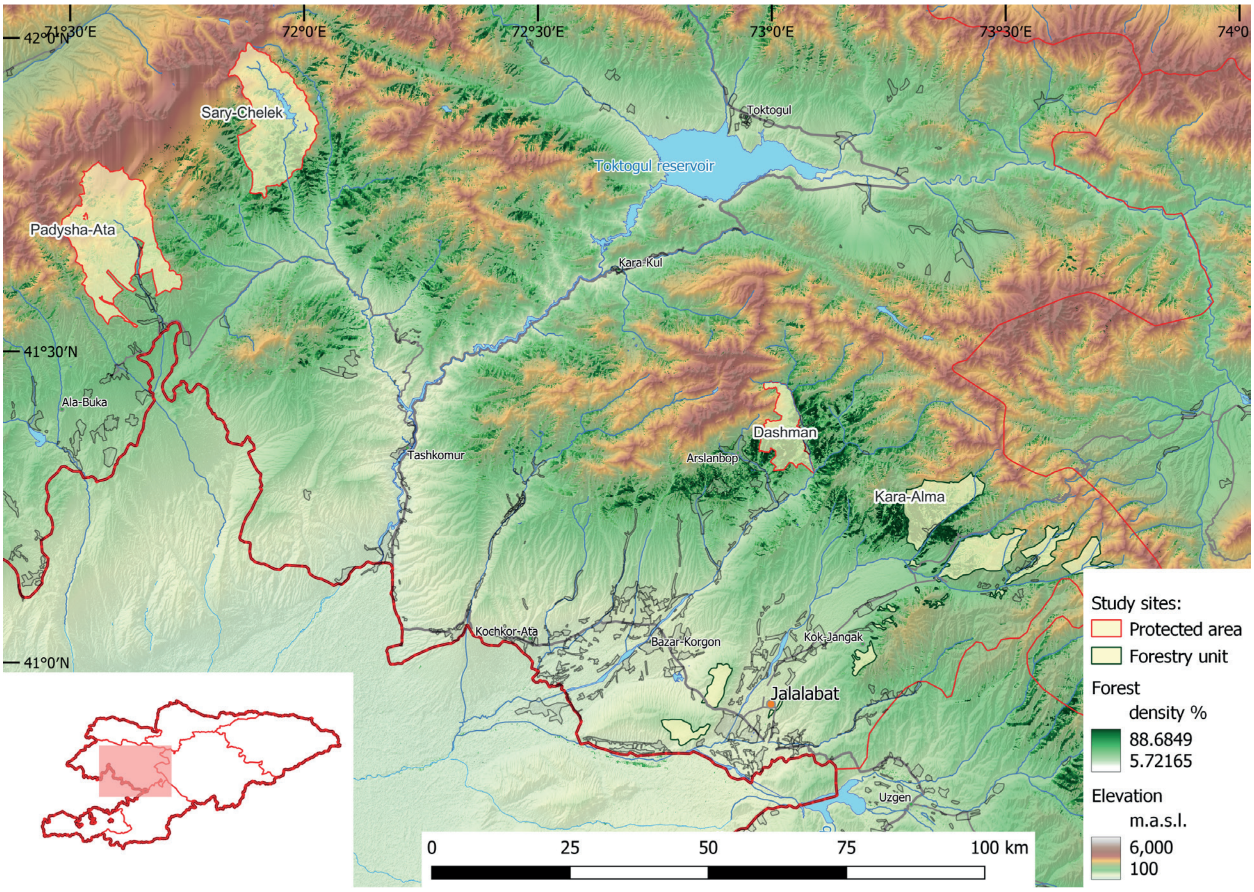


Figure 5. Research area. (Sources: USGS, OpenStreetMap, Global Forest Watch)

The vegetation of walnut-fruit forests consists of large areas of common walnut *Juglans regia* L. trees with patches of native apple *Malus sieversii* (Ledeb.) M. Roem., *M. niedzwetzkyana* Dieck and *Pyrus korshinskyi* Litv., which are globally threatened. The apple trees are sporadically distributed in the walnut forest, some trees have natural origin, whereas others are artificially planted. Currently no mapping or estimation of the coverage of wild versus planted apple trees. Artificial apple culture is either plantations of garden apple varieties or garden varieties grafted on wild rootstock, but their distribution does not appear to follow any pattern. The other tree species do not develop in patches and are distributed sporadically within walnut and apple forests. The forests are characterized by high spatial variability in species and density due to complex orography (Figures 1 – 4).

The forests dominated by *Juglans regia* L. represent one of the main genetic pools for this species, and are a main source for new varieties (Beer et al., 2008; Molnar, 2011; Spengler, 2019; Torokeldiev et al., 2019; Vinceti et al., 2022). The most numerous wild fruit species are

Malus sieversii (Ledeb.) M. Roem. and *Malus kirghisorum* Al. Fed. & Fed.; red apple *Malus niedzwetzkyana* Dieck represents only about ≤10% of the apple trees. Different opinions have emerged on whether *Malus niedzwetzkyana* Dieck and *Malus kirghisorum* Al. Fed. & Fed. are subspecies of *Malus sieversii* (Ledeb.) M. Roem. (van Nocker et al., 2012; Volk et al., 2013). Also, additional research is required to estimate the population of each *Malus* species in the forest. Both *Malus* species are included in the Red Data Book of the Kyrgyz Republic. *Malus niedzwetzkyana* Dieck is rated as 'Vulnerable' in national Red Data Book and 'Endangered' by the IUCN Global Red List, *Malus sieversii* (Ledeb.) M. Roem. is 'Least Concern' and 'Vulnerable', respectively, in the two lists. *Malus sieversii* (Ledeb.) M. Roem. is considered an ancestor of *Malus orientalis* Uglitzk. and *Malus domestica* (Suckow) Borkh., a domestic variety of apple trees (Cornille et al., 2014), which makes it a valuable genetical resource for new varieties.

Problems

Kyrgyzstan is a poor country with more than 60% of its population residing in rural areas (NatStatCom, 2018). Walnut-fruit forests provide income and ecosystem services to local communities (Azarov et al., 2022; Borchardt et al., 2010; Shigaeva et al., 2018) playing an important role in rural economy. These are effectively the main source of income for many families in rural villages. Walnuts are the main crop, which are harvested on an annual basis by locals; however, wild apples contribute to rural family income. Overall, forest products contribute from 22% to 61% to the rural incomes with collection of walnuts being the dominant source followed by wild apples (Dzhakypbekova et al., 2018; Shigaeva et al., 2018). Most households (96%) collect walnuts and only 19% of families collect apples, and these are mainly poor families (Dzhakypbekova et al., 2018; Shigaeva et al., 2018).

Collection of walnuts and animal husbandry are among the few major income sources for rural residents, with walnut collection providing the largest share and animal husbandry the second largest share (Dzhakypbekova et al., 2018). These activities have resulted in overgrazing and selective planting and cutting, contributing to suppression of natural regeneration and loss of genetic diversity. Walnut trees are considered the most profitable and more valuable than apple trees, thus walnut trees are preferred over the apple trees, which leads to selective cutting and higher pressure on apple genetic resources (Beer et al., 2008; Cantarello et al., 2014; Orozumbekov et al., 2014). The apple tree wood has a higher energy value than walnut, and local people understand this distinction.

Following walnuts, apples represent the second most important source of income generated from the forest. However, due to the challenging economic circumstances faced by the local population, they resort to collecting species listed in the Red Data Book of Kyrgyz Republic, which leads to the extensive extraction of seeds from wild populations. This practice can have an unforeseeable impact on the species, potentially resulting in population decline or even extinction. To preserve the natural species composition of the forest, it is recommended to implement a program for artificial reproduction of species typical in the original forest. Additionally, pollen and stomata studies can offer insights into the historical vegetation of these forests and prevailing climatic conditions (Beer et al., 2007, 2008; Beer & Tinner, 2008).

Grazing in the forests poses a major threat to the trees and the ecosystem. Animals destroy grass and walnut seedlings, which leads to forest aging (Borchardt et al., 2010) and soil erosion due to compaction and vegetation loss. Vegetation establishment is one of the main soil conservation factors, as loss of woody vegetation and grasses leads to concentrated runoff (Borchardt et al., 2013; Kulikov et al., 2017) and gully erosion, landslides and debris flows as a consequence. Clearing of trees will exacerbate the mass movement events (landslides, debris flows) in the region. Livestock that browse freely in the forest destroy young trees and damage stems and branches of adult trees. Local people extract apple seeds from the forest by collecting apples and selling them for juicing or drying. These activities strongly limit sexual and vegetative propagation of wild apple species (Cantarello et al., 2014; Orozumbekov et al., 2014). This results in aging trees and major ecosystem change, reducing genetic diversity and converting the forest into a monocultural orchard, which is vulnerable to pests and diseases. Overgrazing and selective cutting for firewood contributes to suppression of natural regeneration and loss of genetic diversity (Beer et al., 2008; Borchardt et al., 2010). In addition to these anthropogenic influences, climate change is increasing drought occurrence frequency and thus altering habitats (Isaev and Omurzakova, 2019; Kretova, 2020; Park et al., 2021).

Monocultural forests promote the rapid spread of pests and diseases. Here, pests like Gypsy moth (*Lymantria dispar*) and diseases like Fire blight (*Erwinia amylovora*) pose serious threats to wild apple populations in Kyrgyzstan and in south Kazakhstan (Djaimurzina et al., 2014; Doolotkeldieva & Bobusheva, 2016). These pests and diseases are spread by industrial fruit orchards and by *Rosaceae* and other species, which are abundant in the forest. Forestry units lack expertise and resources to control these diseases, which constrains natural propagation and leads to loss of wild trees. Nature reserves also lack the capacity and expertise to protect the forest against illegal logging and grazing and to conduct research on tree populations, especially after the closing of scientific departments in nature reserves.

Kyrgyzstan is the third-most-vulnerable country in Eastern Europe and Central Asia to climate change, mainly owing to its climate-sensitive agricultural systems and a lack of an adaptive capacity (Isaev, Ermanova, et al., 2022). Walnut-fruit forests are particularly susceptible to climatic factors (Winter et al., 2009) as are other forests in Kyrgyzstan (Isaev, Ermanova, et al., 2022). Thus, climate change is another threat to the forests, which is exacerbated by their immobility and low adaptive capacity; thus, modelling is needed to elucidate the response of forests to climate change (Wilson et al., 2019). Accurate spatial and temporal monitoring of trees and their phenology is important to understand and protect natural ecosystems. In addition, accurate estimates of the extent of degraded forests and forest clearing are key components of international climate change initiatives, such as reducing emissions from altered and transformed forests in developing countries (REDD+) within the context of the UN framework convention on climate change. Because selective logging and collection of nontimber forest products (NTFP) are widespread, it is imperative to develop a national or subnational system that accurately monitors forest canopy openings, intensity of use, and contributes to improved forest management to recover forest biomass (carbon stocks) and natural regeneration (Vicente et al., 2022).

A number of national and regional projects propose different management schemes for the forests to find a balance between socio-economic and conservation goals. Forest units (leskhoz) are the main official bodies managing the forest; however, they lack resources and technical skills. Scientific agencies also lack the capacity to conduct research to inform management strategies. At the same time, holistic socio-economic surveys on sylvopastoralism and use of nontimber forest products and climate change impacts modelling are rare in the region. This leads to uninformed natural resource management with different levels of success. It is important to apply a multidimensional scheme considering various interests to improve the management and conservation of these forests and globally important genetical resources. These efforts should include research, monitoring, and reproduction of threatened tree species, as well as capacity building of forestry units, raising awareness, sustainable livelihoods for local people, development of management plans for natural resources, and climate change adaptation.

If no measures are taken the deceasing population of wild apples can be severely damaged, and the population dramatically decreased. Walnut trees will age without effective regeneration. Residents will continue cutting fruit trees for firewood and there will be no regeneration as new seedlings will continue to be eaten by livestock and seeds will be extracted from the forest by apple collection. The protected areas and forestry operations will continue inefficient protection practices, which will exacerbate the threats. The wild population of fruit trees age and become extinct in the near future.

Research approach

Our study was designed to encompass a comprehensive range of challenges faced by the forests and woody plant species in southern Kyrgyzstan. It was structured to examine the issues from both socio-economic and environmental angles. Our multidisciplinary research tackles the environmental and socio-economic impacts of deforestation, biodiversity loss, and the unsustainable utilization of forest resources. To reduce poverty and develop sustainable livelihood strategies, it is essential to comprehend the challenges and limitations faced by local communities. Our investigation provides insight into the current state and trends, along with policy suggestions for protecting and promoting endangered fruit species and implementing climate change adaptation strategies for forest management.

Findings of this research and the development part of the project were disseminated on the Life in Kyrgyzstan 2022 conference, where we presented project results and invited other scientists and conservationists, as well as local communities, state agencies, and other stakeholders to share their relevant comments. This event attracted the attention of decision-makers and academia to the issues of threatened fruit species conservation and forest management. The conference was broadly covered in mass media to increase general awareness on the species value and conservation issues and draw public attention to the communities and the problems they face in these forest areas.

The environmental research was devoted to understanding the ecology of *Malus niedzwetzkyana, M. sieversii* and *Pyrus korschinsky*. We conducted research on their occurrence by mapping of tree groups in the forest using field plot surveys, application of photogrammetric methods, and remotely sensed data collection of different seasons to increase classification capacity and data resolution. To map these trees, we conducted field trips to study the target species, their density and distribution, as well as their habitat. Observation plots (100 x 100 m) were established in the field using a stratified random sampling approach to cover different slopes, elevations, and aspects. Next, we classified the forest using field and remotely sensed data (Landsat, Sentinel, UAV) via a random forest algorithm. We used freely available remotely sensed datasets including satellite imagery from Landsat and Sentinel, which feature sufficient spatial, temporal, and radiometric resolution, and climatic data (e.g., land surface temperature, precipitation). UAV data were employed in critical areas for greater accuracy. Time series of remotely sensed vegetation indices (NDVI and EVI) and climatic features (e.g., precipitation and temperature) were cross correlated to understand their relations to elucidate ecosystem and species response to climate change. The spatial distribution data of apple species were used to identify ecological conditions preferred by the species and modelling of their potential distribution, e.g. Bobrowski, Gerlitz, and Schickhoff (2017). This information will be further used for modeling of the extent of fruit and nut forest shifts due to climate change, e.g. Bobrowski et al. (2018).

To test freely available remotely sensed data, it is necessary to compare Sentinel-2 data with more detailed UAV imagery from western Tien Shan related to monitoring walnut-fruit forests. We conducted a detailed analysis and comparison of these products – i.e., decametric resolution satellite and low altitude centimetric resolution UAV. The effectiveness of Sentinel-2 data bias correction was evaluated by considering the well-known relation between the normalized difference vegetation index (NDVI), Vegetation Condition Index (VCI), and Standard Precipitation Index (SPI).

A socio-economic survey was conducted to reveal livelihoods strategies of the local population and understand their development needs. Furthermore, we studied active practices of agropastoralism, agroforestry, and sylvopastoralism and their impact on natural resources. Effects of climate change on natural resources and the target species in particular was studied, e.g. Kulikov et al. (2020). For this we conducted semi-structured interviews on livelihood strategies and climate change impact observations. The questionnaire for the interviews was evaluated by UCA's Ethics review committee to avoid unethical behavior, as required by the UCA policy of research best practices. This research helps to reveal the income generating activities related the threatened species (Shigaeva et al., 2018). Our report offers a summary of the present state of affairs, accompanied by suggestions to enhance the sustainability of local livelihoods while prioritizing the environment. The outcomes of our study will aid policymakers in creating novel tactics for developing more sustainable livelihoods with added value, leading to a decrease in the strain on endangered species.

Methods

Phenological methods

Field data collection

In the summers of 2021 and 2022, field data were gathered. Ecological information was collected in 100 x 100 m plots where the primary environmental characteristics were described. These characteristics included slope gradient divided into three categories (0-15°, 15-30°, 30-45°), bearing, slope form, position on slope, and land cover class (Figure 2). GPS coordinates of all plots were recorded along with stem coordinates of 10 to 15 trees. The tree data included species, circumference at breast height, and whether blossoms or fruits appeared. Selected trees were representative of the forest stand and we maintained the proportion of species to reflect the species composition of the entire forest within the plot. In total, ecological data was gathered from 133 plots across all four study sites, with the GPS coordinates of 1428 trees (by species) recorded on these plots (Figure 6).

Preparation of raster data

Data were analyzed in Google Colab using Python language and applying Google Earth Engine Python API for the remotely sensed data manipulations.

Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) have been extensively used in remote sensing research as vegetation covariates because live and healthy vegetation reflects more in the near-infrared spectrum and less in the red spectrum. Therefore, by utilizing Equation (1), we can calculate a variable that considers values around 0, where values less than 0 indicate "no vegetation" and values greater than 0 indicate green vegetation. The higher the value, the denser the vegetation. We chose EVI because it is more suitable for forest conditions *(Landsat Enhanced Vegetation Index | U.S. Geological Survey, n.d.)*.

