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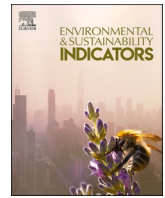
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The role of crop classification in detecting wheat yield variation for index-based agricultural insurance in arid and semiarid environments

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ABSTRACT

The increasing availability of open-source and high-quality satellite data has facilitated market developments in the index insurance sector. So far, research and industry spheres have used administrative boundaries of units to estimate regional index values for insurance design. In areas with heterogeneous land use or land cover, however, these indices do not provide sufficient accuracy. This study analyzes potential accuracy gains from land-use classification that allow to design indices specifically for croplands and wheatlands. The validity of this approach is tested along conventional satellite-based products, including the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), as well as indices that are not yet widely used in crop insurance industry, like the Enhanced Vegetation Index (EVI), Green Chlorophyll Index (GCI) and Leaf Area Index (LAI). The study covers 2060 yield observations from 152 districts across Central Asia and Mongolia with irrigated, mixed and rainfed wheat farming systems. The results show that the majority of these indices are suitable for detecting wheat yield variations in rainfed and mixed agricultural lands, although they remain ambiguous in irrigated lands. Land-use classification and designing indices based on croplands and wheatlands noticeably increases the relationship between indices and wheat yields in rainfed and mixed lands. Notably, the LAI and GCI out-perform other well-known indices. Overall, freely available satellite data could serve as a good source for establishing index insurance products in Central Asia and Mongolia. Nevertheless, a careful assessment and selection of index and land use classification remains essential.

1. Introduction

Over the past two decades, the frequency of weather extremes such as floods and droughts has increased (WMO, 2021). Variable and unpredictable weather significantly limits agriculture and agricultural development (Niles et al., 2015; Rao, 2011), since farmers avoid investments when there is a high risk of weather shocks and yield losses (Benami et al., 2021). Moreover, uninsured production risk also limits access to agricultural credits for producers, substantially hindering agricultural and rural development (Hellmuth et al., 2009). Moreover, these limitations may threaten global food security, in particular in societies where wheat is the main staple (FAO, 2015). Wheat (*Triticum* spp.) is one of the most important and strategic food crops for the majority of the world's countries and populations, being the staple food of about 35% of the world's population and accounting for 20% of the food calories consumed globally (Breiman and Graur, 1995).

Being the main source of wheat yield reduction and climatic

variability (Ray et al., 2015), rising climate risk creates need for new risk management and risk coping strategies in agriculture (FAO, 2015; Hellmuth et al., 2009; IPCC, 2022). One financial tool is agricultural insurance, which is intended to transfer agricultural production risks from farmers to insurance companies (Bobojonov et al., 2019; Giné et al., 2010). However, in developing countries, the hedging effectiveness of conventional agricultural insurance (also known as 'named-peril' and 'multi-peril' crop insurance) is challenged by high premiums, moral hazards and problems of adverse selection (Coleman et al., 2018). To overcome some of these challenges, index-based agricultural insurance (henceforth "index insurance") has been suggested (Coleman et al., 2018; Dick et al., 2011; World Bank, 2011). In index insurance, payoffs are contingent on the value of a pre-determined index (average yield of a unit, temperature, rainfall, soil moisture, vegetation, etc.), which cannot be manipulated by third parties (Barnett et al., 2008), therefore reducing adverse selection and problems of moral hazard (Miranda and Gonzalez-Vega, 2011). Moreover, index insurance does not require a

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ground verification of the reported crop yield losses, thus significantly lowering administrative costs (Benami et al., 2021).

The main challenge of index design is to achieve sufficient correlation between crop yields and the selected index (Norton et al., 2015). Previously, the most common and widely used form of index insurance was weather index insurance (WII). Meteorological station-based WIIs have been the subject of numerous feasibility and efficiency analysis (Bobojonov et al., 2014; Bokusheva and Breustedt, 2012; Conradt et al., 2015; Kath et al., 2019). While being a promising data source in high-income countries, meteorological stations are rarely available in developing countries (Barnett and Mahul, 2007). In Central Asia (CA) specifically, Eltazarov et al. (2021) demonstrate the low insufficiency of meteorological stations for designing index insurance, with sparsely distributed weather stations often failing at capturing wide spatial crop losses and contributing to geographical basis risk (Makaudze and Miranda, 2010). Thus, weather data from meteorological stations rarely correlates with crop yields due to high basis risk (Smith and Watts, 2009). The cost of installation and maintenance of new weather stations every 10–20 km, as suggested for instance by Hazell et al. (2010), would significantly increase the prices of the insurance products. Finally, new weather stations cannot provide historical weather records, which is necessary for index design (Norton et al., 2012).

To overcome these data limitations, scholars have proposed and tested the applicability of satellite-based weather products, especially precipitation data, for index insurance development and implementation (Coleman et al., 2018; Osgood et al., 2018; Tarnavsky et al., 2018). Satellite products are provided in near-real time and available free of charge for most locations worldwide (CHC, 2015; Didan, 2015). Numerous studies have investigated the potential and applicability of satellite-based precipitation products for WII design and implementation in developing and emerging economies (Black et al., 2016; Brahm et al., 2019; Collier et al., 2009; M Enenkel et al., 2018; Osgood et al., 2018; Tarnavsky et al., 2018). While WII is only valid for rainfed farming systems, satellite-based land surface information, in particular the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Land Surface Temperature (LST), Actual Evapotranspiration (ETa) and Soil Moisture Index (SMI), have found to be more potential for crop loss detection and index insurance design (Coleman et al., 2018; Kölle et al., 2020; Vroege et al., 2021). Even though the sensitivity of vegetation indices significantly decreases at moderate-to-high densities of crop aboveground biomass (Li et al., 2010, 2014; Mistele and Schmidhalter, 2008), they are in fact rather suitable for insurance products that primarily focus on detecting low biomass density.

So far, only a limited number of satellite-based products such as NDVI, LST and precipitation have been tested for application in index insurance design during the last two decades in majority of continents (Benami et al., 2021; Kölle et al., 2020). The most popular index is NDVI, which was first proposed by Vicente-Serrano et al. (2006). Later, Makaudze & Miranda (2010) investigated the applicability of an NOAA Advanced Very High Resolution Radiometer (NOAA AVHRR) based on an NDVI to design index insurance using 1980–2001 rainfed maize and cotton yield data from Zimbabwe. They found that the NDVI index has higher correlation with crop yields and greater potential to protect smallholder farmers than the rainfall index.

Later research however pointed out several practical challenges: Turvey and McLaurin (2012) investigated the applicability of NOAA AVHRR for designing index insurance in the US by using yield data for rainfed corn and soybeans. Since their results were highly variable in terms of the relationship between NDVI and crop yields, they advise caution concerning the applicability and scalability of the NDVI without site-specific calibration.

The first weakness is the resolution of weather information: Bokusheva et al. (2016) examined the effectiveness of an NOAA AVHRR-based Vegetation Condition Index (VCI) (NDVI-based calculation) and Temperature Condition Index (TCI) (brightness-temperature-based

calculation) to insure rainfed wheat yield losses of farmers in five counties in Kazakhstan. They conclude that finer spatial resolution would improve the effectiveness of the insurance products as well as the significant relationship between Vegetation Health Indices (VHI) and county-level rainfed wheat yields has the potential to substantially improve risk-sharing options. Bobojonov et al. (2014) analyzed medium-resolution satellite information (Moderate Resolution Imaging Spectroradiometer (MODIS) based on an NDVI) by comparing farm-scale rainfed wheat yield data in Syria, concluding that also an NDVI based on medium-resolution data has sufficient potential to detect yield losses and calculate insurance pay-outs.