We used Sentinel-2 data (product 'COPERNICUS/S2' in Google Earth Engine) as the main remotely sensed source of data for calculation of vegetation indices for the period of 2016 – 2022. Sentinel-2 provides high spatial resolution of 10 m and a frequent revisiting rate of 5 days (*User Guides - Sentinel-2 MSI - Sentinel Online - Sentinel Online*, 2023). All images were masked for clouds using the provided cloud mask. The values of all the spectral bands were divided by 10,000 as they are scaled by 10,000. Next, we calculated Enhanced Vegetation Index (EVI) using Equation (1).

$$\boldsymbol{EVI} = \boldsymbol{G} * \frac{(\boldsymbol{NIR} - \boldsymbol{Red})}{(\boldsymbol{NIR} + \boldsymbol{C_1} * \boldsymbol{Red} - \boldsymbol{C_2} * \boldsymbol{Blue} + \boldsymbol{L})} \quad \textbf{(1)}$$

where:

EVI – enhanced vegetation index,

NIR – near infrared reflectance,

Red – red reflectance,

Blue – blue reflectance,

L – vegetation background correcting coefficient, L = 1,

C_1, C_2 – aerosol correction coefficients, C_1 = 6, C_2 = 7.5,

G – empirical correcting factor, G = 2.5.

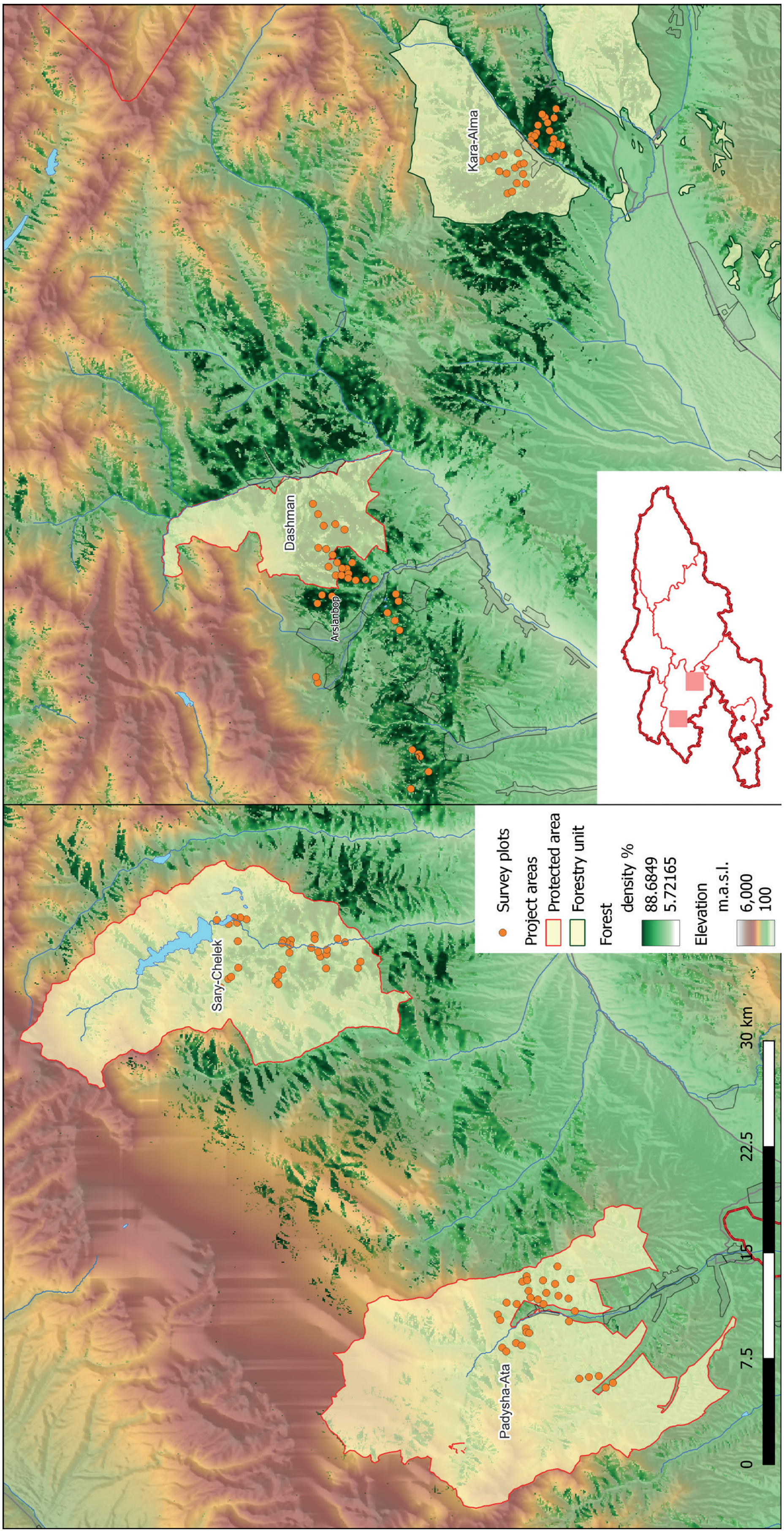


Figure 6. Survey plots. (Sources: USGS, OpenStreetMap, Global Forest Watch)

Then EVI images were combined into monthly vegetation rasters from 2016 to 2022 using the maximum value of pixels to further clean aerosol and haze effects on the signal. Thus, we obtained a monthly time-series of rasters of vegetation indices for our study areas.

To estimate the temperature in our study area, we utilized Landsat 7 and Landsat 8 datasets with pre-calculated land surface temperature (LST) products from 'LANDSAT/LE07/C02/T1_L2' and 'LANDSAT/LC08/C02/T1_L2' on Google Earth Engine, respectively. We used the same time span as with Sentinel-2 images (2016 – 2022). These images were masked for clouds and cloud shadows using the provided mask and values were converted from Kelvin to degrees Celsius. Monthly rasters were created using the maximum function to eliminate any potential impact of aerosols. Therefore, we obtained a monthly time-series of LST raster images.

Precipitation data used in this study were derived from ERA5-Land, i.e., monthly mean values of precipitation ('ECMWF/ERA5_LAND/MONTHLY' product of Google Earth Engine). These are ready-to-use monthly rasters that require no pre-processing.

We selected data from different sources for the vegetation indices, LST, and precipitation to avoid co-variation inherited from the same initial data source.

Preparation of time-series

To determine the monthly values of vegetation indices, land surface temperature (LST), and precipitation associated with the trees, we used their coordinates to calculate the mean values of all pixels within a 10-m radius buffer around each tree. This enabled us to obtain a monthly time-series of the vegetation index (EVI), land surface temperature (LST), and precipitation as spatial means for all the studied plots and for each measured tree.

There were some missing values at some points and months mainly due to masked out cloud areas or missing values on Landsat 7 images due to scanline errors. The missing values were replaced by smoothing with weighted means of the previous and the following months and the same month for the previous and following 3 years, where the values closer in time to the missing value were given higher weights. This approach ensures intra- and interannual data consistency. The following equation precisely outlines the approach used for replacing missing values.

$$\boldsymbol{V_t = \frac{a * V_{t\pm36} + b * V_{t\pm24} + c * V_{t\pm12} + d * V_{t\pm1}}{2 * (a + b + c + d)}} \tag{2}$$

Where:

V_t – missing value (weighted mean) at time t,
$V_{t\pm n}$ – existing value at time t + n and t - n (in months), if some of these values were also missing, they were omitted, and the denominator changed accordingly,
a, b, c, d – weights for the variables, we used values 1, 2, 3, 4 respectively.

For the analysis we used the time-series of *Malus spp.* and *Juglans regia* L. trees, as these species were present in all the study sites and could be used for comparative analysis.

Data analysis

All time-series of vegetation indices and climate factors were decomposed to additive seasonal and trend components using the Python (Google Colab) package "*statsmodels.tsa.seasonal.seasonal_decompose*" (*Statsmodels.Tsa.Seasonal.Seasonal_decompose — Statsmodels*, 2023). Then, lagged correlation analysis of seasonal and trend components of climatic factors and the original time-series of the vegetation index was conducted.

Next, we conducted regression analysis using the ordinary least squares (OLS) method to predict EVI from trends and seasonal components of LST and precipitation with different temporal lags and different nonlinear transformations. We used coefficient of determination (R^2) as the main metric for model accuracy and *p-value* as the main metric for selection of predictors. Equation (3) outlines our regression approach.

$$EVI_t = a * TS^k_{t+w} + b * TT^l_{t+x} + c * PS^m_{t+y} + d * PT^n_{t+z} + e \quad \textbf{(3)}$$

where:

EVI_t – Enhanced Vegetation Index at time *t*,
TS – temperature seasonal component,
TT – temperature trend component,
PS – precipitation seasonal component,
PT – precipitation trend component,
a, b, c, d, e – regression coefficients and error,
k, l, m, n – nonlinear transformation exponent,
w, x, y, z – temporal shifts in months.

For the model fitting we did not use negative lags to avoid artificial overfitting because EVI is not expected to respond to future changes in temperature or precipitation. We also did not use lags greater than 6 months as we do not believe that any meaningful impact from climatic factors on EVI can occur after 6 months, but the covariation could be attributed to annual cycles. Missing values of predictors after shifts were not replaced because both LST and precipitation had data before 2016, so real data were used after shifts.

Remote-sensing methods

Datasets

A DJI Phantom 4 Multispectral drone equipped with a built-in multispectral camera was used to capture UAV images. The camera includes one RGB sensor and five multispectral sensors: Red (R), Green (G), Blue (B), Red-Edge (RE), and Near Infra-Red (NIR). With its high-resolution multispectral images, the camera can achieve mapping accuracy at the centimeter scale. Additionally, the drone features a sunlight sensor on its top that captures lighting intensity for lighting correction, ensuring greater consistency and comparability in the collected data.

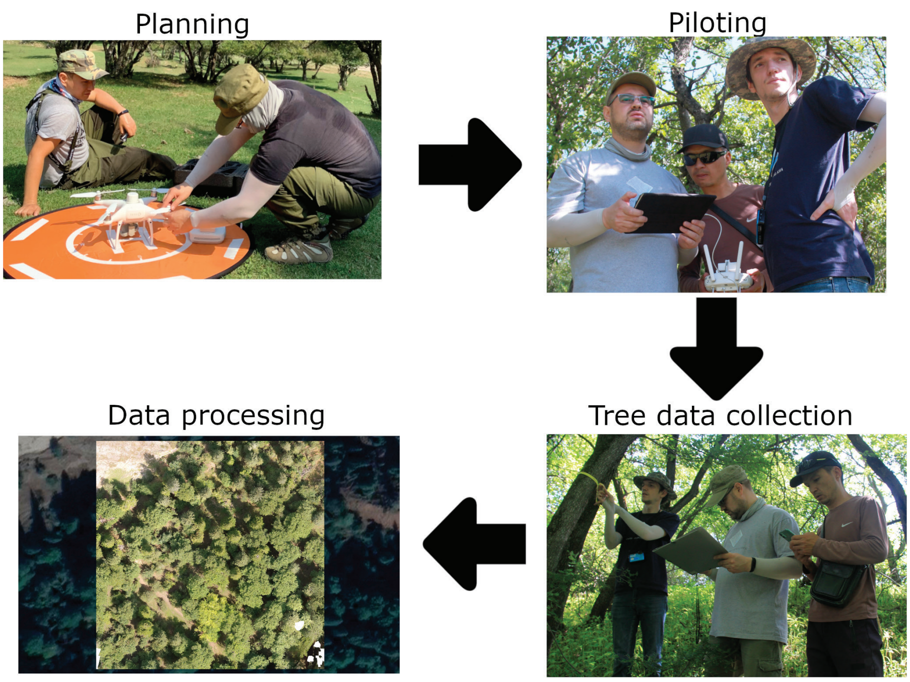


Figure 7. Remote sensing workflow.

The flights were conducted in July and August 2021, each covering an area of 105 x 105 m, at an altitude of 50 m above the launch point with a 90% front overlap and an 80% side overlap. This results in ~2.6 cm resolution on the ground and potentially higher resolution at treetops. The plots were selected to cover the greatest vegetation variability in the study region. In total, we conducted 59 drone flights over various plots (each 11,025 m^2).

Sentinel-2 images (Sentinel-2 MSI: MultiSpectral Instrument, Level-1C) (Table 2) available from the Google Earth Engine platform were used in this analysis. We used all available data from Sentinel-2 scenes with <5 % cloud cover acquired between April and September of 2016 – 2021.

Table 2. The characteristics of the remote sensing UAV and Sentinel – 2: MSI, multispectral instrument, level-1C datasets.

Sentinel – 2 A/B			**DJI Phantom 4 Multispectral**		
Name	**Pixel Size**	**Wavelength**	**Wavelength**	**Pixel Size**	**Description**
B1	60 m	443.9nm (S2A) / 442.3nm (S2B)	-	-	Aerosols
B2	10 m	496.6nm (S2A) / 492.1nm (S2B)	450 nm ± 16 nm	2 cm	Blue
B3	10 m	560nm (S2A) / 559nm (S2B)	560 nm ± 16nm	2 cm	Green
B4	10 m	664.5nm (S2A) / 665nm (S2B)	650 nm ± 16 nm	2 cm	Red
B5	20 m	703.9nm (S2A) / 703.8nm (S2B)	-	-	Red Edge 1
B6	20 m	740.2nm (S2A) / 739.1nm (S2B)	730 nm ± 16 nm	2 cm	Red Edge 2
B7	20 m	782.5nm (S2A) / 779.7nm (S2B)	-	-	Red Edge 3
B8	10 m	835.1nm (S2A) / 833nm (S2B)	840 ± 26 nm	2 cm	NIR
B8A	20 m	864.8nm (S2A) / 864nm (S2B)	-	-	Red Edge 4
B9	60 m	945nm (S2A) / 943.2nm (S2B)	-	-	Water vapor
B10	60 m	1373.5nm (S2A) / 1376.9nm (S2B)	-	-	Cirrus
B11	20 m	1613.7nm (S2A) / 1610.4nm (S2B)	-	-	SWIR 1
B12	20 m	2202.4nm (S2A) / 2185.7nm (S2B)	-	-	SWIR 2
QA10	10 m	-	-	-	Always empty
QA20	20 m	-	-	-	Always empty
QA60	60 m	-	-	-	Cloud mask

The Kyrgyz Statistical Committee (NatStatCom, 2018) provided data on annual crop yields for Jalal-Abad region. This dataset encompasses various crops such as wheat, barley, corn, rice, sugar-beet, cotton, tobacco, vegetable oils, potatoes, vegetables, melons, fruits, berries, and grapes, spanning 1990 to 2021. We used this dataset for verification purposes, as elaborated in the subsequent sections.

Meteorological data were obtained from previous research by Kyrgyzhydromet on droughts in Kyrgyzstan (Isaev & Omurzakova, 2019) and from decadal agrometeorological bulletins (*Early Warning Portal of KG*, n.d.). The data represent monthly precipitation from 1981 to 2021 collected by Kyrgyzhydromet at Pacha-Ata meteorological station.

Automatic photogrammetric adjustments

Photogrammetric adjustments and developing orthomosaic UAV images were conducted using Agisoft Metashape 1.8.3 Professional Edition. This software uses the coordinates of exposure centers of each image performing aerial triangulation in each cell and reconstructs the photogrammetric blocks (Vicente et al., 2022). It also conducts automatic lightning adjustments of scenes based on the information from the UAV lightning sensor. These adjustments ensure data consistency among flights. Finally, we obtained 59 multispectral orthomosaics, which were resampled to a 2 cm spatial resolution and 100 x 100 m tile size. Specific information regarding the camera and image overlays of the UAV image processing is presented in Table 3.

Table 3. Parameters used in the Agisoft Metashape software for image orthomosaic generation and georeferencing the UAV image of the study site.

Attribute	Value
Number of scenes per tile	~410
Number of tiles	59
Flying altitude	50 m
Image resolution	0.02 m pix^{-1}
Coverage area (tile size)	100 x 100 m
Spectral channels	Red, Green, Blue, Red edge, NIR

NDVI was calculated in Agisoft Metashape with a raster calculator as follows.

$$\boldsymbol{NDVI} = \frac{(\boldsymbol{NIR}-\boldsymbol{Red})}{(\boldsymbol{NIR}+\boldsymbol{Red})} \tag{4}$$

where:

NIR – near infrared band

Red – red band.

In the analysis, only NDVI images were utilized. While the UAV image composite (Figure 8a) helped in recognizing individual trees, the corresponding NDVI image sections from Sentinel-2 (Figure 8b) provided lesser details.