Second, Valverde-Arias et al. (2020, 2018) urge taking the variability of agro-ecological zones into account while designing index insurance. They applied a MODIS-based NDVI, finding that rice phenology and the relationship between NDVI and rice yields significantly differs through agro-ecological zones. Using barley, wheat, sorghum and barley yield data as reported by 34 farmers, Eze et al. (2020) compared the feasibility of a MODIS-based NDVI and satellite-based precipitation products for designing index insurance in Ethiopia. Based on their findings, they contend the use of an NDVI based on area-specific crop insurance indices rather than weather parameters that are currently in use in their study area.

Thirds, as demonstrated by Turvey and McLaurin (2012), these well-known indices may yet fail to detect variation in crop yields in all environments. Therefore, there remains fundamental need for exploring additional satellite-based indices and develop specifications increasing their performance (Hazell et al., 2010; Hellmuth et al., 2009). Other, less prominent indices have not yet been taken into consideration for index insurance applications. Until just recently, a small number of studies investigated into the potential of EVI and LAI for index insurance (Báez-González et al., 2002; Cheng, 2006; Doraiswamy et al., 2002; Li et al., 2011; Wang and Lin, 2005). Dou et al. (2020), Shirsath et al. (2020) and Van Khanh Triet et al. (2018) suggest an EVI as a potential source of satellite data for the crop insurance industry. GCI has not been explored yet at all. Kölle et al. (2020) analyzed the efficiency of a MODIS-based VCI (EVI-based calculation), a TCI (land surface temperature-based calculation) and a VHI that included weather (temperature and precipitation) parameters for improving the hedging of yield risk for rainfed olives trees in Spain. They found that the VCI- and VHI-based index insurance contracts outperform index insurance contracts based on precipitation and temperature, and can serve as a potential source for index insurance development. Setiyono et al. (2018) propose a MODIS-based LAI as a possible source of data for area-yield index insurance for rainfed rice in Vietnam. Later on, Raksapatcharawong et al. (2020) suggest using a MODIS-based LAI in combination with other remote sensing and field data for index insurance design for rainfed rice in Thailand.

Finally, higher accuracy may also be reached by combining indices: Hochrainer-Stigler et al. (2014) conducted a case study with teff yield data in Ethiopia and suggest a solution of an NDVI (same source as above) integrated with land surface temperature data as a Vegetation Health Index (VHI), concluding that VHI allows for trigger points to be identified and premiums to be calculated. Moreover, one of the main requirements is that site-specific calibration of the satellite-based data to index-based insurance product design and the variability of agro-ecological zones should be taken into account when designing index insurance (Turvey and McLaurin, 2012; Valverde-Arias et al., 2018, 2020).

Based on this literature overview, following research gaps are identified: Many wheat producing regions worldwide are not purely rainfed, but at least partially irrigated or fully irrigated. According to Wang et al. (2021), around 35% of global wheat is produced in irrigated areas. Nevertheless, in practice, these regions also suffer from high variation in water availability, as surface water used for irrigation also reacts to variability in weather conditions. As can be seen in this summary, so far there are no studies focused on testing the applicability of the satellite

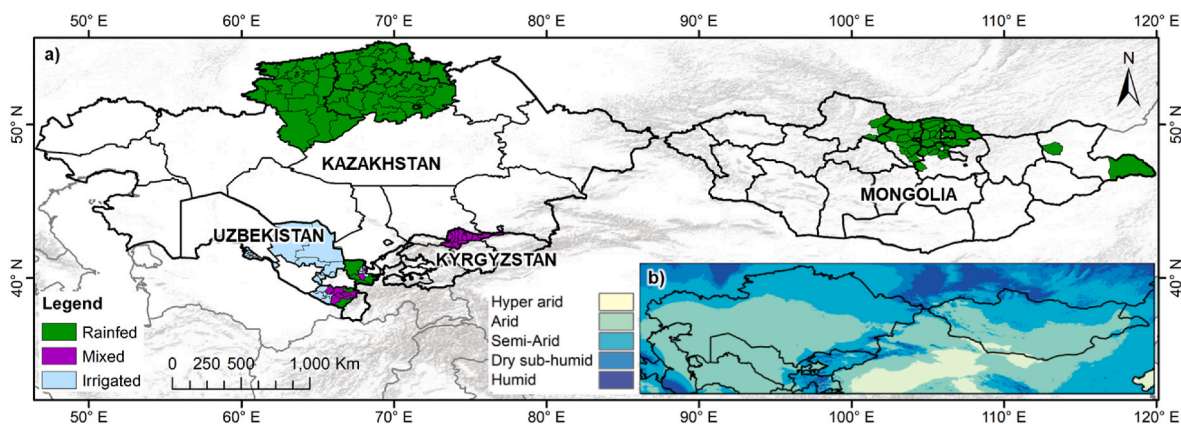


Fig. 1. Locations of the study regions and farming systems (a) and climate classes (b). Source: Authors' presentation based on data from Trabucco and Zomer (2019).

data sources for index insurance development for wheat producers in irrigated and mixed lands. Additionally, in all of the above-mentioned studies, the satellite data samplings are determined by administrative regions, which omits the effects of crop rotation, diversity, allocation and land cover/use change on regional index values. Meanwhile, in areas with strong spatial heterogeneities in land use/cover, estimating regional index value based on all pixels from all land cover/use types within administrative boundaries may not have good power for detection of crop yield variation and index insurance design. All in all, this literature review shows a need for a comprehensive and comparative analyses of the applicability of various satellite-based data to index insurance among various farming types and land cover/use classifications.

The study thus provides several key contributions to the literature: Firstly, to the best of the authors' knowledge, this study is the first to study the effect of using land cover classification (e.g. croplands and wheat cultivated lands, hereafter cropland and wheatland masks) in addition to administrative boundaries for index insurance design. Second, the applicability of MODIS-based vegetation indices, such as an EVI, GCI and LAI, as well as a well-known NDVI and LST (all five indices will from here on be referred to as "vegetation index" for convenience) are compared for index insurance development in rainfed, irrigated and mixed lands. To test the robustness of the findings across climatic zones, the sample includes districts across Central Asia and Mongolia. In these countries, frequent climate shocks in the past years have created particular need for financial instruments for risk sharing (Bobojonov et al., 2019).

For this analysis, district level wheat yield data is used; this choice may admittedly lead to aggregation biases that likely cause farm-level risk underestimation. Nevertheless, the presented findings are valid for district scale index insurance and area-yield insurance programs in the region.

2. Methods and materials

2.1. Study area and wheat yield data

Central Asia was selected as case region for following reasons: For once, here the effect of climate change is above the global average (de Beurs et al., 2018; Haag et al., 2019). For instance, drought events during 2000–2001 and 2007–2008 had a great effect on crop production and the socio-economy of Central Asia (Bobojonov et al., 2014; Patrick, 2017). In 2000–2001, the loss of agricultural production was evaluated at \$800 million USD for the whole region and contributed to a loss of 80% of rural households' incomes. The consequences of this were increased poverty rates and a negative impact on food security and public health (Patrick, 2017; World Bank, 2005) as well as a decline in grassland productivity and a loss of lakes, resulting in a huge migration

of herders to the capital city and adverse effects on food security in Mongolia (Densambuu et al., 2015; Hessel et al., 2018).

This study covers wheat growing regions in Kazakhstan (KAZ), Kyrgyzstan (KYR), Mongolia (MON) and Uzbekistan (UZB) (Fig. 1), where wheat is one of the most strategic crops. It is grown on irrigated land in the vast majority of Uzbekistan (Khalikulov et al., 2016) and mostly on rainfed lands in Kazakhstan and Mongolia (Fehér et al., 2017; Tuvdendorj et al., 2019), and mixed lands in Kyrgyzstan (ADB, 2013). The heterogeneity of farming systems (e.g., irrigated, rainfed, mixed), frequent weather events and high variability among harvests in this region provide a unique environment for comparing the suitability of indices across farming systems, which has not yet been tackled within the international literature yet. Three provinces from Kazakhstan were selected, particularly Akmola (Akm), Kostanay (Kos) and the North Kazakhstan (N. Kaz) provinces (*oblasts*), which together account for around 70% of wheat production in the country (Fehér et al., 2017). For Kyrgyzstan, the province Chuy covers the vast majority of national cropland (Dzunusova et al., 2008). The Mongolian provinces of Bulgan (Bul), Darhan Uul (Dar), Dornod (Dor), Huvsgul (Huv), Selenge (Sel) and Tuv are main steady cultivation regions of spring wheat (FAO, 2020). The Uzbek provinces of Djizzakh (Djiz), Kashkadarya (Kash), Khorezm (Khor) and Navai (Nav) were chosen as this combination of provinces covers all three varieties of farming systems that exist in the country. Overall, the analysis used annual district-level spring wheat yield data for 50 districts in Kazakhstan, and winter wheat yield data for 8 districts in Kyrgyzstan, spring wheat yield data for 43 districts in Mongolia and 41 districts in Uzbekistan. Figure A1.1 exhibits the location of croplands in the study area and in vast majority of lands wheat is being cultivated continuously or in rotation with other crops (USDA, 2022). Fig. 2 presents the cropping calendars for wheat in the three countries. While cropping calendars may locally vary by a few days according to local weather conditions and farm management strategies, unbiased results over the whole sample can be expected due to the large numbers of observations.

All wheat yield data was obtained from local state statistical organizations and is reported in tons per hectare (ton/ha). Wheat yield data was obtained for the years 2000–2015 in Kazakhstan, for 2007–2017 in Kyrgyzstan, for 2000–2018 in Mongolia, and for 2007–2017 in Uzbekistan. The data was checked for outliers by using a Grubbs's test (Grubbs, 1950).¹ In total 2060 yield observations from 152 districts across Central Asia and Mongolia were employed. The average record length is 15.9 years for Kazakhstan, 11 years for Kyrgyzstan, 17.7 years

¹ Initially, 2063 yield observations were obtained. After checking for outliers using a Grubbs's test (Grubbs, 1950) only three outliers (p-values = 0.0035, 0.0196, 0.025) were detected and eliminated from the Mongolian dataset.

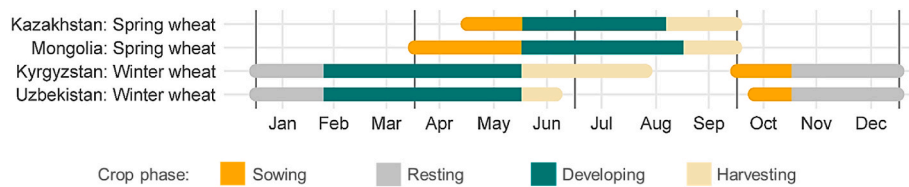


Fig. 2. The cropping calendar of spring wheat in Kazakhstan and Mongolia and winter wheat in Uzbekistan and Kyrgyzstan. Source: Authors' illustration based on data adapted from Conrad et al. (2014), the FAO (2021, 2020) and Shamanin et al. (2016).

Table 1
Summary of MODIS based land surface metrics.

Metric	Equation	Available since	Temporal resolution	Spatial resolution	Data reference	Data
NDVI	$(\text{NIR-RED})/(\text{NIR} + \text{Red})$	2000	16 days	250 m	Didan (2015)	MOD13Q1 V6
EVI	$2.5 \times (\text{NIR-RED})/(\text{NIR}+6 \times \text{RED}-7.5 \times \text{BLUE}+1)$	2000	16 days	500 m	Didan (2015)	MOD13Q1 V6
GCI	$\text{NIR}/\text{GREEN} - 1$	2000	8 days	500 m	Vermote (2015)	MOD09A1 V6
LST (Day)	See reference for algorithm	2002	8 days	1000 m	Wan et al. (2015)	MOD11A2 V6
LAI	See reference for algorithm	2002	4 days	500 m	Myneni et al. (2015)	MCD15A3H V6
LCU	See reference for algorithm	2001	1 year	500 m	Friedl and Sulla-Menashe (2019)	MCD12Q1 V6

for Mongolia and 10.2 years for Uzbekistan. Descriptive statistics of wheat yield data can be found in Table A2.

2.2. Satellite data

This study employs data produced by a Moderate Resolution Imaging Spectroradiometer (MODIS), which is an instrument that's been installed in the board of the Terra and Aqua satellites since the 2000s for observing the earth's surface and making images on a daily basis. For the analyses, Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) layers from a MOD13Q1 V6 product were used. Both vegetation indices have a 250 m spatial resolution with a composite of 16 days (Didan, 2015). Moreover, the Leaf Area Index (LAI) product has a 500 m spatial resolution with a 4-day composite dataset from MCD15A3H V6 (Myneni et al., 2015), while the Land Surface Temperature (LST)² product from the MOD11A2 V6 dataset has a pixel size of 1 km and 8-day averaged images (Wan et al., 2015). Additionally, the analysis employs the Green Chlorophyll Index (GCI), which was calculated according to Gitelson et al. (2005) who employed an NIR and GREEN bands. The underlying data was obtained from the MOD09A1 V6, which provides 500 m resolution with an 8-day composite (Vermote, 2015). Temporal and spatial resolution as well as historical range of data availability is listed in Table 1.

2.3. Spatial scales of index value extraction

The index values for each study site were extracted in three spatial scales: 1) the entire area of the districts, 2) cropland and 3) wheatland. The area of croplands was obtained from an open access yearly Land Cover and Use (LCU) product. The location of the wheatlands in each district were identified by us based on cropping calendars and wheat phenology (Edlinger et al., 2012; Hao et al., 2016; Zhang et al., 2011); details of the cropland and wheatland masks are provided in the following sections.

² Following Zhang et al. (2022), daytime LST were employed. Also according to Chen et al. (2019) daytime temperature has greater and consistent effect on wheat yield.