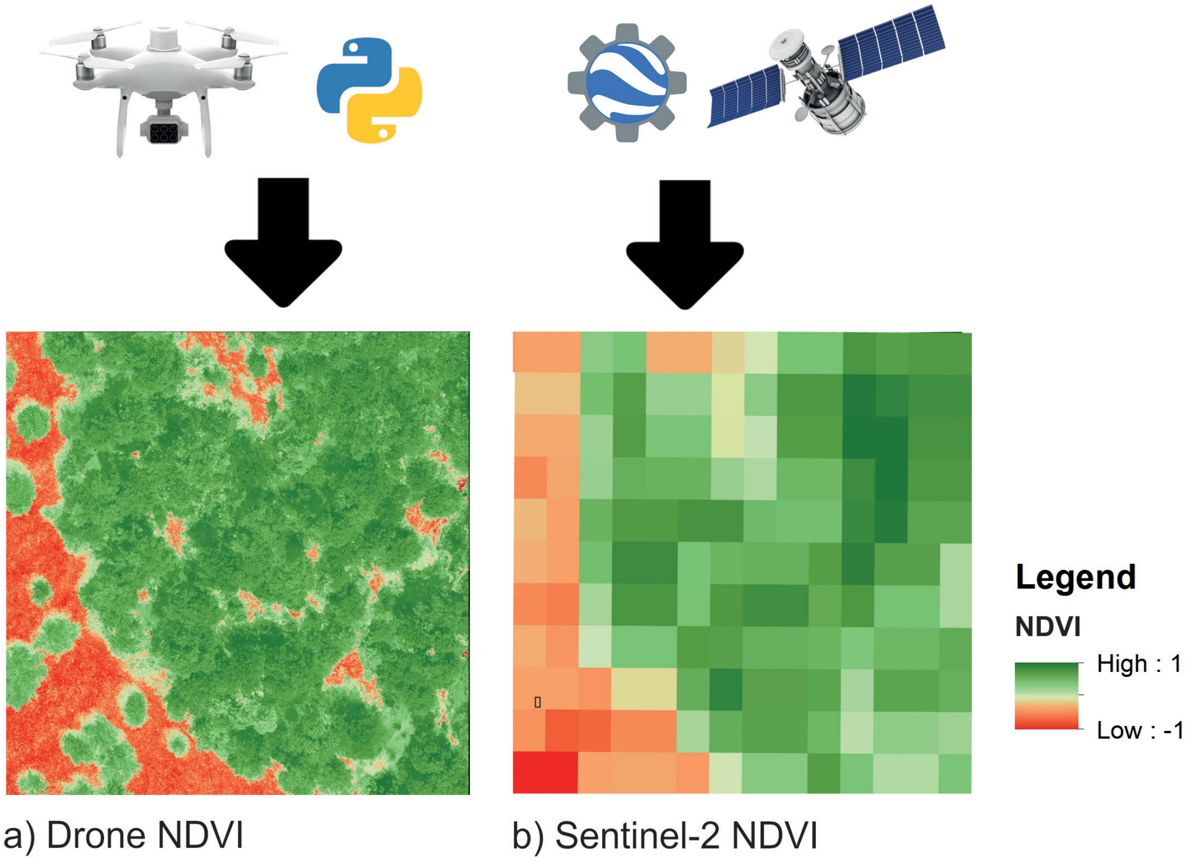


Figure 8. One tile of the remotely sensed images of the study site: in August 2021. (a) UAV NDVI image (0.02 m spatial resolution); (b) Sentinel-2 NDVI image (10 m spatial resolution).

Data processing

In this section, specific methods for data processing, developed to compare and investigate the imagery derived from the two platforms with different spatial resolutions, are presented and discussed in detail.

We utilized Sentinel-2 data to compute NDVI by applying equation (4) in Google Earth Engine for dates that were closest to the UAV flights and where the cloud cover was less than 10%. This process resulted in 59 Sentinel-2 NDVI tiles, each covering an area of approximately 100 x 100 m (Figure 8a), which were then superimposed with UAV NDVI tiles. However, since the spatial resolution of Sentinel-2 images is 10 m and that of UAV images is 0.02 m, there was not always an exact overlap between the pixels, resulting in a fragmentation issue (Figure 9). In some cases, the Sentinel-2 tiles were larger than UAV tiles due to the difference in pixel size. Therefore, we excluded these fragmented pixels from further analysis. For each tile, we created a polygon grid with each cell precisely representing the pixels of Sentinel-2 images superimposed over the UAV images (Figure 9a, b). For each unfragmented cell, the mean NDVI value of each UAV image was computed.

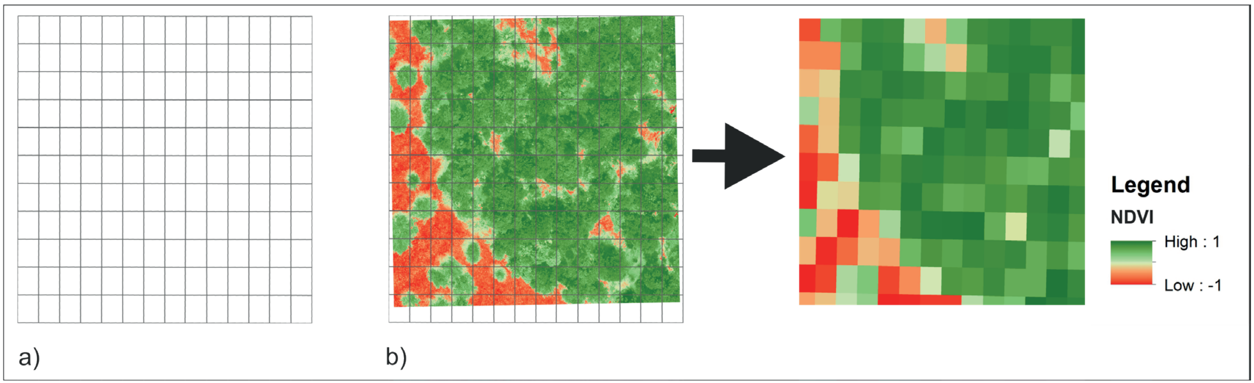


Figure 9. a) Ordered grid of pixels from Sentinel-2; b) Polygon grid exmaple higleted with blue.

Bias correction

Then we calculated mean error (ME) a root mean squared error (RMSE) metrics of compared NDVI for each unfragmented cell:

To assess the spatial patterns on bias distribution we calculated NDVI difference between Sentinel and UAV mean values for each Sentinel pixel as

$$\boldsymbol{NDVI_{diff\ (x,y)} = NDVI_{Sent\ (x,y)} - NDVI_{UAV\ (x,y)},} \quad \textbf{(5)}$$

where:
(x, y) – the pixel coordinates in Sentinel-2 and the overlayed UAV NDVI,
$NDVI_{diff}$ – the difference in NDVI values between Sentinel-2 and UAV images,
$NDVI_{Sent}$ – NDVI values calculated from Sentinel-2 images,
$NDVI_{UAV}$ – NDVI values calculated from UAV images.

To assess potential errors, mean error (ME):

$$\boldsymbol{ME = \frac{1}{n}\sum_{i=1}^{n}(NDVI_{Sent} - NDVI_{UAV}),} \quad \textbf{(6)}$$

and the root mean squared error (RMSE) were calculated:

$$\boldsymbol{RMSE = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}(NDVI_{Sent} - NDVI_{UAV})^2},} \quad \textbf{(7)}$$

To assess systematic patterns in errors for overestimation and underestimation of NDVI we selected all the pixels with absolute values of $NDVI_{diff}$ greater than *RMSE* (i.e., pixels with significant error) and divided them into pixels with positive ($NDVI_{diff} > 0$) and negative ($NDVI_{diff} < 0$) error, comprising overestimation and underestimation of NDVI by Sentinel-2. For all pixels with significant <u>negative</u> $NDVI_{diff}$ we calculated spatial maximum and minimum NDVI values ($NDVI_{max}$ and $NDVI_{min}$), comprising the upper and lower NDVI envelope of <u>underestimated</u> values (see equations 8 and 9). Likewise, for all the pixels with significant <u>positive</u> $NDVI_{diff}$ we calculated spatial maximum and minimum NDVI values ($NDVI_{max}$ and $NDVI_{min}$), comprising the upper and lower NDVI envelope of <u>overestimated</u> values (see equations 10 and 11).

$$UNE = NDVI_{\max\ (x,y)}\ \forall\,(x,y) \in \left(\left|NDVI_{diff\ (x,y)}\right| > RMSE\right) \cap \left(NDVI_{diff\ (x,y)} < 0\right) \quad (8)$$

$$LNE = NDVI_{\min\ (x,y)}\ \forall\,(x,y) \in \left(\left|NDVI_{diff\ (x,y)}\right| > RMSE\right) \cap \left(NDVI_{diff\ (x,y)} < 0\right) \quad (9)$$

$$UPE = NDVI_{\max\ (x,y)}\ \forall\,(x,y) \in \left(\left|NDVI_{diff\ (x,y)}\right| > RMSE\right) \cap \left(NDVI_{diff\ (x,y)} > 0\right) \quad (10)$$

$$LPE = NDVI_{\min\ (x,y)}\ \forall\,(x,y) \in \left(\left|NDVI_{diff\ (x,y)}\right| > RMSE\right) \cap \left(NDVI_{diff\ (x,y)} > 0\right) \quad (11)$$

where:

(x, y) – values at pixel coordinates x, y,

UNE – represents the upper negative envelope,

LNE – is the lower negative envelope,

UPE – is the upper positive envelope,

LPE – is the lower positive envelope.

As noted, we developed different bias correction rates for values of NDVI ∈ (*LNE*, *UNE*) and NDVI ∈ (*LPE*, *UPE*). All the NDVI values outside of these ranges are assumed not to require bias correction as the error is less than *RMSE*. We used *RMSE* and *ME* for bias correction to compare which of these metrics perform better. The following equation represents this approach with *RMSE*; the same was conducted with *ME*:

$$NDVI_{Sent}^{corr} = \begin{cases} NDVI_{Sent} + RMSE,\ NDVI_{Sent} \in \ (LNE, UNE) \\ NDVI_{Sent} - RMSE,\ NDVI_{Sent} \in \ (LPE, UPE) \\ NDVI_{Sent},\ NDVI_{Sent} \neg\in \ (LPE, UPE) \cup (LNE, UNE) \end{cases} \quad (12)$$

where:

$NDVI_{Sent}^{corr}$ – the bias-corrected Sentintel-2 NDVI.

Verification of bias correction

Verification of bias correction with VCI and SPI

To verify the accuracy gained from bias correction we calculated VCI using a method proposed by Kogan (1995) for NDVI values with and without correction:

$$VCI_{(x,y,t)} = \frac{NDVI_{(x,y,t)} - NDVI_{\min\ (x,y,n)}}{NDVI_{\max\ (x,y,n)} - NDVI_{\min\ (x,y,n)}} \times 100\%, \quad (13)$$

where:

(x, y, t) – values at pixel coordinates x, y at a certain time t (month),

(x, y, n) – vector values at pixel coordinates x, y for the entire period of observation n,

$VCI_{(x,y,t)}$ – vegetation condition index values for specified pixels at times (month),

$NDVI_{min\ (x,y)}$ and $NDVI_{max\ (x,y)}$ – the monthly minimum and maximum NDVI values for many years (from April to September from 2016 to 2021) for each pixel.

To evaluate and confirm the effectiveness of the bias correction techniques for Sentinel-2, the region surrounding the Pacha-Ata meteorological station was selected because it is representative of the ecosystem and is close to UAV plots and the meteorological station. Monthly precipitation data from the Pacha-Ata meteorological station from 1981 to 2021 were used to calculate monthly SPI values. The SPI drought index was employed since it was identified as the most appropriate drought index for Kyrgyzstan in a Kyrgyzhydromet study (Isaev & Omurzakova, 2019).

In 2009, the World Meteorological Organization (WMO) recommended using Standardized Precipitation Index (SPI) for drought monitoring, which has been adopted in research or operational practice by more than 70 countries (*Handbook of Drought Indicators and Indices | World Meteorological Organization*, n.d.). "SPI depth" denotes the precipitation sum for the number of months used in the calculation. WMO recommends using the following SPI depth classification for detecting different drought types: 1 or 2 months for meteorological drought, 3 – 6 months for agricultural drought, 6 - 12 months or more for monitoring hydrological drought (*Handbook of Drought Indicators and Indices | World Meteorological Organization*, n.d.).

To analyze the vegetation trends in the region, we first calculated the NDVI using Sentinel-2 images, and then performed NDVI bias correction using two methods (*RSME* and *ME*) described in equations 6 and 7. This was done for the vegetation period from April to September from 2016 to 2021. To assess the relationship between vegetation growth and drought, we computed the spatial mean of the corrected NDVI images for each month and then calculated Pearson's correlation coefficients between these mean values and SPI with different depths ranging from 1 to 12.

As vegetation and precipitation interactions have inertia and vegetation tends to have a delayed response to precipitation, correlation coefficients were calculated with different monthly shifts of corrected NDVI and VCI against SPI (Kulikov & Schickhoff, 2017).

Verification of bias correction with crop yield

To validate the corrected NDVI from Sentinel-2 using ground data, we compared the mean annual corrected NDVI for croplands in the Jalal-Abad province during the vegetation period (April-September from 2016 to 2021) with the crop yield productivity for the province obtained from the National Statistical Committee of Kyrgyz Republic. We performed a correlation analysis of the yield of different crops and SPI for September with varying precipitation depths to identify the crops that were most affected by precipitation and drought. These crops were then used to validate the NDVI correction. September was selected for SPI calculation as it is the most representative month for yield estimations (Isaev & Omurzakova, 2019). However, since only six annual NDVI observations (2016 – 2021) were available, we could not conduct a proper correlation analysis, thus only qualitative assessment of the relation between NDVI and crop yield data was performed.

Socio-economic methods

Data collection

Three villages were selected within or near protected areas whose forest resources are directly affected by residents. Elevations of these villages range from 500 to 4000 m.a.s.l., and the total area of forest in our locations is about 14,000 ha. The study area is characterized by continental arid and semi-arid climate with relatively warm winters, warm summers and average annual precipitation of 800 to 1000 mm, peaking in winter and spring (Forsline et al., 2003). A total of 1125 families lived in the three villages (Doolotkeldieva et al., 2016), and the typical production system in all three villages is smallholder silvopastoral farming. Most smallholder silvopastoral farms are characterized by the collection of forest products in combination with grazing in the forests around the settlements as well as in the forest pastures designated for this purpose.

Figure 10. Interviews with local population.

Socio-economic surveys of farm-households were conducted in three villages from June to July 2021. A structured questionnaire was administered to 220 randomly selected households (Figure 10). The number of farm-households sampled in each village was approximately 20% of the total population of each village. The questionnaire included queries on the main aspects of local livelihoods, i.e., economic contribution of annual collection of NTFPs, animal husbandry, cultivation, and income obtained from non-agricultural activities. Additionally, questions were asked about recent developments affecting farmers' livelihoods, especially at the household and farm level, and about plans to improve agricultural production and other sources of income.

Data analysis

The quantitative data were analyzed initially in Microsoft Excel, followed by descriptive and inference statistics performed in the IBM SPSS program version 22 (IBM Corp., 2017). We indicated only NTFPs revenues as well as animal revenues based on actual farm gate prices. The main variable costs in NTFP harvesting were transport costs as well as hiring workers to harvest walnuts, while in animal husbandry, costs for fodder roughage were the most important variable costs. In both NTFP and livestock revenues, the share of these costs averaged 35% of revenues; subtracting this value makes it possible to obtain a gross margin to assess the operational performance of farmers in livestock production and NTFP collection. Total off-farm income was summed for all sources of non-agricultural activities.

To determine the winter fodder supply of farm households and subsequently to assess the impact on forest pastures we constructed a fodder calendar. This calendar roughly shows the shortage or sufficiency of fodder in households at a certain period. For this purpose, we calculated the amount of fodder harvested annually from forest meadows by farmers based on the farmers' assumed yields in bundles of 17 kg. Then we added the amount of fodder (mainly hay and grain) purchased yielding the gross amount of winter fodder. Feed requirements for different animal types were calculated based on the gross energy content (GE) of harvested and purchased forages. Nutritional values (mediocre quality) of some roughages and feed requirements (energy and protein content) for animals were taken from different sources (LfL, 2010, 2017; Tommea, 1964).

Total livestock population of interviewed households was converted to a livestock unit (LU). Conversion factors recommended by Government Decree No. 386 of 19 June 2009 (On Measures to Implement the Law On Pastures, 2009) were used, and a conversion factor of 0.2 was selected for sheep and goats; the conversion factor for horses remained as recommended at 0.8. The DM requirement of an animal was calculated based on the daily DM requirement of 300 kg dual purpose cattle (equivalent to one LU), with a maintenance requirement ranging from 7.5 to 9 kg DM per day and LU on average. The requirements for sheep and goats were 1.3 kg DM per day and animal and for horses 7.6 kg DM per day and animal.

Results

Now that the methods section has outlined the procedures and techniques utilized in this environmental and socio-economic study, it is time to delve into the results of our research. The data collected through our methodology provides crucial insights into the ecological and environmental factors at play in this study. By analyzing and interpreting these results, we can gain a better understanding of the impact that human activities have on the environment and the steps that can be taken to mitigate these effects. Through our analysis of the data, we can gain a better understanding of the challenges facing individuals and communities and identify potential solutions to address these issues. By exploring the results of this study, we can draw meaningful conclusions that can inform policies and programs aimed at improving socio-economic outcomes while preserving valuable forest ecosystems. In the following sections, we will present the findings of our research and discuss their implications for environmental conservation and management.