2.3.1. Cropland classification

The croplands were masked using the land cover and -use product MODIS-MCD12Q1 V6, which provides yearly information on global land cover types since 2001 (Friedl and Sulla-Menashe, 2019). For this study, the cropland mask used is a merge of all-time series croplands generated by MCD12Q1-V6 during 2001–2019. Specifically, the “Annual International Geosphere-Biosphere Programme (IGBP) classification” sub-model was employed. In order to capture all possible croplands in the selected areas, layers 12 and 14, as well as all years since 2001 until 2019 were combined in order to produce a single mask for croplands. The used cropland mask from the MCD12Q1-V6 (500 m pixel size) product has an overall accuracy of approximately 75–80 percent (Friedl and Sulla-Menashe, 2019).

There are some alternative land cover/use products like the European Space Agency based WorldCover (Zanaga et al., 2021) and the Copernicus Global Land Service (Buchhorn et al., 2020). However, these products only provide data for the most recent years, which makes them unsuitable for this study. In the end, MOD13Q1-V6 based on NDVI images was chosen for wheatland classifications due to their large spatial coverage and the shortage of continuous cloudless images for the long-time period in Landsat images.

2.3.2. Wheat classification

Following the Knowledge-Based Detection method suggested by Edlinger et al. (2012), the data on wheat areas for each year and district were classified and extracted based on the cropping calendar (Fig. 2) and the phenology of spring wheat in Kazakhstan and Mongolia, and winter wheat in Kyrgyzstan and Uzbekistan. Additionally, croplands mask from MCD12Q1-V6 product, high resolution images from Google Earth and ground truth data (38 locations) from the Bukhara province (Uzbekistan) were employed to clarify the wheatland classification parameters. For phenology detection, the MOD13Q1 V6-based NDVI was employed. For avoiding to mistakenly classifying grasslands, which have similar phenology with winter wheat, as winter wheat in Kyrgyzstan and Uzbekistan's hilly and mountainous areas, a surface slope map was calculated based on The Shuttle Radar Topography Mission (SRTM) digital elevation dataset (Jarvis et al., 2008). The 90-m spatial resolution of SRTM dataset was considered sufficient for this study, as the spatial resolution of the tested vegetation indices varies from 250 to 1000 m.

Equations (1)–(3) classify and mask the wheat cultivated lands from selected vegetation indices:

$$\text{Spring wheat lands in Kazakhstan} = (\text{NDVI}_{81-96} < 0.1) \text{ AND } ((\text{NDVI}_{193-208} > 0.35) \text{ OR } (\text{NDVI}_{209-224} > 0.35)) \text{ AND } (\text{NDVI}_{273-288} < 0.30) \quad (1)$$

$$\text{Spring wheat lands in Mongolia} = (\text{NDVI}_{97} < 0.25) \text{ AND } (\text{NDVI}_{129} < 0.25) \text{ AND } ((\text{NDVI}_{209} > 0.35) \text{ OR } (\text{NDVI}_{225} > 0.35)) \text{ AND } (\text{NDVI}_{289-305} < 0.35) \text{ AND } (\text{SLOPE} < 5) \quad (2)$$

$$\text{Winter wheat lands in Kyrgyzstan and Uzbekistan} = (\text{NDVI}_{17-32} < 0.1) \text{ AND } (\text{NDVI}_{97-128} > 0.40) \text{ AND } ((\text{NDVI}_{161-176} < 0.30) \text{ OR } (\text{NDVI}_{177-193} < 0.30)) \text{ AND } (\text{SLOPE} < 4) \quad (3)$$

where SLOPE is the inclination of land surface of measured in degrees and NDVI are the NDVI values within the indicated time period during which wheat has a specific phenological pattern. This definition was developed based on the respective region’s cropping calendar as presented in Fig. 2 and NDVI-based phenology dynamics of winter and spring wheat. Based on these specific phenology dynamics at specified times, it is possible to precisely distinguish spring or winter crop lands from other crops.

A similar classification method showed approximately 90 percent accuracy using Landsat images that have 30 m spatial resolution (Edlinger et al., 2012). Conrad et al. (2011) obtained 75–96 percent accuracy for wheatland classification using the same MODIS images. The wheatland classification accuracy for this study was tested for a subsample in Bukhara province (Uzbekistan) based on ground truth data from 2019, reaching accuracy levels of 79 percent accuracy, which is within the range of above studies’ accuracy.

2.4. Satellite data processing and acquisition platform

One of the main disadvantages of using satellite products in index insurance is the fact that the acquisition and processing of satellite products requires special technical skills. Therefore, a user-friendly web platform was established that allows users free convenient access to satellite products. For accessing above-mentioned MODIS-based products, a unique automatic web platform using the Google Earth Engine (GEE) was developed for this project (Gorelick et al., 2017). This Satellite Data Extractor can be accessed under the following link: <http://www.klimalez.org/satellite-indices>. All of the satellite-based data processing and extractions within this study are based on the GEE platform.

2.5. Correlation and regression of wheat yields with vegetation indices

One of the key requirements for applying satellite-based products for the development of agricultural index insurance is that the index should be highly correlated with crop yields (Barnett and Mahul, 2007; Siebert, 2016) in order to increase the hedging efficiency of the resulting insurance product (Breustedt et al., 2008; Kölle et al., 2021; Norton et al., 2012). In order to check the applicability and potential of the selected vegetation indices, correlation and regression analyses between wheat yield data and satellite-based indices are performed. Borrowing from Turvey and McLaurin (2012), the mean and maximum values of indices during the vegetation period are the best predictors of crop yields and the most widely used temporal aggregation method in the index insurance industry. Adapted from Markus Enenkel et al. (2018); Kogan et al. (2018) and Wang et al. (2014), time series Pearson’s correlation analyses between wheat yields and each periodical record of the indices for each district were conducted. Pearson’s correlation is a suitable measure for linear relationship between continuous data (vegetation indices and wheat yield data), whereas Spearman’s correlation is rather used for monotonic relationships between ordinal variables. Along Pearson’s correlation, the time periods with the strongest correlation between index and wheat yield data were chosen as the timespan for the mean

value calculation for each index and country (Panek and Gozdowski, 2020). In cases of max index value calculation, the entire vegetation period of wheat in the respective country was used, which was 1–274 days for Kazakhstan; 1–290 days for Mongolia; 1–220 days for Kyrgyzstan; and 1–162 days for Uzbekistan. In the following, the max and mean temporal aggregations were calculated, and correlation analyses between them and wheat yields conducted.

In order to investigate the potential of the selected satellite data sources for modelling the wheat yields, linear regression analyses were applied, using the index values within the period that was identified to exhibit the strongest correlation with wheat yields. Despite the availability of time series, panel data analysis was not an option, as this approach would assume the same marginal response to indices in every district (Turvey and McLaurin, 2012), whereas this study sought to understand how marginal effects differ by districts and the overall ability of the variables to model the actual wheat yields.

The detailed estimation model is adapted from Kogan et al. (2018) in terms of indices and the strongest correlated time periods (critical stages of crop growth). The application of a similar model was suggested for index insurance development by Xu et al. (2008), which employed time series precipitation and temperature data.

$$dY = \beta_0 + \beta_1 VI_1 + \beta_2 VI_2 + \beta_3 VI_3 + \dots + e \quad (4)$$

where dY is the district-scale wheat yield data, VI is the value of the respective vegetation index in the period that has high correlation between yield and indices. β_0 is a constant, e the error term. This method has been applied for all selected indices and mask types.