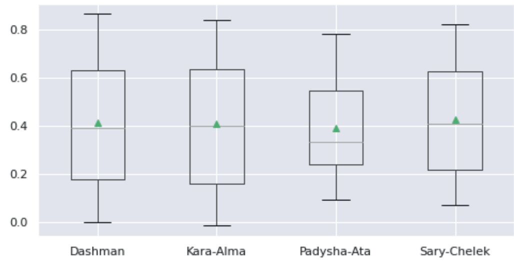
Phenological results

The monthly mean EVI values in all sites fluctuate around 0.4 (Figures 12 a, b) with *Juglans regia* L. EVI being slightly greater than *Malus* spp. The lowest monthly mean precipitation level is in Kara-Alma – 0.272 cm month^{-1}, the greatest level is in Dashman – 0.445 cm month^{-1}, and in Padysha-Ata and Sary-Chelek – 0.335 and 0.303 cm month^{-1}, respectively (Figure 11 c). Precipitation is denoted in cm to make the scale comparable to that of EVI, so that their values could be depicted on the same axis (Figure 12). The greatest monthly mean land surface temperature was in Dashman (18.0°C), the least in Padysha-Ata (15.9°C), and Kara-Alma and Sary-Chelek (16.2 and 17.1°C, respectively) (Figure 11 d). The mean elevations of the plots were 1824 m.a.s.l. in Padysha-Ata, 1614 m.a.s.l. in Dashman, 1518 m.a.s.l. in Sary-Chelek, and 1585 m.a.s.l. in Kara-Alma (Figure 11 e). Sary-Chelek had noticeably greater variability in plot elevations (Figure 11 e). The mean slope gradients of study plots were as follows: Padysha-Ata – 24.8°, Sary-Chelek and Kara-Alma – 16.7°, and Dashman – 15.2° (Figure 11 f).

Table 4. Monthly mean values of EVI, precipitation and Land Surface Temperature in study sites.

	Padysha-Ata	**Sary-Chelek**	**Dashman**	**Kara-Alma**
Monthly mean of EVI *Malus* spp.	0.392	0.427	0.415	0.407
Monthly mean of EVI *Juglans regia* L.	0.401	0.434	0.417	0.395
Monthly mean precipitation (cm)	0.335	0.303	0.445	0.272
Monthly mean LST (°C)	15.92	17.11	18.02	16.23
Mean plot elevation (m.a.s.l.)	1824.75	1518.07	1614.66	1585.58
Mean slope (°)	24.84	16.65	15.16	16.65

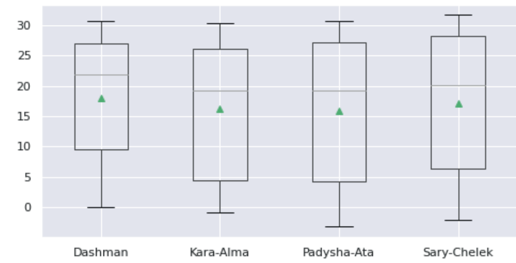
Therefore, Sary-Chelek had the highest variation in study plots and was the site with the highest vegetation cover, as shown in Figures 11 a, b, and e. In contrast, Dashman had the highest land surface temperature and precipitation (Figures 11 c, d), while Padysha-Ata had the steepest plots and the highest elevation (Figures 11 e, f). Kara-Alma was an average study site with mean values for all variables.



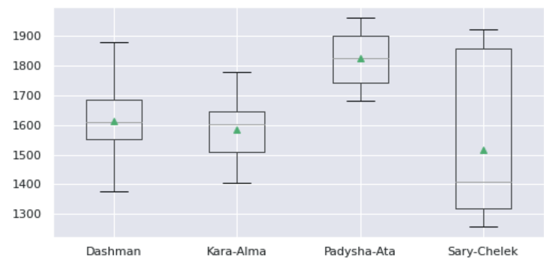
a) Monthly EVI for *Malus* spp.

b) Monthly EVI for ***Juglans regia*** L.

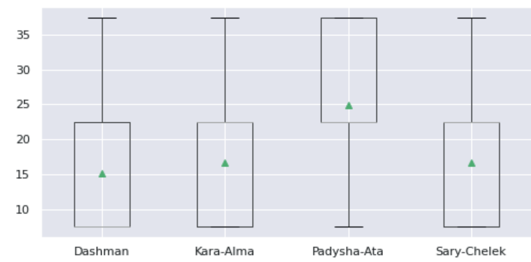
c) Monthly precipitation (cm)



d) Monthly LST (°C)



e) Elevation of plots (m.a.s.l.)



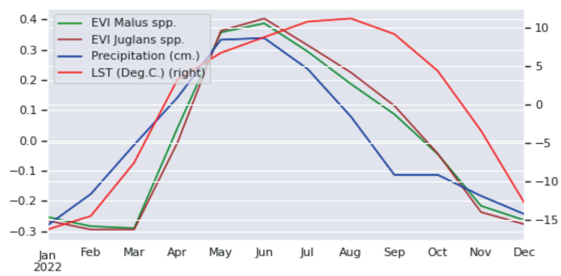
f) Slope of plots (°)

Figure 11. EVI, precipitation, temperature, elevation and slope of plots for the 4 study sites. The box edges extend from Q1 to Q3 with a line at the median and green triangle at mean. Whiskers show the range of data but not greater than 1.5* (Q3-Q1).

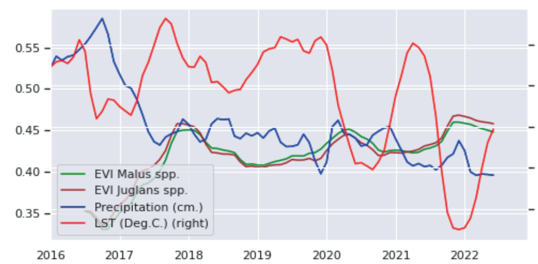
The study sites show similar seasonal temperature distributions, with the lowest values in winter, gradual increases, and a peak in August (Figures 12 a, c, e, g). However, the temperature trend components appear slightly different, with the trend component in Dashman similar to Kara-Alma and the trend in Padysha-Ata similar to Sary-Chelek. The temperature trend curve does not follow any of the EVI trend curves in the study sites (Figures 12 b, d, f, h) and their maximum correlation coefficients were 0.009 - 0.02 at lag 4, whereas the correlation coefficient of seasonal components of temperature with EVI reached 0.77 - 0.87 at lag 0 depending on species and the study area.

The seasonal distributions of precipitation were very different among the study sites (Figures 12 a, c, e, g). Dashman has the greatest variability with one peak in May-June (Figure 12 a), similar to Padysha-Ata (Figure 12 e), whereas in Kara-Alma, one larger precipitation peak occurs in April-May and another smaller peak in October-November (Figure 12 c), similar to Sary-Chelek (Figure 12 g). The greatest correlation coefficient of the precipitation trend component with EVI spans ranges between -0.1 and -0.14 at lag 0 in Dashman and Kara-Alma, and between -0.12 and -0.14 at lag 4 in Padysha-Ata and Sary-Chelek.

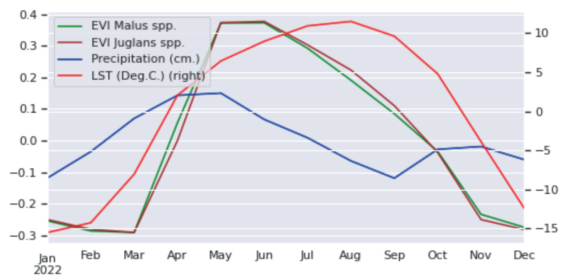
The seasonal distributions of EVI are similar among all the study sites and they follow vegetation phenological patterns reaching their maxima in May-June after the precipitation peak and before the temperature peak (Figures 12 a, c, e, g). The ascending and descending EVI seasonal component of *Malus* spp. is more linear compared to that of *Juglans regia* L. (Figures 12 a, c, e, g), particularly in April and August-September.



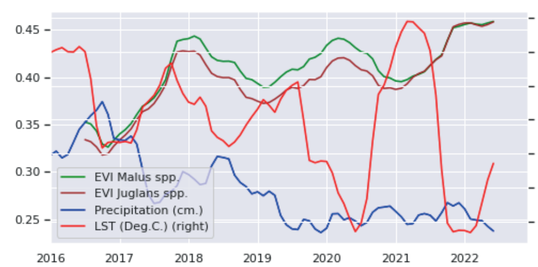
a) Dashman seasonal components



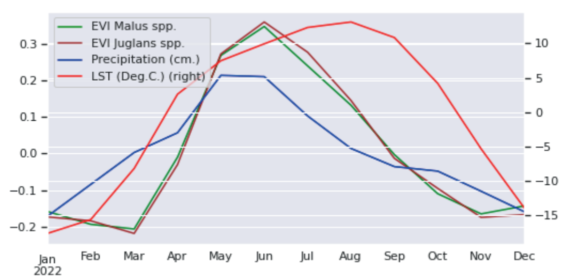
b) Dashman trend components



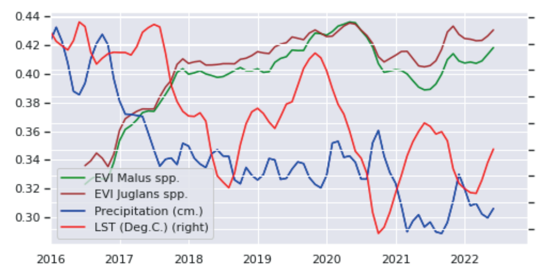
c) Kara-Alma seasonal components



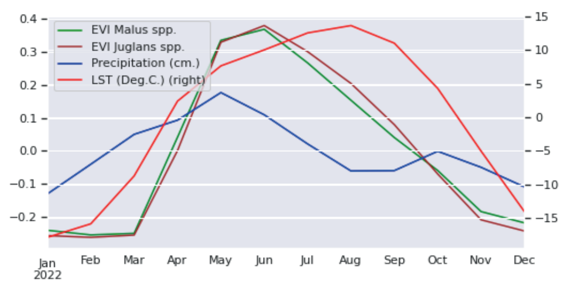
d) Kara-Alma trend components



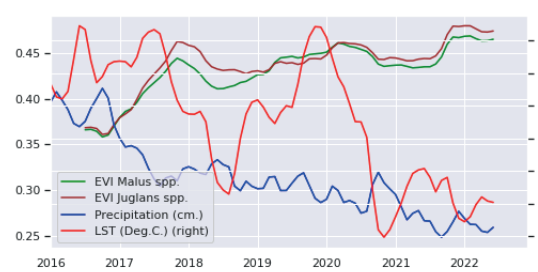
e) Padysha-Ata seasonal components



f) Padysha-Ata trend components



g) Sary-Chelek seasonal components

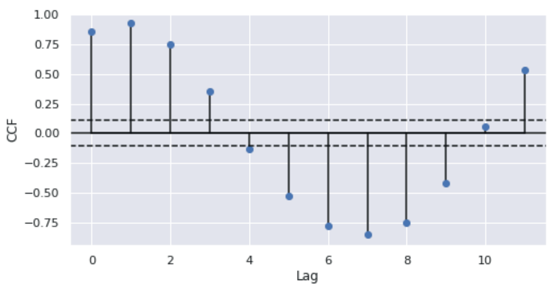


h) Sary-Chelek trend components

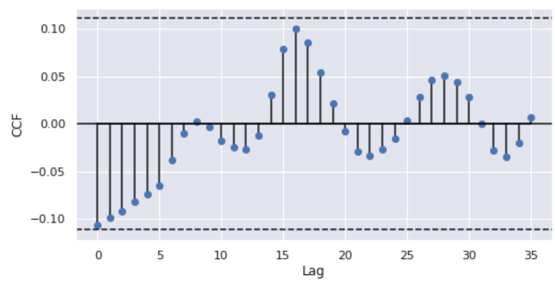
Figure 12. Seasonal and trend components of *Malus spp.* EVI (green), *Juglans regia* L. EVI (brown), land surface temperature (red), and precipitation (blue).

The temperature trend component was not a strong predictor; in all the regression models its *p* value varied between 0.3 and 0.5 regardless of lag or transformation. Thus, the temperature trend component was omitted from the final model, i.e., we used *b* = 0 in Equation (3). The temperature trend component curve did not coordinate with the EVI trend line (Figures 12 b, d, f, h), where the LST graph does not appear to reflect the EVI graph either in a positive or in a negative way. This is also supported by the very low correlation coefficient between the temperature trend component and the EVI time-series described previously. In contrast, the precipitation trend curve indicated behavior opposite to that of EVI (Figures 12 b, d, f, h).

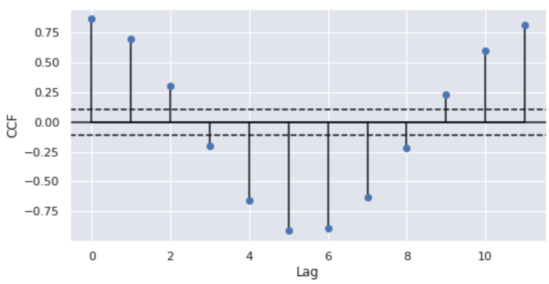
The cross-correlation analysis of EVI with climatic data at different lags for different species and in different study sites indicates no significant correlation between EVI time-series and temperature trends in any sites and among all species (Figures 13 d, h, l, p, and Figures 14 d, h, l, p). In contrast, the precipitation trend component indicates significant correlation with EVI but with different lags: with 0 lag in Dashman and Kara-Alma (Figures 13 b, f and Figures 14 b, f) and with mainly a 4-month lag in Padysha-Ata and Sary-Chelek (Figures 13 j, n and Figures 14 j, n). Thus, Dashman and Kara-Alma differ from Padysha-Ata and Sary-Chelek with regards to the precipitation and temperature trend components.



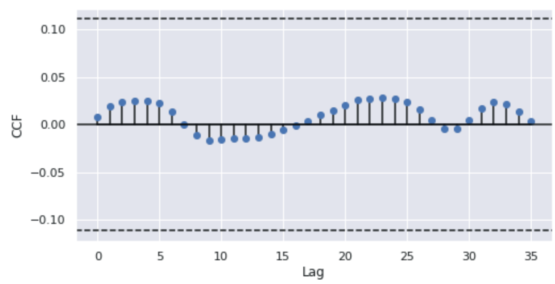
a) Dashman EVI~precipitation seasonal



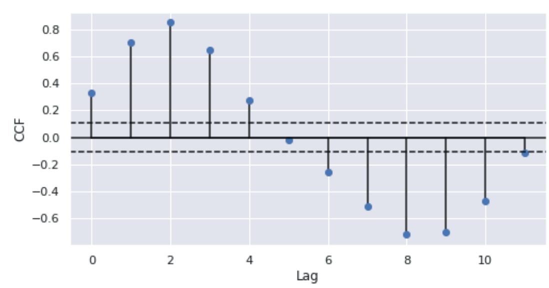
b) Dashman EVI~precipitation trend



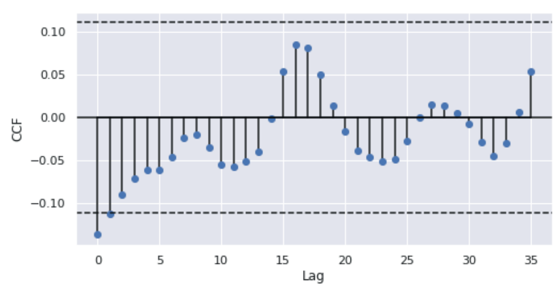
c) Dashman EVI~temperature seasonal



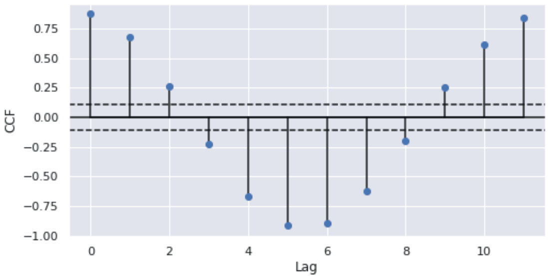
d) Dashman EVI~temperature trend



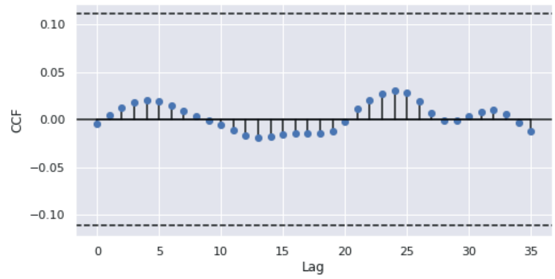
e) Kara-Alma EVI~precipitation seasonal



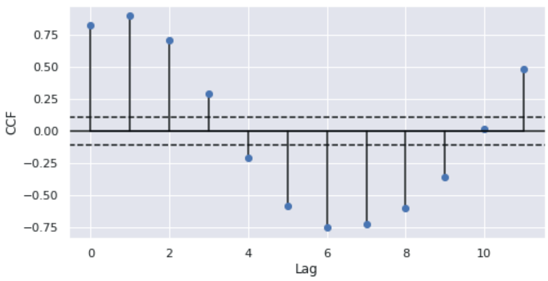
f) Kara-Alma EVI~precipitation trend



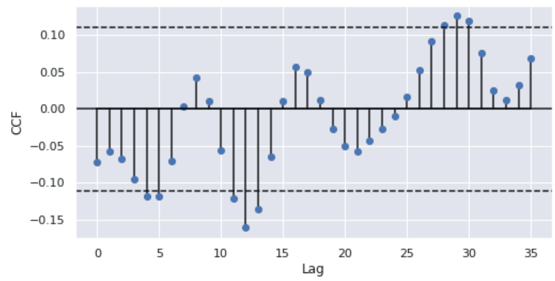
g) Kara-Alma EVI~temperature seasonal



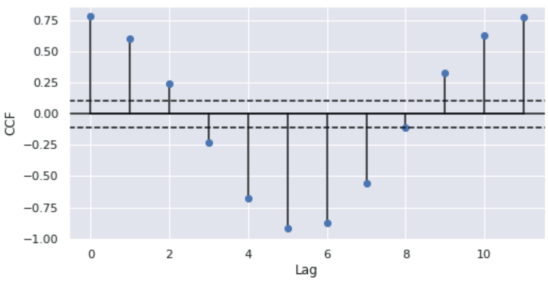
h) Kara-Alma EVI~temperature trend



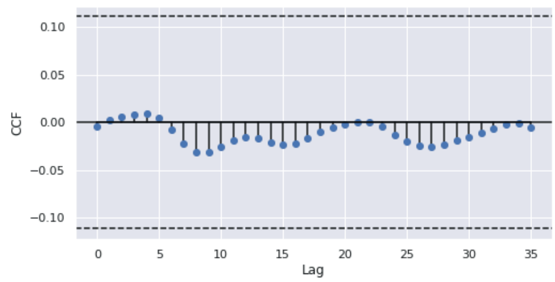
i) Padysha-Ata EVI~precipitation seasonal



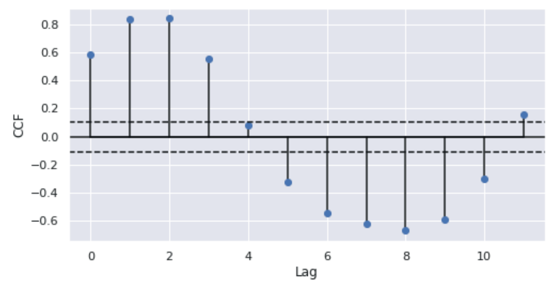
j) Padysha-Ata EVI~precipitation trend



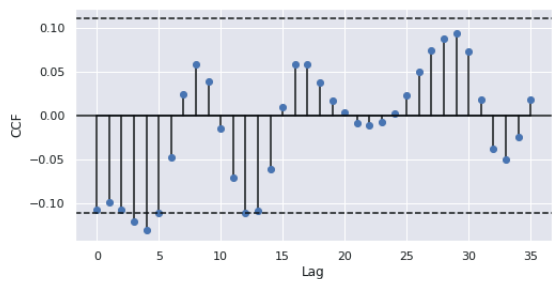
k) Padysha-Ata EVI~temperature seasonal



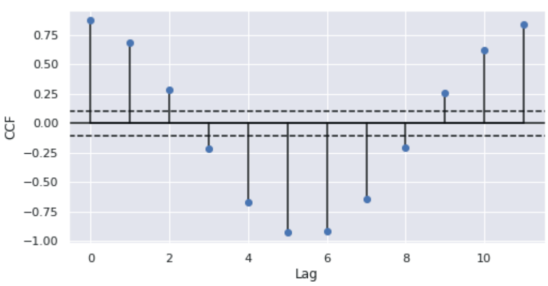
l) Padysha-Ata EVI~temperature trend



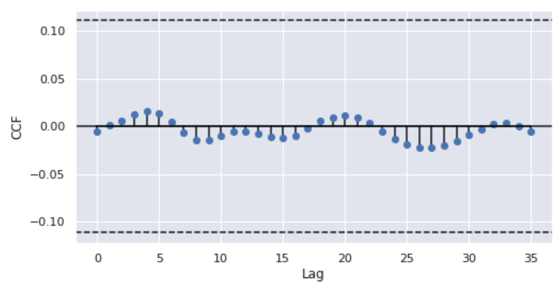
m) Sary-Chelek EVI~precipitation seasonal



n) Sary-Chelek EVI~precipitation trend



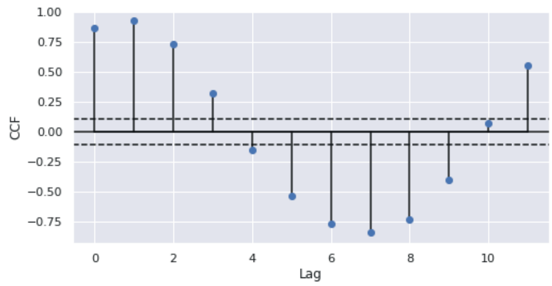
o) Sary-Chelek EVI~temperature seasonal



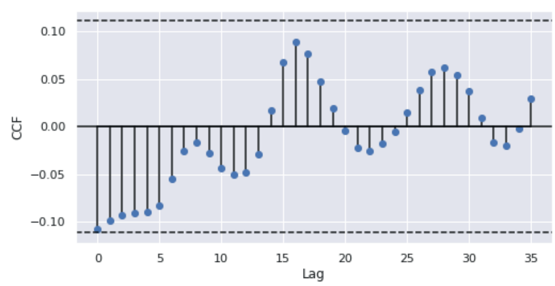
p) Sary-Chelek EVI~temperature trend

Figure 13. Cross-correlation charts of EVI, LST and precipitation components of *Juglans regia* L.

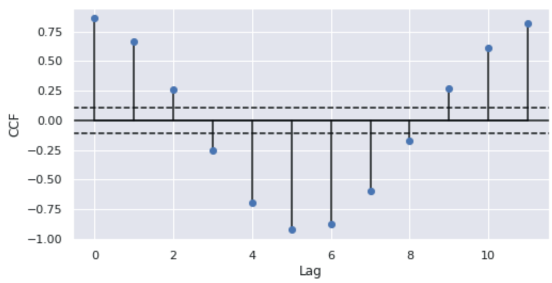
Considering seasonal components, the highest correlation between EVI and the temperature seasonal component was at lag 0 regardless of the study site or species, i.e., EVI reacts to temperature without any lag on an intra-annual basis. Whereas EVI correlation with the seasonal component of precipitation shows differs depending on the study site (Figures 13 c, g, k, o and Figures 14 c, g, k, o). The highest correlation of EVI and precipitation seasonal component is at lag 1 in Dashman and Padysha-Ata (Figures 13 a, i, and Figures 14 a, i) and at lag 2 in Kara-Alma and Sary-Chelek (Figures 13 e, m, and Figures 14 e, m).



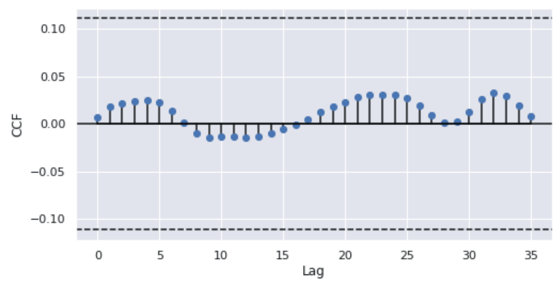
a) Dashman EVI~precipitation seasonal



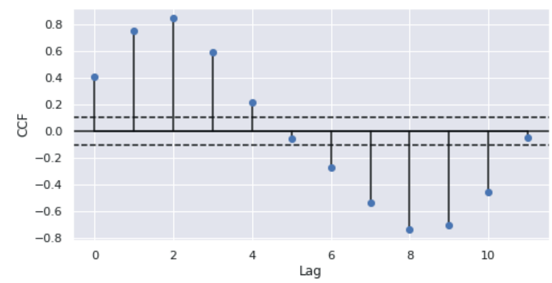
b) Dashman EVI~precipitation trend



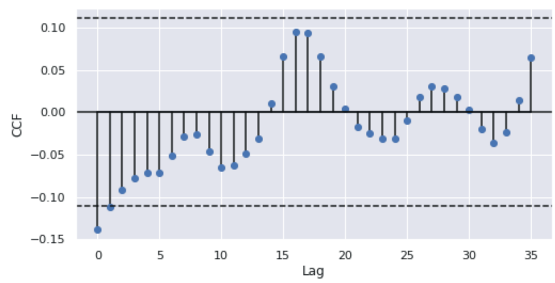
c) Dashman EVI~temperature seasonal



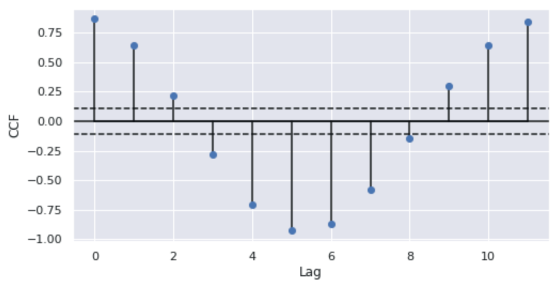
d) Dashman EVI~temperature trend



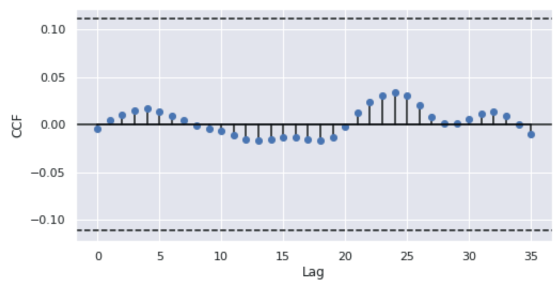
e) Kara-Alma EVI~precipitation seasonal



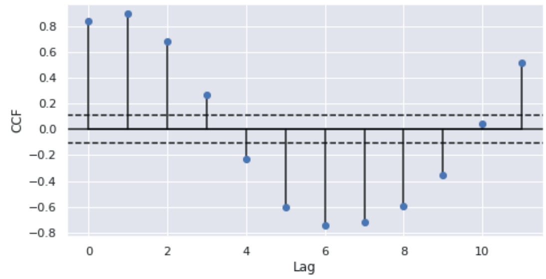
f) Kara-Alma EVI~precipitation trend



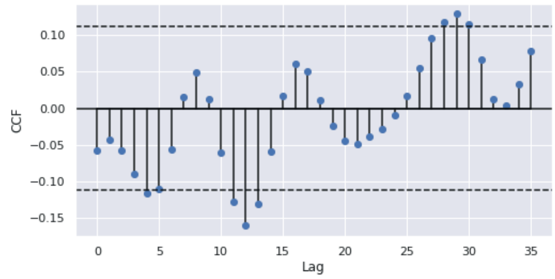
g) Kara-Alma EVI~temperature seasonal



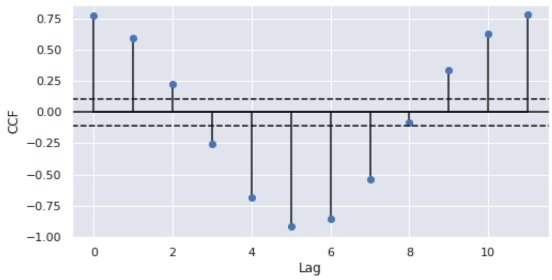
h) Kara-Alma EVI~temperature trend



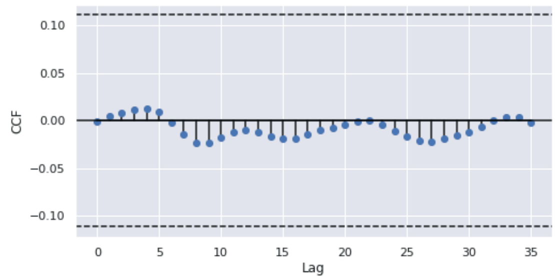
i) Padysha-Ata EVI~precipitation seasonal



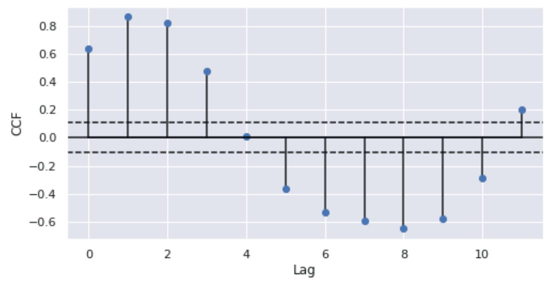
j) Padysha-Ata EVI~precipitation trend



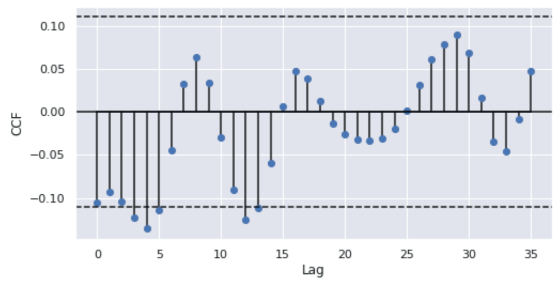
k) Padysha-Ata EVI~temperature seasonal



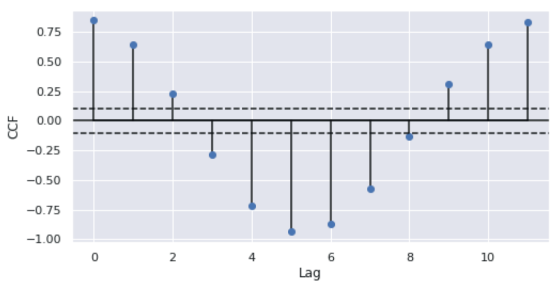
l) Padysha-Ata EVI~temperature trend



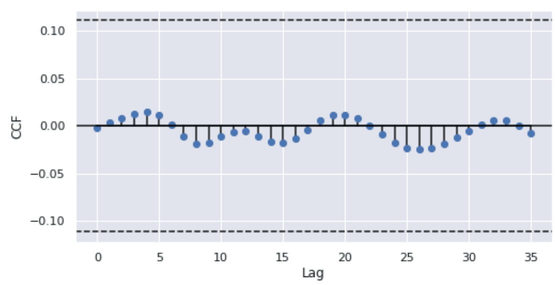
m) Sary-Chelek EVI~precipitation seasonal



n) Sary-Chelek EVI~precipitation trend



o) Sary-Chelek EVI~temperature seasonal



p) Sary-Chelek EVI~temperature trend

Figure 14. Cross-correlation charts of EVI, LST and precipitation components of *Malus* spp.

We generated eight linear regression models for both *Malus* spp. and *Juglans regia* L. in the four study sites using Equation (3). The nonlinear transformation of only the temperature seasonal component and only of *Malus* spp. in Padysha-Ata and Kara-Alma (Tables 4, 6) and *Juglans regia* L. in Padysha-Ata (Table 8) led to significant increases in R^2 values. But in general, the models with seasonal components of precipitation and temperature and the trend component of precipitation have great predicting power for EVI with R^2 varying from 0.827 to 0.916 (Tables 4, 10).

The precipitation trend lag for the best model was 3 – 5 months in Sary-Chelek and Padysha-Ata, whereas in Dashman and Kara-Alma it was 0. The precipitation seasonal component lag for the best model was 1 month in all study sites except Kara-Alma, where it was 2 (Tables 4 – 11). The temperature seasonal component lag for the best model was 0 in all sites and for all species. The p-value for all the predictors exceeded the 0.05 significance level, thus all the predictors have a significant relation with the response variable in the models.