Additionally, the Wilcoxon test (Bauer, 1972) was performed to compare the group of correlation coefficients and to check for improvements in the significance of the relationship between indices and wheat yields after the application of land cover and use masks.

2.6. Wheat yield loss detection

To evaluate the ability of the indices to capture the wheat yield losses among various correlation coefficients, two categorical metrics were applied, namely Probability of Detection (POD) and False Alarm Ratio (FAR). POD measures the probability of an index to capture the yield losses, while FAR indicates the probability of falsely detecting yield losses. These metrics were estimated based on the contingency matrix shown in Table 2 and the equation of the selected metrics, which are exhibited in Table 3.

The equation for estimating the trigger value was adapted from Turvey and McLaurin (2012), which is defined as *average Yield – (0.25standard deviation)*. Actual yield and modelled yield values with district masks from all selected indices and locations were used for categorical metric estimations.

Table 2
Contingency table for comparing indices and crop yields.

	Yield ≤ Trigger	Yield > Trigger
Index ≤ Trigger	a	b
Index > Trigger	c	d

Table 3
Formulas of categorical metrics, where a = number of hits; b = number of false alarms; and c = number of misses.

Statistics	Formula	Range	Perfect value
Probability of Detection	$POD = \frac{a}{a+c}$	0 to 1	1
False Alarm Ratio	$FAR = \frac{b}{a+b}$	0 to 1	0

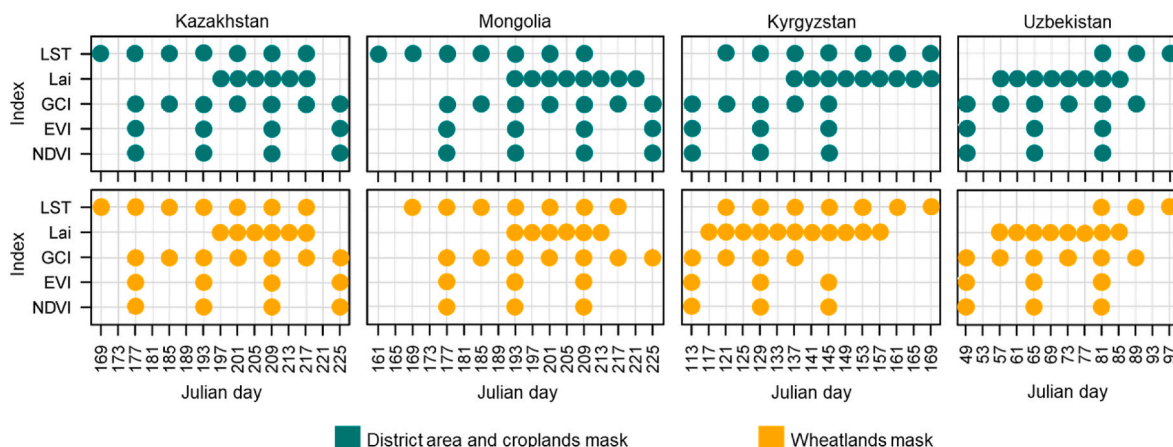


Fig. 3. Strongest correlated time periods of satellite-based indices with wheat yields.

Based on the trigger equation, the yield loss cases were identified for each study location and index. In the next step, the data were filtered and grouped according to their correlation level with actual yield data. For each grouped dataset, the identified yield loss cases were compared with the POD and FAR matrices. In total 18,848 observations were used for calculations. All statistical calculations and figures for this study were developed using the R project (R Development Core Team, 2018).

3. Results

Fig. 3 indicates the time periods of strongest correlation between vegetation indices and wheat yields (for exact coefficient values see Appendix B). For the majority of indices, no large differences can be observed between district areas, cropland masks and wheatland masks.

As assumed, the periods with the strongest correlation between indices and wheat yields differ among countries. It can be observed that these differences in periods among countries and indices are caused by a variety of climate conditions and are consequently due to different cropping calendars, farming systems and types of wheat (Fig. 2). At the same time, some similarities between the correlated periods for spring wheat in Kazakhstan and Mongolia can be observed. For all vegetation indices in Kazakhstan and Mongolia, the strongest correlation occurred at the second half of the developing crop phase, which was July and the first half of August. Meanwhile, there are remarkable differences between the correlated periods for Kyrgyzstan and Uzbekistan, even though both of them produce winter wheat. In Kyrgyzstan, the strongest correlation between vegetation indices and winter wheat yields exists for April and May, which are in the second half of the developing crop phase. In terms of Uzbekistan, apart from the vegetation period, the strongest correlation with the wheat yields was during the first half of the developing crop phase, which was the months of February and March. Fig. 3 and Appendix B present how there is not a strong relationship between vegetation indices and wheat yields during the sowing and resting period in all four study countries. Overall, results show that the highest correlation between the vegetation indices and wheat yields are in second half of the development period of crops, except for Uzbekistan, where this is the beginning of the crop’s development period.

Fig. 4 presents the results of correlation analyses between the mean and max values of the indices with wheat yields for individual districts. The figure demonstrates, which type of mask and index has better relationships in each country and wheat type. The figure also shows the correlation coefficients, which was used to describe the relationship between insurance index and crop yields by Eze et al. (2020). For yield estimation purposes, the positive correlation coefficient represents the ability of an index to detect wheat yield variations with the following categories: 0.0–0.2 is very weak; 0.2–0.4 is weak; 0.4–0.6 is moderate;

0.6–0.8 is strong; and 0.8–1.0 is very strong (Eze et al., 2020). Additionally, Pietola et al. (2011) found that demand for the index insurance remains strong when the correlation between index and yields is greater than 0.6, but it starts to decrease when correlation is lower than 0.5.

The results show that the strengths of indices capturing the variation in wheat yields differs among countries when various masks were applied. It can be observed that index values from entire district areas and croplands have similarly strong correlations with wheat yields in Kazakhstan. The Wilcoxon test (Figure C1) also showed insignificant differences between the groups of correlation coefficients. Determining which of them result in better performance is complex, as in both masks the indices in most cases are strongly correlated with wheat yields except for a few districts. For the districts under the numbers 13, 17, 21, 36 and 50 (Fig. 3), masking croplands have improved relationships between vegetation indices and wheat yields and vice versa; the relationship increased when the value from an entire district was used in districts under the numbers 11, 15, 34 and 44. In the case of Mongolia, cropland could not be masked as MODIS-MCD12Q1 does not provide the location of croplands in this area. Moreover, cropland masks do not exist for the district under the number 141 from Uzbekistan. It can be seen that the index values for the entire district areas have higher correlation coefficients than the wheatland mask (Figure C2). However, in the case of district numbers 59, 81, 82 and 85 (Fig. 3), the application of wheatland masks significantly improved the correlation between index values and wheat yields. For Kyrgyzstan, using all three masks showed sufficient correlation coefficients between the vegetation indices and wheat yields. However, the strongest relationship for the vegetation indices was observed when cropland masks were applied, which improved the vast majority of the correlation values from moderate-strong to strong-very strong compared to entire district area and wheatland mask. The statistical significance of the improvement after the application of cropland and wheatland masks was confirmed by a Wilcoxon test (see Figure C3). In the case of Uzbekistan, the performance of vegetation indices was ambiguous due to the large proportion of irrigated and mixed farming systems. Vegetation indices were mostly moderately correlated just for over half of districts in irrigated lands, while the relationship between indices and wheat yields were below weak except for a few cases of mixed agricultural lands in Uzbekistan. For rainfed lands, noticeably higher relationships between indices and wheat yields could be observed. Even though this was not proven by the Wilcoxon test, for the case of rainfed agricultural lands, the application of cropland and wheatland masks narrowed the range of correlation coefficients and slightly increased the correlation between indices and wheat yields (see Fig. 4 and C6). In general, index means were found to correlate stronger with wheat yields than max values in the vast majority of districts. While all indices showed the potential to detect wheat yield variation in the majority of the study areas, a slightly higher