Table 4. Padysha-Ata *Malus* spp. EVI regression			*R-squared: 0.827*		Adj. R-squared: 0.820	
	coef	**std err**	**t**	**P>|t|**	**lag**	**exponent**
Precipitation trend	-76.2743	25.743	-2.963	0.004	5	1
Precipitation seasonal	148.646	7.795	19.069	0	1	1
Temperature seasonal	0.0003	0	2.418	0.018	0	2
Const	0.6252	0.09	6.939	0	NA	NA

Table 5. Sary-Chelek *Malus* spp. EVI regression			*R-squared: 0.879*		Adj. R-squared: 0.874	
	coef	**std err**	**t**	**P>|t|**	**lag**	**exponent**
Precipitation trend	-74.7606	22.196	-3.368	0.001	3	1
Precipitation seasonal	139.7237	14.093	9.914	0	1	1
Temperature seasonal	0.0094	0.001	8.375	0	0	1
Const	0.6626	0.07	9.415	0	NA	NA

Table 6. Kara-Alma *Malus* spp. EVI regression			*R-squared: 0.914*		Adj. R-squared: 0.910	
	coef	**std err**	**t**	**P>|t|**	**lag**	**exponent**
Precipitation trend	-81.659	24.236	-3.369	0.001	0	1
Precipitation seasonal	264.778	9.843	26.899	0	2	1
Temperature seasonal	-0.0016	0	-13.325	0	0	2
Const	0.7909	0.069	11.391	0	NA	NA

Table 7. Dashman *Malus* spp. EVI regression			*R-squared: 0.877*		Adj. R-squared: 0.873	
	coef	**std err**	**t**	**P>|t|**	**lag**	**exponent**
Precipitation trend	-81.7082	21.703	-3.765	0	0	1
Precipitation seasonal	87.4237	10.255	8.525	0	1	1
Temperature seasonal	0.0051	0.002	2.35	0.021	0	1
Const	0.7888	0.1	7.918	0	NA	NA

Table 8. Padysha-Ata *Juglans regia* L. EVI regression			*R-squared: 0.848*		Adj. R-squared: 0.842	
	coef	**std err**	**t**	**P>|t|**	**lag**	**exponent**
Precipitation trend	-81.9911	25.467	-3.22	0.002	5	1
Precipitation seasonal	162.4961	7.878	20.628	0	1	1
Temperature seasonal	0.0003	0	3.142	0.002	0	2
Const	0.6442	0.089	7.251	0	NA	NA

Table 9. Sary-Chelek *Juglans regia* L. EVI regression			*R-squared: 0.872*		*Adj. R-squared: 0.867*	
	coef	**std err**	**t**	**P>|t|**	**lag**	**exponent**
Precipitation trend	-74.6323	23.916	-3.121	0.003	4	1
Precipitation seasonal	122.4259	15.521	7.888	0	1	1
Temperature seasonal	0.0123	0.001	9.796	0	0	1
Const	0.6692	0.076	8.817	0	NA	NA

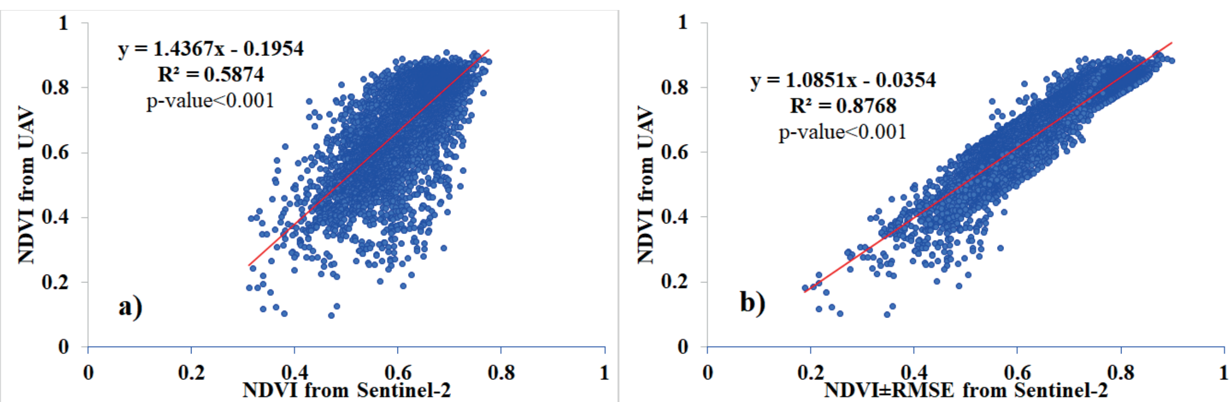
Table10 Kara-Alma *Juglans regia* L. EVI regression			*R-squared: 0.916*		*Adj. R-squared: 0.913*	
	coef	**std err**	**t**	**P>|t|**	**lag**	**exponent**
Precipitation trend	-90.7489	24.42	-3.716	0	0	1
Precipitation seasonal	146.8769	12.959	11.334	0	2	1
Temperature seasonal	0.0151	0.001	13.117	0	0	1
const	0.6489	0.069	9.451	0	NA	NA

Table 11. Dashman Juglans regia L. EVI regression			*R-squared: 0.884*		*Adj. R-squared: 0.880*	
	coef	**std err**	**t**	**P>|t|**	**lag**	**exponent**
Precipitation trend	-80.4827	22.127	-3.637	0	0	1
Precipitation seasonal	91.4425	10.358	8.828	0	1	1
Temperature seasonal	0.0053	0.002	2.307	0.024	0	1
const	0.7905	0.103	7.676	0	NA	NA

Remote sensing results

Bias correction

After visual analysis of $NDVI_{diff}$ (equation 5) on 59 UAV plots we determined that Sentinel-2 data overestimates NDVI in the areas with open terrain and grass (low NDVI values), and underestimates NDVI in the areas with trees (high NDVI values). The error analysis (equations 6 and 7) resulted in the following: *RMSE* = 0.1228 and *ME* = -0.077. The relation between $NDVI_{Sent}$ and $NDVI_{UAV}$ is positive (Figures 15a, b). The linear regression model yielded an R^2 = 0.59 and a p-value < 0.001 (Figure 15a) for uncorrected data. The envelope interval estimates were: LNE = 0.6, UNE = 0.8, LPE = 0.5, and UPE = 0.6. After implementation of the bias correction with *RMSE* and *ME* for Sentinel-2 using equation (9), the accuracy of the Sentinel-2 derived NDVI increased (Figure 15b).



a) b)

Figure 15. The relation between NDVI derived from Sentinel-2 and NDVI derived from UAV imagery; number of pixels = 6486; (a) Sentinel-2 without bias correction; (b)) Sentinel-2 with bias correction.

Verification with VCI indicates that using *RMSE* for bias correction of NDVI provides better results than *ME* (Table 12). After correction, R^2 increased to 0.88 with p-value<0.001 (Figure 15 b). Thus, we describe the bias correction by the following conditional equation:

$$NDVI_{Sent}^{corr} = \begin{cases} NDVI_{Sent} + 0.1228, \; NDVI_{Sent} \in [0.6, 0.8] \\ NDVI_{Sent} - 0.1228, \; NDVI_{Sent} \in [0.5, 0.6) \\ NDVI_{Sent}, \; NDVI_{Sent} \neg\in [0.5, 0.6) \cup [0.6, 0.8] \end{cases} \quad (14)$$

Verification of bias correction with VCI

To verify the bias-corrected NDVI with VCI, we calculated correlations between SPI indices and NDVI with VCI for the area near Pacha-Ata meteorological station and the climatic data from that station indicates that correlation increases between VCI and SPI when corrected NDVI Sentinel-2 data are used (Table 12). In general, correction of NDVI with *RMSE* indicates better results than with *ME* (Table 12). Therefore, *RMSE* correction was used for the final bias correction (Equation 14).

Table 12. Correlation coefficients between Sentinel-2 derived corrected and uncorrected NDVI and VCI with 0- and 1-month lag, and SPI indices with depth from 1 month to 12 months; bold coefficients are the significant ones with $p < 0.05$.

	SPI1	SPI2	SPI3	SPI4	SPI5	SPI6	SPI7	SPI8	SPI9	SPI10	SPI11	SPI12
VCI	0.13	**0.40**	0.31	0.30	0.26	0.28	0.25	0.33	**0.37**	**0.36**	**0.36**	0.34
$VCI_{Corr\text{-}RMSE}$	0.13	**0.41**	0.31	0.31	0.27	0.31	0.27	**0.35**	**0.39**	**0.37**	**0.37**	**0.35**
$VCI_{Corr\text{-}ME}$	0.13	**0.40**	0.31	0.30	0.26	0.28	0.25	0.33	**0.37**	**0.36**	**0.36**	**0.34**
$VCI_{+1\ month}$	**0.41**	**0.36**	0.28	0.21	0.25	0.22	0.28	**0.35**	**0.37**	**0.38**	**0.36**	**0.39**
$VCI_{Corr\text{-}RMSE+1\ month}$	**0.42**	**0.36**	0.29	0.22	0.28	0.24	0.29	**0.37**	**0.37**	**0.40**	**0.37**	**0.42**
$VCI_{Corr\text{-}ME+1\ month}$	**0.41**	**0.36**	0.28	0.21	0.25	0.22	0.28	**0.35**	**0.37**	**0.38**	**0.36**	**0.39**
NDVI	0.05	0.09	0.12	0.11	0.11	0.07	0.10	0.08	0.10	0.17	0.13	0.13
$NDVI_{Corr\text{-}RMSE}$	0.02	0.11	0.14	0.13	0.12	0.10	0.13	0.11	0.13	0.19	0.16	0.15
$NDVI_{Corr\text{-}ME}$	0.05	0.09	0.12	0.11	0.11	0.07	0.10	0.08	0.10	0.17	0.13	0.13
$NDVI_{+1month}$	0.22	0.29	0.17	0.17	0.14	0.16	0.17	0.22	0.25	0.25	0.21	0.19
$NDVI_{Corr\text{-}RMSE+1month}$	0.20	0.27	0.16	0.16	0.14	0.17	0.18	0.22	0.25	0.25	0.20	0.21
$NDVI_{Corr\text{-}ME+1month}$	0.22	0.29	0.17	0.17	0.14	0.16	0.17	0.22	0.25	0.25	0.21	0.19

When calculating vegetation indices with a one-month shift, the correlation relationship increased as precipitation affects vegetation with an approximately 2–3-week lag. The highest correlation is between VCI corrected with RMSE and a 1-month lag with SPI1 and SPI12 ($r = 0.42$, $p < 0.05$), which shows the rate of precipitation of one month relative to the multi-year norm (Table 12). The correlation coefficients between vegetation indices with 2- and 3-month lags and SPI were less than those with a 1-month lag, so they are not reported in the results.

Verification of bias correction with crop yields

By using yield productivity data for different crops in Jalal-Abad province together with correlating with SPI indices for September, we identified that wheat and barley are the crops most related to precipitation and drought (Table 13). Thus, these crops were used for verification of NDVI correction.

Table 13. Correlation coefficients between yield productivity (1991 – 2021) and SPI indices; SPI with depth from 1 month to 12 months; Bold coefficients are significant (p < 0.05).

	SPI1	SPI2	SPI3	SPI4	SPI5	SPI6	SPI7	SPI8	SPI9	SPI10	SPI11	SPI12
Grains	0.15	0.09	-0.13	-0.09	-0.08	-0.02	-0.04	-0.09	-0.08	-0.21	-0.21	-0.21
Wheat	0.25	0.32	0.20	0.14	0.16	0.26	0.14	0.09	0.05	0.22	0.22	0.22
Barley	0.26	0.33	0.11	0.24	0.29	**0.35**	0.27	0.22	0.19	-0.01	-0.02	-0.01
Corn	0.15	0.14	0.07	0.05	0.04	0.13	0.11	0.07	0.08	-0.08	-0.09	-0.09
Rice	0.19	0.16	-0.13	-0.09	-0.12	-0.06	-0.09	-0.14	-0.10	-0.15	-0.16	-0.16
Cotton	0.11	0.13	-0.11	-0.02	-0.04	0.03	0.02	-0.03	-0.02	-0.08	-0.08	-0.08
Tobacco	0.14	0.21	0.30	0.02	0.04	0.00	0.02	-0.02	-0.04	0.10	0.10	0.10
Vegetable oils	0.18	0.18	0.05	-0.01	-0.05	-0.01	-0.02	-0.07	-0.03	-0.06	-0.06	-0.06
Potatoes	0.22	0.16	-0.01	-0.05	-0.05	-0.01	-0.01	-0.03	0.00	-0.12	-0.12	-0.12
Vegetables	0.15	0.16	-0.11	-0.03	-0.03	0.01	0.00	-0.05	-0.01	-0.16	-0.16	-0.16
Melons	0.13	0.13	-0.05	-0.05	-0.05	-0.03	-0.03	-0.09	-0.04	-0.17	-0.17	-0.17
Fruits and berries	0.11	0.00	-0.10	-0.15	-0.13	-0.11	-0.12	-0.17	-0.13	-0.16	-0.16	-0.16
Grapes	-0.21	-0.12	-0.04	-0.09	-0.12	-0.09	-0.14	-0.14	-0.18	0.15	0.15	0.16

The greatest correlation coefficients between yield and SPI are between barley/wheat and SPI6. A significant correlation was found between barley and SPI6 (r = 0.35, p<0.05). Only visual qualitative assessment of yield related to bias corrected NDVI was possible (Figure 16).

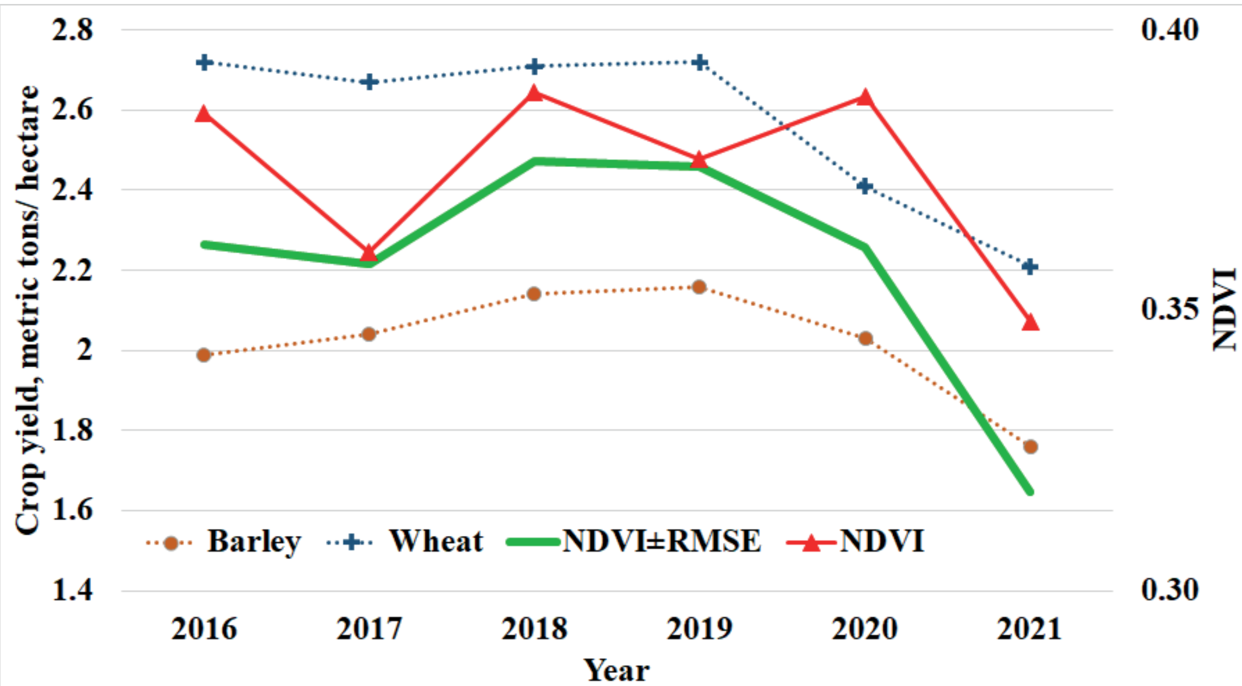


Figure 16. Crop yield and NDVI time series for Jalal-Abad region (spatially averaged).

The same tendency of the bias corrected NDVI and yield productivity is evident (Figure 16). The corrected annual NDVI curve is smoother than the uncorrected one and is in closer agreement with the annual yield curve of barley and wheat (Figure 16). The maximum yields for wheat and barley in 2018 were 2720 kg per hectare and 2140 kg per hectare, respectively, and NDVI with bias correction was 0.38. The minimum yields for wheat and barley in 2021 were 2210 kg per hectare and 1760 kg per hectare, respectively, and NDVI with bias correction was 0.31.

Socio-economic results

Discussions were held with local forestry experts, local government representatives, and the farmers to obtain general information about local economic activities. These discussions showed that walnut-fruit forests play an important role in the rural economy. For local households, in addition to NTFP collection, forests are also important for grazing livestock. As these households exist in forests with different legal frameworks (i.e., protected areas or forestry unit), collection of NTFPs varies in their types and quantities. Notably, in Kara-Alma, locals could lease forest land which gave them exclusive rights to harvest walnuts from leased forest plots. Since walnuts have the highest value compared to other NTFP species, we differentiated walnuts and other NTFPs. Because NTFP yields vary across years, we requested data on average annual yields for the last three years. Major average economic indicators of households in three villages are shown in Table 14.

NTFP collection

In Kara-Alma village, the average annual income from walnuts and other NTFPs was 336,111 and 48,635 KGS respectively. The importance of wild apples was very high when walnut collection opportunities were limited (farm-households note that good walnut harvests occur every 3-4 years). Therefore, the share of wild apples among other NTFPs was the highest at 73%. This is also because there demand for wild apples by local firms in villages that process wild apples for juice; also, no restrictions were placed on wild apple collection in Kara-Alma. Notably, the price per kg of apples was 3-5 KGS. The share of marketed walnuts and wild apples reached 90% and 100%, respectively. The share of mushrooms and other NTFPs (mainly wild berries, hawthorn, rose species and other medicinal plants) were not high at 10% and 17%, respectively; these species were collected mainly for home use and consumption. In Arkyt, harvested walnuts were less than in Kara-Alma and average annual income was 48,635 KGS. Collection of other NTFPs was the lower in other villages amounting to only 1207 KGS, the largest share of which were mushrooms (75%) and wild berries (25%), mainly for household consumption. Collection of other NTFPs was low because there was a ban on collecting many species and there was no market for them. In Kara-Suu village, NTFP income was only 1667 KGS because there are no walnut forests and only 7% of households hired people to collect walnuts in the neighboring village (Aflatun). The share of mushrooms and other NTFPs (mainly wild berries, hawthorn, rose species and other medicinal plants) was not high (10% and 17%, respectively). These species were collected mainly for home use. In Kara-Suu village, walnut harvesting contributed only 1667 KGS annually and was the lowest among the three villages. This is because walnut forests are absent in Kara-Suu village, and only 7% of surveyed households hired people to harvest walnuts in Aflatun. Income from wild raspberries was the highest (93%) of the other NTFPs indicating the importance of this species to local households. Mushrooms accounted for only 7% of all other forest products and were collected mostly for home consumption. Other NTFPs were not collected as there were restrictions on collection due to the protected status of the forest.