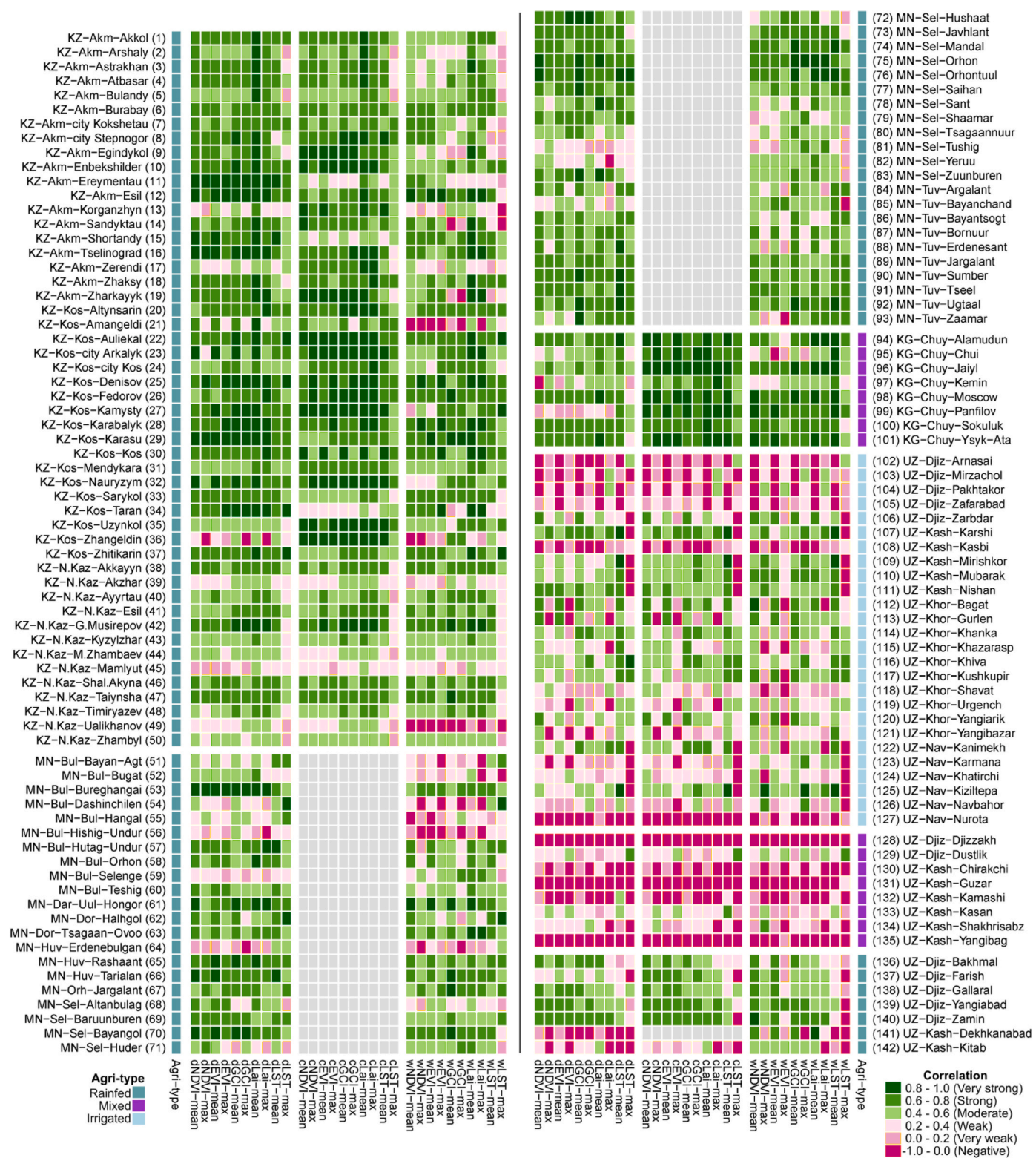


Fig. 4. Correlation Heatmap between wheat yields and mean/max values of indices for entire district areas, croplands and wheatlands^{31 42}.

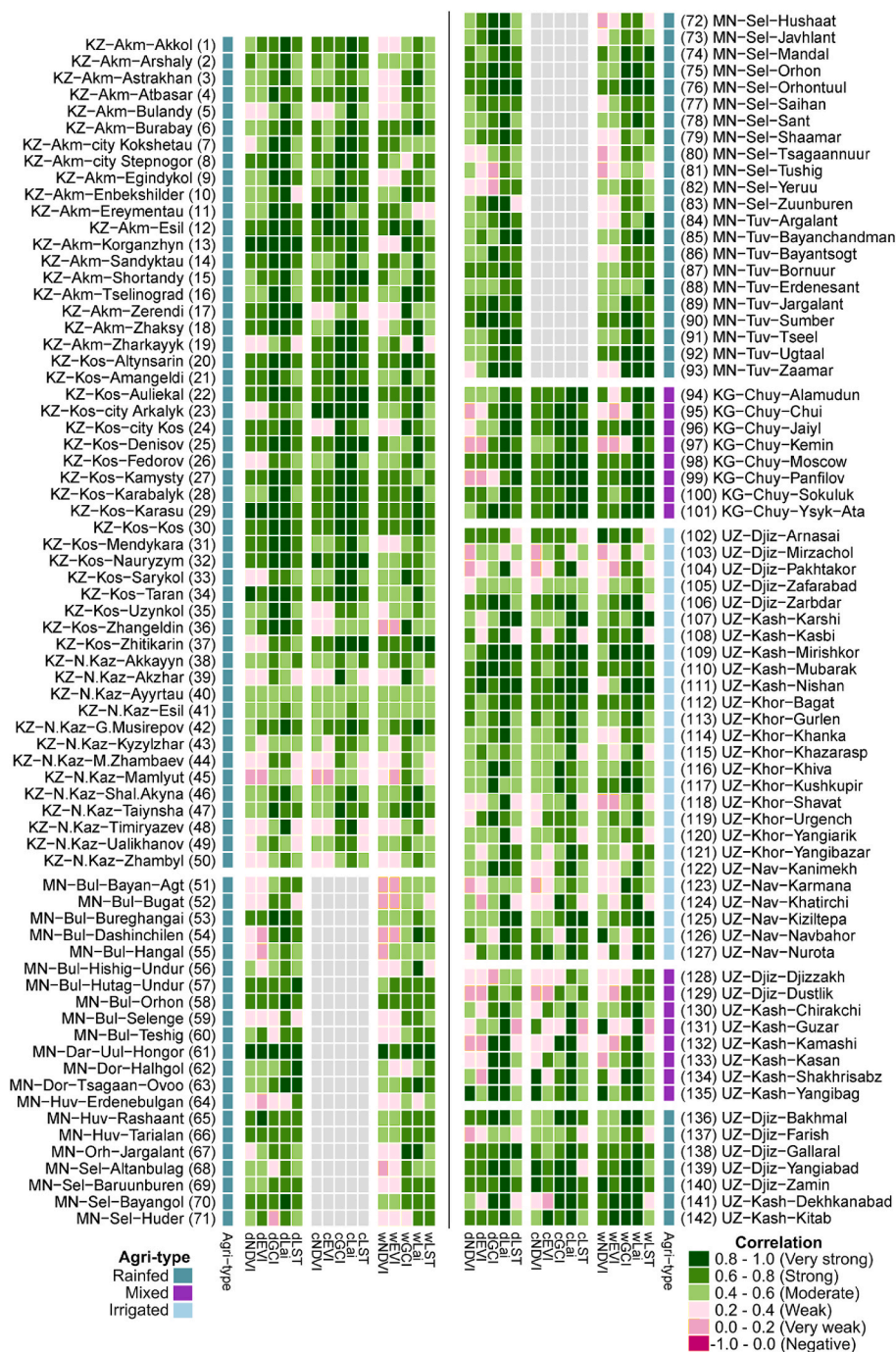


Fig. 5. R² Heatmap between wheat yields and modelled yields based on indices using cropland and wheatland masks in the selected areas.⁵¹

performance was found for LAI and GCI in Kazakhstan and Mongolia, LAI, GCI and LST in Kyrgyzstan, as well as NDVI and EVI in Uzbekistan (seen in Appendix C).

From Fig. 5, it can be seen that the application of the modelling approach notably improved the relationship between indices and wheat yields in all countries and farming systems. Even the districts that had been weakly or negatively correlated in the mean/max approach now upgraded to be highly correlated. In addition, remarkable improvements

³ The letter for the beginning of the indices represents the type used mask: d = district, c = croplands and w = wheatlands.

⁴ The values from the LST were inverted from a negative to positive correlation for better presentation.

can be seen for the case of irrigated and mixed agricultural land in Uzbekistan. Overall, among the vegetation indices, LAI and GCI showed better correlation with wheat yields once again in all countries, farming systems and masks.

Fig. 6 provides results from the categorical accuracy assessment, which demonstrate the dynamic of POD and FAR values over the various correlation coefficients (CC). Overall, the results clearly show that the accuracy of indices to correctly detect the yield losses, represented by POD and FAR, improves with an increasing correlation coefficient indicated on the x-axis. According to both graphs shown in Fig. 6, the classification accuracy slowly increases until a 0.5 correlation coefficient, when it then begins to rise sharply from this point.

As demonstrated in Figs. 7 and 8, the results of this study show that

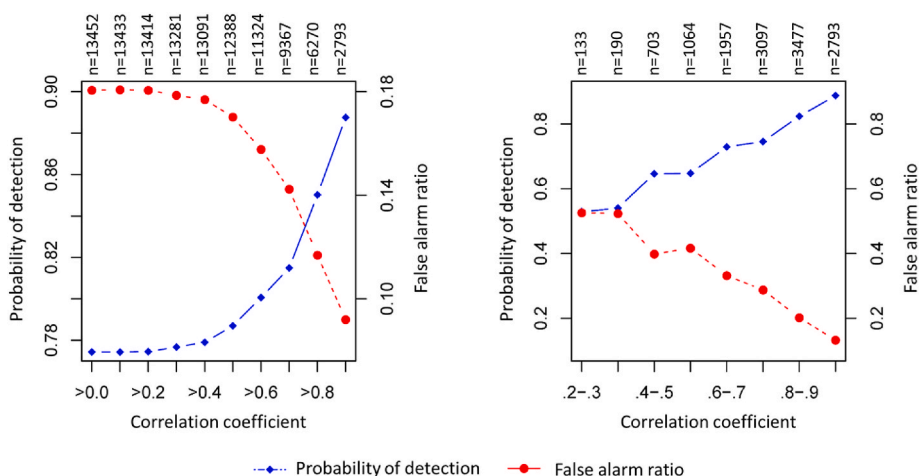


Fig. 6. Results of the categorical accuracy assessment between yield loss events by indices and wheat yield data over the various correlation coefficients.

Country	Farming system	Correlation	d					c					w				
			dNDVI	dEVI	dGCI	dLai	dLST	cNDVI	cEVI	cGCI	cLai	cLST	wNDVI	wEVI	wGCI	wLai	wLST
Kazakhstan	rainfed	>0.5	76	80	88	92	72	80	84	84	92	76	72	72	66	88	62
		>0.6	64	66	72	84	58	64	68	78	86	64	44	48	48	76	44
Mongolia	rainfed	>0.5	74	74	79	70	79						60	58	79	72	72
		>0.6	65	65	65	60	67						37	44	58	63	56
Kyrgyzstan	mixed	>0.5	63	63	75	75	100	100	88	100	100	100	75	75	88	88	100
		>0.6	50	50	50	75	88	88	88	88	100	100	75	63	75	75	100
Uzbekistan	rainfed	>0.5	42	35	50	19	62	50	42	54	31	62	46	38	54	38	65
		>0.6	19	12	23	0	42	19	15	31	8	38	23	23	27	12	42
	irrigated	>0.5	0	0	0	0	13	0	0	0	0	13	0	0	0	0	13
		>0.6	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0
	mixed	>0.5	57	57	71	57	0	83	83	67	50	17	86	86	86	71	0
		>0.6	57	57	43	29	0	83	83	50	17	0	86	86	57	29	0

Legend: 80-100% 60-80% 40-60% 20-40% 0-20%

Fig. 7. Percentage of districts having satisfactory correlation (>0.5) and sufficient correlation (>0.6) between indices and wheat yields (Pietola et al., 2011); mean value of index approach.

Country	Farming system	Correlation	d					c					w				
			dNDVI	dEVI	dGCI	dLai	dLST	cNDVI	cEVI	cGCI	cLai	cLST	wNDVI	wEVI	wGCI	wLai	wLST
Kazakhstan	rainfed	>0.5	60	64	96	98	70	66	68	96	98	76	52	46	84	92	62
		>0.6	36	42	84	88	48	50	46	86	86	60	30	32	66	72	34
Mongolia	rainfed	>0.5	60	63	79	98	84						35	42	86	86	79
		>0.6	30	47	67	98	70						14	14	72	77	65
Kyrgyzstan	mixed	>0.5	38	38	75	100	100	88	88	100	100	100	75	50	75	100	100
		>0.6	25	38	50	100	100	88	88	100	100	100	75	50	75	100	100
Uzbekistan	rainfed	>0.5	54	65	73	92	62	54	58	85	96	62	50	58	81	96	62
		>0.6	31	31	50	85	38	38	27	69	92	35	23	42	65	96	35
	irrigated	>0.5	25	13	75	100	38	38	38	75	100	38	38	25	75	100	38
		>0.6	13	0	75	75	13	38	25	50	88	13	38	0	75	100	25
	mixed	>0.5	71	71	86	86	43	71	86	86	100	71	100	100	100	100	57
		>0.6	71	71	86	86	29	43	43	86	100	57	71	71	100	100	29

Legend: 80-100% 60-80% 40-60% 20-40% 0-20%

Fig. 8. Percentage of districts having satisfactory correlation (>0.5) and sufficient correlation (>0.6) between indices and wheat yields (Pietola et al., 2011); regression approach.