Animal husbandry

Livestock was identified as one of the most important common economic activities in all villages supporting local livelihoods. This was particularly intensified during times of poor NTFP harvest. According to farmers, the number of animals has gradually increased in recent years. On average, farmers owned between 5 and 7 livestock per household (cf. Table 14). The average herd structure in livestock production consisted of local steppe cattle (>55%), horses (15% to 34%), and fat-tailed sheep (up to 11%). Animals were kept mainly for meat production; cows were used primarily as dual-purpose breeds. The dominance of cattle and horses in the herd structure is because sheep require constant supervision during grazing while cattle and horses are more independent, grazing without a herder. Sheep were more common than goats because the price of goat meat was much lower than mutton, but both had the same upkeep cost. In addition, goats, according to the farmers, tend to injure young trees in the forest. Few sheep were kept mainly indoors, neither wool nor milk from sheep was used.

Farmers primarily kept animals for sale, with an average of 40% of the herd sold and the rest retained for herd reproduction. Only a small percentage of animals (less than 5% annually) were slaughtered for home consumption; this mainly occurred for celebrations like weddings or funerals. Typically, households kept one or two dairy cows for milk production, with cows milked twice a day for a lactation period of about five months. Horses were also preferred by farmers, not just for traditional reasons, but also because they often fed in pastures year-round, reducing the need for winter fodder. Poultry farming was not a major focus of production, with families keeping only a few chickens for egg consumption. Due to the limited availability of pastures, silvopastoral households grazed their animals in designated forest lands, even in areas where grazing was not permitted. Grazing lasted up to 12 months depending on environmental conditions, primarily to reduce the amount of fodder needed during winter. The most efficient grazing period for animals was around 7.5 months a year when there was enough forage in pastures and the animals did not suffer from a lack of fodder. However, fodder shortages during winter were common, leading to emaciated animals and forcing farmers to graze their animals in forests to browse on plant remains, branches, and the bark of trees, such as wild apple.

In all villages, more than 90% of winter fodder for livestock was purchased because farm households usually did not have arable lands to cultivate fodder crops. Although arable land existed in Kara-Suu village, this was not cultivated due to lack of irrigation systems. Most farmers have meadows which were informally allocated to households, where a small portion of winter fodder (mainly hay) was collected. In Kara-Alma many farmers did not collect hay from meadows. However, several farmers said they collected meadow hay and mentioned that yields were low because the meadows were not hedged, and animals grazed in these meadows.

Additional farm income

In all villages, cultivation occurred only in small plots (kitchen gardens) ranging from 0.05 to 0.15 ha in size. While mainly vegetables were grown for subsistence consumption, there were also some fruit trees (e.g., plums, apples) in these kitchen gardens. The composition of other agricultural income was dominated by the sale of dairy products (often processed) on all farms, 90% of which was sold, while on average 10% remained for home consumption. About 10% of farmers in each village had apiaries, with more appearing in recent years. Farmers noted that producing honey has become more attractive compared to livestock production. The production of hay as a proportion of total agricultural income was low, along with the sale of plums. None of the farms were observed to sell meadow hay, whereas 70% of the farms relied on income from selling plums.

Table 14. Main average economic indicators of households

		Village		
	Unit	**Kara-Alma**	**Arkyt**	**Kara-Suu**
		(n=108)	(n=52)	(n=60)
Elevation of village, location	m a.s.l/	1390	1440	1423
Family size	person	6.5	5.5	5.8
Total walnut value	KGS/year	336,111	48,635	1667
Total value of other NTFPs	KGS/year	18,664	1207	19,916
Share of other NTFPs:				
Share of wild apple	%	73%	0%	0%
Wild raspberry	%	0%	0%	93%
Mushrooms	%	10%	75%	7%
Other NTFP	%	17%	25%	0%
Herd size (livestock units)	LU*	6.80	5.22	7.04
Total value of livestock herd	KGS	424,734	291,263	412,088
Herd composition:				
Cattle	%	64%	76%	55%
Horses	%	28%	15%	34%
Sheep	%	7%	9%	11%
Other farm income		36958	64964	46514
Milk products	%	68%	64%	60%
Hay price, KGS/bundle	%	5%	19%	24%
Total plum price, KGS	%	6%	1%	1%
Beekeeping, KGS/year	%	20%	17%	15%
Total off-farm income	KGS/year	161,069	184,687	198,083
Pension	%	14%	18%	20%
Public sector	%	13%	13%	11%
Private business	%	17%	28%	31%
Remittances	%	56%	41%	38%

Off-farm income

The farmer survey showed that non-agricultural employment and non-agricultural business opportunities were generally low in all three villages. Average annual income from non-agricultural activities in each village was similar, ranging from 160,000 to almost 200,000. Across all villages, the proportion of pensions and civil service salaries in the total off-farm income was similar, ranging from 14% to 20% and 11% to 13%, respectively. The income from self-employment/ private business (e.g., shops, taxi drivers, tourism) and work in the private sector was higher in Arkyt and Kara-Suu villages at 28% and 31% of total off-farm income. In Arkyt, a significant proportion of such income was from tourism, while in Kara-Suu the contribution from tourism and salaried employment were the most significant. Farmers tried to capitalize on growing tourism by selling agricultural products or providing services to tourists. The development of tourism in these two villages was due to visits to pilgrimage sites. In Kara-Alma, the share of income from the private sector was the lowest of the two villages (17%), mainly taxi services, shops and hired labor (construction), indicating a lack of non-agricultural opportunities in the village.

Remittances accounted for the largest share of off-farm income in all households. External migration and remittances (mainly from Russia) played the largest role in the household economy and accounted for the largest share of all off-farm income in all villages. Internal migration, i.e., work in large cities (Osh, Jalalabad, Bishkek) was seasonal and accounted for 15 – 25% of remittances. According to farmers in Kara Alma and Arkyt villages, migration has become an integral part of village life and has intensified during the last decade, mainly to compensate for unsustainable walnut harvests, in Kara-Suu, due to generally low employment opportunities.

Family income

The analysis of income (Figure 17) shows the total family income of farm-households in each village. It includes income from farming activities (selling animals, dairy products, crop products, apiary), income from NTFP collection, and total off-farm income. Income from farming activities as well as NTFP collection are shown in net of variable costs, i.e., gross margins. Overall, the shares of annual income from off-farm activities prevail in all villages, although farm households from Arkyt and Kara-Suu villages had slightly higher income compared to farmers in Kara-Alma. Annual farm incomes were generally similar for all farm-households. Income from collection and sale of NTFPs exhibited significant deviations: farmers from Kara-Alma village had the highest NTFP income. Clearly the legal frameworks influence these income compositions, as collection of NTFPs is restricted in protected areas, whereas Kara-Alma being a forestry unit provides more possibilities for forest use. Overall, farm households from Kara-Alma had significantly higher family incomes compared to farmers in the other villages.

Feeding calendar of animals

The “Feeding Calendar” (Figure 18) illustrates the annual opportunities and gaps in feeding. Results were calculated based on dry matter intake estimated by farmers. Total feed requirement remained constant throughout the year as animals walked more distance and expended more energy during warm months, while during the cold months, animals used less energy due to restricted movement but needed more energy to maintain optimum body temperature. The main parameter determining sufficient amounts of feed was the condition of the animals, such as weight gain or loss.

Our findings show that the main sources of feed were forest pastures, arable land, and grassland (near settlements). Farmers usually tried to keep their animals on these lands for as long as possible to reduce the amount of feed needed for animals kept indoors in winter.

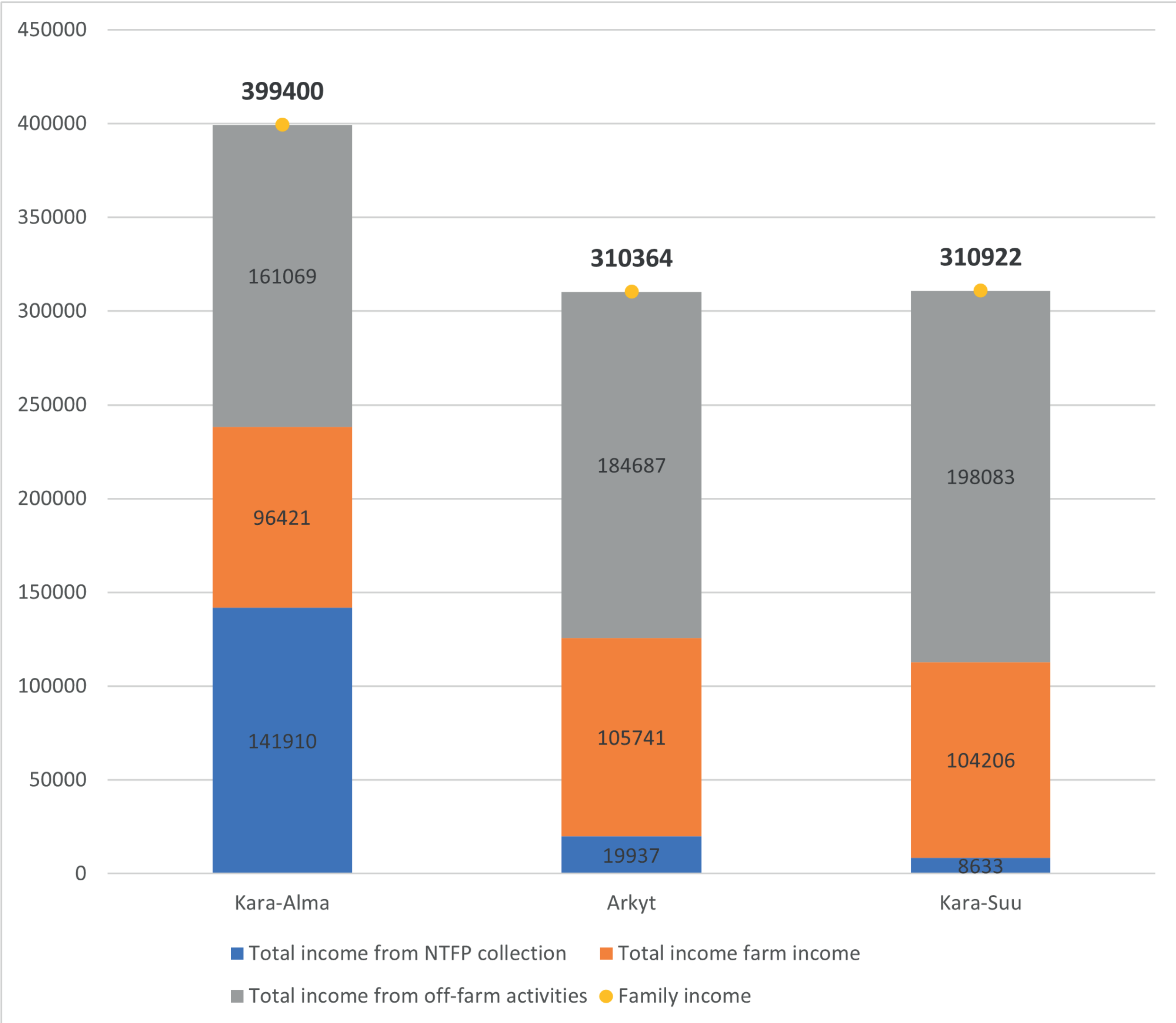


Figure 17. Family income composition.

Animals usually return to designated pastures in the villages in September or October after the harvest. Until the onset of winter, animals grazed in pastures and meadows near villages where they were well-fed due to ample availability of fodder during October. From November, after the snow cover appeared, winter fodder supplies were generally no longer the main source of fodder. However, depending on weather conditions, they were supplemented by grazing in forest pastures close to settlements. From December onwards, animals tended to suffer considerably from feed shortages and from that time onwards began to lose body weight due to insufficient feeding. The shortage of winter fodder persisted until April, as farmers tried to preserve fodder as long as possible from late autumn to late spring. With the onset of spring, animals were left to graze on bushes and grass in the forests. However, according to most farmers, during this grazing period, the feed intake of animals was low, and they remained emaciated. From March through April, as the growing season began, farmers fed the remaining winter fodder reserves to their animals and increasingly kept them in the pastures near the villages, which became the main source of fodder again, but the animals generally did not gain weight during these weeks as there was not yet enough fodder in these forest pastures. From mid-May to June, animals, except dairy cows (which were kept in the forest pastures near villages year-round), migrated again to specially designated pastures where there was sufficient fodder, and they gained weight again. By July all the animals were well-fed and in good condition.

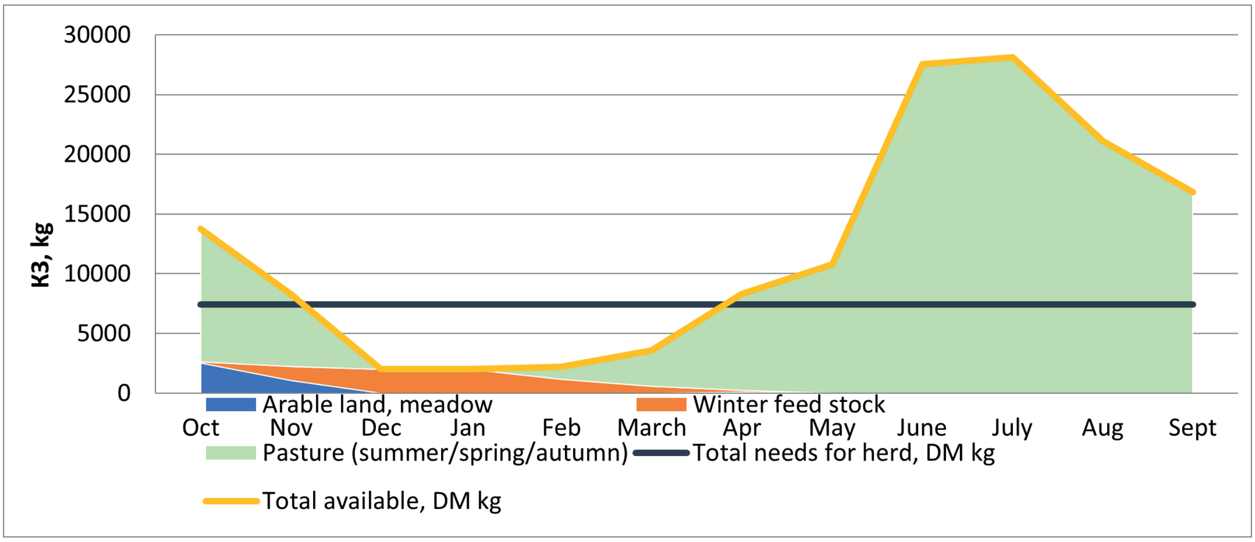


Figure 18. Estimated monthly feed availability according to main feed sources and total needs of herd.

Summarizing the annual feeding cycle, fodder supply depended on the forest pastures near the settlements as well as specially designated pastures. The forest pastures near the villages were used intensively during spring and autumn due to insufficient winter feed, inducing significant pasture degradation. Also, fodder supplies were sufficient to cover the animals' needs for approximately five months from June to November, while animals suffered from a lack of fodder during the remaining months.

Discussion

Phenological discussion

We selected EVI instead of NDVI as it is an "optimized" vegetation index designed to enhance the vegetation signal from trees and increase sensitivity in regions with high biomass, resulting in improved vegetation monitoring by separating the background signal from the canopy signal and reducing atmospheric effects *(Landsat Enhanced Vegetation Index | U.S. Geological Survey, n.d.)*. EVI was found to be a better vegetation covariate for phenological studies conducted in Northern America with MODIS data (Peng et al., 2017). But for land cover assessment in northeast China MODIS-NDVI showed better predicting power than MODIS-EVI (Z. Li et al., 2010).

Although NDVI is highly responsive to chlorophyll, EVI is more responsive to canopy structure, such as leaf area index (LAI), canopy type, and vegetation appearance. Thus, EVI is a valuable predictor of various plant ecosystems. While NDVI and EVI can be used together in environmental research, because we focused on phenology and EVI was specifically developed to provide a better representation of tree canopies, we opted to use EVI.

We used the OLS (ordinary least squares) linear regression model with nonlinear transformations and lag shifts instead of more complex machine learning approaches to create a more user-friendly model. Using the OLS model, relationships between variables can be better understood, and applying transformations to predictors can help to reveal the complexity of these relationships.

Both seasonal and trend components of precipitation demonstrated great predicting capacity for EVI. This is supported by many phenological studies in the region, but mainly working with grasslands and wider geographic scales (Gessner et al., 2013; Klein et al., 2012). The high prediction capacity of seasonal components of climatic factors indicates that any substantial change in the amount or seasonal distribution of precipitation would greatly impact forests, namely *Malus* spp. and *Juglans regia* L. species.