⁵ The letter in the beginning of indices are represents type of used mask: d = district, c = croplands and w = wheatlands.

almost all indices have potential for index insurance design under suitable conditions. However, in majority of the cases, the LAI and GCI slightly outperforms other indices.

4. Discussion

In the vast majority of study locations, there was a moderate to strong relationship between wheat yields and indices. However, there are differences between the individual regions in terms of those stages of vegetation periods that are most closely linked to the wheat yields. These differences are due to the wheat type and their cropping calendar, which depends on climatic conditions and farming systems. The strongest correlation between indices and wheat yields was found mainly for the second half of the developing crop phase, which is in line with Kogan et al. (2018), Panek and Gozdowski (2020) and Wang et al. (2014).

One important aim of this study was the incorporation of cropland and wheatland masks. Generally, it can be contended that the application of cropland and wheatland masks has different effects on the precision of indices for detecting wheat yield variation depending on location, climate and agricultural practice. As Figs. 4 and 5 and Appendix C display, in all selected districts the application of cropland and wheatland masks noticeably improves the ability of indices to detect wheat yield variation for mixed lands of Kyrgyzstan and rainfed lands of Uzbekistan. These improvements might be due to high topographic variety in these regions, which contain mountains and foothills, thus significantly affecting index values. Moreover, in some cases of mixed agricultural lands in Uzbekistan, the application of cropland and wheatland masks improves the association between vegetation index and wheat yields, where there is some degree of positive correlation using index values from entire district areas. In cases of Kazakhstan, the index values from croplands and the entire district area outperform indices calculated from wheatlands only. This may be due to monotone agricultural practices, a wide breadth in the geographical location of croplands and low topological variety in these areas. However, in some areas the application of cropland and wheatland masks significantly improves the correlation between vegetation indices and wheat yields. Meanwhile, index values from the entire district area show the highest performance in Mongolia, since using wheatland mask may capture only the areas with regular phenology and a cropping calendar, which may result in missing the abnormal areas due to crop delays because of climate or human factors. However, there are some cases when wheatland mask improved the ability of indices to detect the wheat yield variety. Moreover, there is not a monotonous positive relationship between indices and the wheat yields of irrigated and mixed agricultural lands. The weak relationship of irrigated and mixed agricultural lands might be caused by a geographical situation, topographic types and crop varieties in the areas (Dick et al., 2011; Kölle et al., 2020). Further investigations should be conducted on irrigated lands by using farm and village scale wheat yield data.

It is important to mention that the mean values from indices show noticeably higher correlation with wheat yields than the max values among the vast majority of districts. Moreover, the wheat yield modeling approach using highly correlated periods of satellite data (critical stages of crop growth), as suggested by Kogan et al. (2018), demonstrates vital enhancements on the relationship between indices and wheat yields in all of the study sites and farming systems. These improvements can especially be observed for irrigated and mixed agricultural lands of Uzbekistan (see Figs. 7 and 8).

Further results concern the suitability of novel indices as compared to conventional solutions like NDVI. Several prior studies found NDVI and precipitation to be most successful for capturing crop yield conditions, and as a data source for index insurance design and development (Bobojonov et al., 2014; Hochrainer-Stigler et al., 2014b; Makaudze and Miranda, 2010). However, in the presented case GCI and LAI indices slightly outperform and have higher correlation with wheat yields and a greater potential for index insurance development and implementation,

even though these indices were not investigated and taken into account by other authors as a potential source for index insurance development.

Moreover, it is clear that the increase in correlation between the index and crop yields leads to a reduction in design and basis risk (Breustedt et al., 2008; Kölle et al., 2021; Norton et al., 2012), which are crucial during the index insurance design and implementation phases (Norton et al., 2015). According to the study conducted by Pietola et al. (2011), the critical threshold of index insurance from the demand side is situated at a correlation coefficient of 0.5–0.6. These findings are also in line with the results of this study, in which the precision of crop loss detection rises abruptly from a level of 0.5 correlation coefficient onwards (see Fig. 6).

5. Conclusions

The main aim of the study was to explore the potential gains of using land use classification for designing and implementing an index insurance by comparing the suitability of multiple well-known and less prominent satellite-based indices in various wheat farming systems located in Central Asia and Mongolia. For this assessment, the study used 2060 yield observations from 152 districts across Central Asia and Mongolia with irrigated, mixed and rainfed wheat farming systems.

The results of this study highlight the importance of testing cropland and wheatland masks during the process of index insurance design and development. Moreover, LAI and GCI indices was found to slightly outperform other well-known indices in detecting wheat yield variation and thus have greater potential for index insurance design. Overall, globally available MODIS-based indices could serve as a suitable source for establishing index insurance products in Central Asia and Mongolia; however, a careful selection of sources, boundaries, indices and methods is required.

Moreover, it is important to note that the usage of district level data can induce an aggregation biases, which means farm-level risks are likely underestimated. Nevertheless, the featured results are still informative for district scale index insurance and area-yield insurance programs in the region (e.g., which may be applied by industry or farmer cooperatives). It would be interesting to also analyze the relationship between indices and wheat yields at the farm and county scale, which would allow us to more deeply investigate the capacity of satellite data for index insurance development and implementation. Additionally, there are limitations regarding crop diversity, cultivated area, crop quality, fertilizers and re-seeding data, and it would also be interesting to examine the effects of these factors on the relationship between indices and wheat yields.

The lack of high-quality weather and yield data is a dominant limiting factor in developing countries for the implementation of index insurance. These findings are therefore relevant for improving insurance markets in Central Asia and Mongolia, being a potential source of data for index insurance design and operation. Moreover, the results of this study are also important for improving know-how of policymakers and farmers within the region on index insurance. There are, however, few start-up projects focused on piloting the implementation of index insurance in the region (see Eltazarov et al. (2021)). It should be also mentioned that, based on the initial results of this study, 385 farmers and 22,338 ha in Mongolia have been insured based on a MODIS-NDVI.

Future advances in satellite technology could further increase precision of crop loss prediction. For once, the correlation between vegetation indices and wheat yields obviously depends on the proportion of wheatland per pixel of the satellite images. Furthermore, data availability also limits the generation of cropland mask for each year individually. One disadvantage of MCD12Q1-V6 is that the delay of the land cover product is 1–1.5 years, which is not practical in terms of the index insurance establishment. Furthermore, MCD12Q1-V6 does not provide the areas of cropland located in Mongolia. For that reason, open source satellite data with a higher spatial resolution, such as Sentinel 2 or Landsat satellite series, could improve the accuracy of cropland and

wheatland identification. Additionally, using state developed cadaster maps would lead to further improvements in correlation and reduction of basis risk of spatial resolution.

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Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.indic.2023.100250>.

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