In Padysha-Ata and Sary-Chelek the precipitation trend component was used in the regression model with temporal lags of 3 – 5 months, whereas in Kara-Alma and Dashman no lags used, indicating that in Padysha-Ata and Sary-Chelek there is a substantial lag between changes in precipitation and vegetation response, whereas in Dashman and Kara-Alma the vegetation responds quickly. These areas are distant from one another and Padysha-Ata and Sary-Chelek are on hillslopes of Chatkal range, and Dashman and Kara-Alma are on the Fergana range (Figure 5). Thus, differences between these groups can be explained by their spatial separation. This can also indicate a "buffer" effect in Padysha-Ata and Sary-Chelek, which holds moisture from precipitation and releases it slowly. Soils in all study sites are similar (Adyshev et al., 1987; Mamytov, 1974), so these differences can be attributed more to local landscape, climate, or snow seasonality. The actual explanation of this phenomenon needs further investigation.

The impact of the seasonal component of temperature on the EVI time-series is non-linear. During spring, the seasonal flow of temperature promotes vegetation growth and EVI increases along with temperature. However, as temperatures peak in summer, they begin to suppress vegetation growth, causing EVI to decline in July. We attempted to capture this complexity by applying an exponential transformation to the seasonal component of temperature, but this approach did not work well in all cases. Although a machine learning regression algorithm could potentially capture this complex behavior, it would be difficult to interpret, and the underlying processes would likely not be revealed. Another approach that could be considered is the use of a "hat" function to transform the temperature seasonal component, which would grow until a certain threshold and then decline. However, further research is necessary to estimate the parameters of such a function.

The low predicting capacity of temperature trend component was surprising as temperature is one of the main driving factors of vegetation development. However, we have not found any other studies using time-series components as predictors to compare this result. Apart from Kulikov & Schickhoff (2017) that identified a significant correlation between NDVI and LST trend components only in the high Central Tien Shan but almost no correlation in Fergana and Chatkal ranges, the latter which supports our findings. This interesting finding requires further research to elucidate this behavior, especially in the prevailing climate warming reports and impacts on vegetation.

The limited predictive ability of the temperature trend component suggests that the annual mean temperature change may not have a significant impact on walnut-fruit forests. However, the seasonal component has a significant effect with no lag. As mentioned earlier, high temperatures in summer can inhibit vegetation growth of shallow-rooted species, so if heat is redistributed seasonally or if increases in temperature occur earlier and exceed a certain threshold, it may have a negative impact on the forests. However, as deep-rooted trees can have access to water for longer periods and can have a greater resilience to higher temperatures, but not to water shortages.

Within each study site, *Malus* spp. and *Juglans regia* L. exhibited similar phenological behavior, but different behavior was observed among the four sites, which may be due to a mixed signal from under canopy vegetation and other trees. Despite this, the two genera exhibited a small but consistent difference in EVI response among the different species in all four sites, with higher EVI values for *Malus* spp. in April and for *Juglans regia* L. in June-September (Figures 12a, c, e, g). Such subtle differences in phenology may be better captured by more advanced machine learning algorithms in classification tasks, to tell one species from another, which could be useful for more detailed forest mapping. Additionally, remote imagery with higher resolution could lead to improved results.

This research shows that decomposed time-series of climatic factors can provide accurate predictions, but creating these models is challenging due to the need for extensive field data and appropriate lag selection. However, with modern computing capabilities, it is possible to develop spatially explicit models with discrete modelling for each pixel, provided clear images are available, which could further improve the accuracy of the results. To enhance the accuracy of our findings, we could consider obtaining more precise tree coordinates, using a finer spatial resolution, and applying bias correction techniques (Isaev, Kulikov, et al., 2022). Additionally, using more sophisticated predictor transformations, such as the "hat" function for the seasonal temperature component, may further improve the model's predictive capacity.

Remote sensing discussion

Although remote sensing is a major data source for forests, croplands, and pastures, investigation of vegetation succession has primarily been based on fieldwork within a space-for-time framework. This approach lacks the valuable historical remote sensing information, except for a few cases (Bayle et al., 2021). Nonetheless, challenges remain to find an optimal and reliable relationship between remotely detected changes in vegetation indices (e.g., NDVI, VCI) and actual vegetation changes on the ground.

Our investigation discovered that decametric resolution satellite imagery was inadequate to provide reliable information on the condition of walnut-fruit forests in the Western Tien Shan. This was confirmed by our analysis of the relationship between corrected satellite derived NDVI and NDVI derived from UAV surveys, the latter which was superior (Figure 15a). Furthermore, we observed that Sentinel-2 data overestimated NDVI in regions with open terrain and grass, and underestimated NDVI in regions with trees. However, applying a bias correction based on RMSE for different NDVI intervals improved the accuracy of the Sentinel-2 derived NDVI. Specifically, we observed a negative RMSE for NDVI values between 0.5 and 0.6 and a positive RMSE for NDVI values between 0.6 and 0.8 (Figure 15b). With this correction, the R2 value increased to 0.88 with a p-value of less than 0.001 (Figure 15b).

Furthermore, we observed that the drought index obtained from remote sensing data exhibited a strong correlation with the ground-based SPI drought index. With the implementation of our proposed bias correction technique, the correlation between VCI and SPI increased by an average of 3% (Table 12). We also found that the highest correlation with SPI indices was achieved when VCI was shifted by one month ahead of precipitation data. This delay in vegetation response in relation to precipitation has been documented in other studies as well (Kulikov & Schickhoff, 2017).

The crop yields of barley and wheat exhibited the highest correlation with SPI drought indices. Specifically, a significant correlation was observed between barley yield and SPI6 ($r = 0.35$). Barley and wheat are mainly grown on unirrigated lands making them more susceptible to drought, which explains their stronger correlation with SPI drought index. In our case the bias-corrected NDVI time-series accurately replicated barley and wheat yield productivity (Figure 16). Likewise, the WMO recommends the use of SPI6 to determine agricultural drought, which is indicative of yield response to drought. In contrast, other crops such as corn, rice, cotton, tobacco, vegetables, potatoes, vegetable oil crops, melons, fruits, and berries are typically cultivated on flatter, irrigated lands and are thus less affected by meteorological and soil drought.

We assumed that the very high spatial resolution due to the near ground surface UAV surveys provided a “ground truth” quality layer with respect to Sentinel-2 imagery. Nonetheless, true field data collection coupled with hyperspectral imagery would still be required to further investigate the effects of complex and steep topography on Sentinel derived NDVI values. Furthermore, the spectral bands of DJI Phantom 4 Multispectral and Sentinel-2 a/b are not identical (Table 2), which contributes some uncertainty.

Despite the lack of consideration of some factors discussed herein, we are confident that our work is a step forward towards understanding how a combination of UAV and satellite remote sensing methods can improve monitoring of droughts, pastures, croplands, and walnut-fruit forest conditions. Because other investigations obtained similar results for Sentinel-2 sensitivity to vegetation cover (Bollas et al., 2021; Mancini et al., 2019), we believe that our analysis is relevant for other mountains regions and that the bias correction method can be used to correct the Sentinel-2 images to obtain improved results in similar contexts.

In this study, Sentinel-2 satellite images were compared with imagery from a UAV equipped with a multispectral camera to evaluate both techniques based on NDVI and VCI indices. The statistical comparison between Sentinel-2 and UAV imagery shows that:

- The trend of the average NDVI is almost identical for both remote sensing techniques.
- There is a strong correlation of the NDVI indices between the two techniques.
- The implementation of bias correction significantly increases NDVI and VCI indices derived from Sentinel-2.

To summarize, both UAV and Sentinel-2 platforms are valuable sources of information for monitoring and managing vegetation cover in mountainous ecosystems, such as walnut-fruit forests, pastures, and croplands in Kyrgyzstan. The choice of the most suitable technology (UAV or satellite) depends on the purpose and use of the collected data given their distinct spatial and temporal features, costs, and requirements. However, our proposed bias correction method can significantly enhance the accuracy of Sentinel-2 data.

Socio-economic discussion

The lack of opportunities to harvest NTFPs was identified as a major problem affecting livelihood strategies in local silvopastoral farming systems. The degree of exposure to NTFP crop failure (especially walnuts) for a particular group of farmers can be determined by their revenues from harvesting forest products. For example, farmers from Kara-Alma and Arkyt were more dependent on revenues from NTFP collection as the share of NTFP in total family income was substantial. Farm-households from Kara-Suu had the least access to collect NTFPs and the smallest income from NTFPs, mainly due to the prohibition or restrictions on collection and lack of walnut forests.

The collection of prohibited NTFPs (e.g., mushrooms, hawthorn) often occurs in all villages despite the restrictions but typically revenues from these comprise a small percentage of household income. There appears to be an increase in the collection of protected NTFPs during stressful times. Collection of banned NTFPs has also been recognized by both nature reserves and forestry officials, and it is obvious that prohibitive measures are not enough to stop the collection of such NTFPs. It is noteworthy that no surveyed farms that collected NTFPs processed these products for family consumption, which implies the sale of NTFPs without added value.

Livestock has become a savings account on farms in all three villages, which is typical of mountain farmers throughout Kyrgyzstan. A major challenge in livestock production is the lack of winter fodder, which was in short supply on all farms because farmers had no or little arable lands unlike in other parts of the country where fodder crops can be grown. Furthermore, the available forest meadows did not provide sufficient fodder. To save fodder, farmers try to keep livestock in forest pastures if possible, including during winter. In all villages livestock became emaciated from winter to mid-spring due to lack of roughage in their diet as illustrated in feeding calendar. Grazing in autumn and spring has a negative impact on the forest soil, particularly in wet areas as indicated in other studies. It is obvious that bans on livestock grazing in unauthorized areas of nature reserves are the only current measures preventing pressure on forest pastures; however, this ignores the importance of livestock for silvopastoral family livelihoods especially during times of low NTFP harvest. Therefore, improving pasture management and controlled grazing around the villages is necessary to ensure sustainable use of forest pastures, conserve biodiversity, and protect soils.

According to farmers, remittances from abroad have become a more profitable source of income compared to income from animal husbandry and NTFP collection. During times when NTFPs could not be harvested (particularly in Arkyt and Kara-Alma), migration of family members increased - mostly to Russia, less within Kyrgyzstan. Farmers from Arkyt and Kara-Suu had substantial income from private businesses due to the increased involvement of local silvopastoral families in tourism (e.g., hotel services, cafés, horse rentals) in recent years. Because of natural tourist attractions (e.g., Sary-Chelek Lake, Padysh-Ata pilgrimage site), as well as the improvement of roads to these destinations, the number of tourists has increased (Jenish, 2018; NSC, 2022). More than 20% of surveyed farmers in these villages plan to invest their savings in tourism development.

Overall, the typology of farming systems showed three different categories of farms with different livelihood strategies. Although most all farm types say that their livelihoods will remain in the near future, there is strong evidence to strengthen their farming and non-farming activities.

Recommendations

The MSRI, as part of the UCA, is committed to improving the quality of life for mountain communities, which is one of its strategic goals. The MSRI and its team have extensive experience and expertise in delivering research, development, and capacity building projects. Their trans-disciplinary research approach aims to contribute to the Sustainable Mountain Development agenda in Central Asia, considering both social and ecological factors at various spatial and temporal scales. MSRI, along with its staff and international partners, has successfully implemented a range of projects related to forestry, research, and sustainable use of forest products. These include the SusWalFood project, which focused on analyzing and sustainably utilizing the nutritional potential and secondary plant compounds in underutilized plant species of walnut-fruit forests in Kyrgyzstan, the PALESCA project, funded by the German Federal Ministry of Education and Research, which aimed to understand the palaeoclimate, environmental change, and social interaction in Central Asia, and the JuniperCA project, funded by the German Federal Office for Agriculture and Food, which aimed to balance and optimize the multifunctional use of Juniper forests in Central Asia.

The current research and development project on the walnut-fruit forests in the south of Kyrgyzstan is aiming at sustainable development of mountain communities together with increase of wild populations of apples and walnuts.

General recommendations

Walnut-fruit forests are important natural resources in Kyrgyzstan, providing ecological, economic, and social benefits. Here are some recommendations for better management of these forests:

1. **Conduct a comprehensive forest inventory:** The first step in managing walnut-fruit forests is to conduct a comprehensive inventory to gather data on forest characteristics, such as tree species composition, age structure, tree height, diameter at breast height, and forest health status. This information will help forest managers to make informed decisions about forest management activities.

2. **Develop a management plan:** Based on the forest inventory data, a management plan should be developed that outlines the objectives of forest management, strategies for achieving those objectives, and the activities required to implement those strategies. The management plan should also address issues such as fire prevention, pest management, and soil conservation.

3. **Ensure sustainable harvesting practices:** Sustainable harvesting practices should be adopted to ensure that the economic benefits of forest products are realized without degrading the forest ecosystem. Harvesting practices should be based on scientific principles and should consider the age and health of the trees, the timing of harvesting, and the techniques used.

4. **Promote agroforestry:** Agroforestry practices can be promoted in walnut-fruit forests to increase the economic and ecological benefits of the forest. Agroforestry involves combining trees with agricultural crops to create a more diverse and sustainable ecosystem. This can help to reduce pressure on the forest for wood and NTFPs, while providing additional income for local communities.

5. **Enhance community involvement:** Local communities should be involved in forest management activities, including planning, implementation, and monitoring. This will help to ensure that forest management activities are aligned with local needs and priorities, and that the benefits of forest management are shared equitably.

6. **Promote research and development:** Research and development should be promoted to address gaps in knowledge and to identify new opportunities for sustainable forest management. This can include research on the ecology of the forest, the economic benefits of forest products, and the development of new technologies for forest management.

Overall, effective management of walnut-fruit forests in Kyrgyzstan requires a holistic approach that considers ecological, economic, and social factors. By adopting sustainable forest management practices, promoting community involvement, and promoting research and development, these forests can continue to provide important benefits for generations to come.

Recommendations to farmers

We have several recommendations for farmers in all villages based on this study. Firstly, it is crucial to acknowledge the importance of income from livestock and to implement sensible pasture stewardship practices, such as ensuring adequate forage supplies to alleviate pressure on forest pastures or implement rotational grazing practices to alleviate excessive soil compaction. Secondly, generating income from off-farm activities is a common trend in all farming systems. Developing sustainable rural tourism is a promising strategy to pursue and should continue to be supported in the future. Moreover, given the significance of income from NTFPs collection, particularly for farmers in Kara-Alma and Arkyt villages, it is vital to focus efforts on increasing local value-added products through NTFP processing, direct marketing, and other approaches. Training programs and the introduction of processing technology, along with market establishment, are necessary. Although there have been several projects aimed at developing small and medium-sized enterprises (SMEs) for local food processing in the past, most of these efforts ended with the termination of funding, indicating the importance of more long-term support and better engagement of farmers to continue such work.

Community engagement

To address the challenges faced by local communities and promote sustainable practices that reduce their impact on the environment, research and practical experience can be leveraged. Sustainable harvesting methods should be introduced, and marketing approaches employed to better position the products of local communities. For example, providing local residents who work in fruit collection with apple cutters and dryers could be beneficial. Currently, the collected apples are sold to middlemen entrepreneurs who take them to small-scale factories where they are cut, dried, or juiced, and the seeds are wasted outside the forest. However, with the use of cutters and dryers, local people can produce dried apples, increase their income, and store and transport the product in better ways. The apple seeds can also be planted in forests to decrease support natural regeneration. Other environmentally friendly livelihoods, such as beekeeping, baking, and sewing guilds are also recommended, with training conducted on alternative livelihoods.

Management, capacity building and awareness campaigns

To promote protection and reproduction of apple species, research reports and technology transfer papers with policy recommendations should be developed and shared with forestry units in the walnut-fruit forest area. To educate local people about the value of wild apple species and how to care for them, supporting materials need to be developed and distributed. Regular training on measures to prevent Gypsy moth and Fire blight should be provided to both forestry units and locals to reduce the spread of pests and prevent tree loss. Additionally, regular training on the value of wild tree species and the impact of cattle should be conducted to raise awareness and foster a sense of responsibility and land stewardship amongst the local population.

Propagation and protection

To enhance sexual reproduction and maintain genetic diversity, establishing local tree nurseries is recommended. The wild apple seeds obtained from drying and juicing factories should be collected for this purpose. The saplings produced in the nurseries should be planted in appropriate locations in the forest to ensure survival and increased population connectivity. These plantations should be established outside of protected areas where any kind of activity is prohibited. The exact locations for planting should be determined based on our ecological research. Seedlings growing under adult trees must be collected and transplanted to other patches of apple trees or protected in place to increase genetic diversity and exchange of genetic material between different areas. To ensure active pollen exchange among the areas, new patches of wild apples should be created in the most suitable areas within a such a distance from each other, which could be covered by pollinators, so that the patches could exchange genetic material. The young seedlings must be protected from grazing by fencing with three poles secured with strings. Notes detailing the need for conservation of these trees and their state and international protected status should be printed and attached to the trees and saplings. Additionally, afforestation will contribute to soil development and organic matter accumulation and decrease erosion potential. These activities must be guided by relevant research.

It is also recommended to organize a network of fenced forest patches, which will be protected from livestock and not used by people for anything. Such fenced areas will serve as sanctuaries, where native vegetation will be propagating and spreading seeds in surrounding areas. This will maintain natural plant communities in the forest and ensure species diversity. They will also be asylums for small animals and birds.

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