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Article — Published Version

Mapping weather risk – A multi-indicator analysis of satellite-based weather data for agricultural index insurance development in semi-arid and arid zones of Central Asia

Climate Services

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Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle (Saale)

Suggested Citation: Eltazarov, Sarvarbek; Bobojonov, Ihtiyor; Kuhn, Lena; Glauben, Thomas (2021) : Mapping weather risk – A multi-indicator analysis of satellite-based weather data for agricultural index insurance development in semi-arid and arid zones of Central Asia, Climate Services, ISSN 2405-8807, Elsevier, Amsterdam, Vol. 23, <https://doi.org/10.1016/j.cliser.2021.100251>

This Version is available at:

<https://hdl.handle.net/10419/242479>

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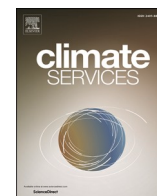
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Original research article

Mapping weather risk – A multi-indicator analysis of satellite-based weather data for agricultural index insurance development in semi-arid and arid zones of Central Asia

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ARTICLE INFO

Keywords:

Climate service
Weather index insurance
Drought
Flood
Metrological drought index
CHIRPS
GSMaP
GLDAS

ABSTRACT

Index insurance has been introduced as a solution to tackle several challenges that prevail in the agricultural insurance sector of developing countries. One of the main implementation challenges in these countries is the lack of reliable weather data for index development and implementation. The increasing availability of satellite data could ease the constraints of data access. Meanwhile, the suitability of various satellite products for yield estimation across world regions has to undergo a thorough assessment. This study contributes to the literature by systematically analyzing the accuracy of some globally available satellite data, namely the Global Satellite Mapping of Precipitation (GSMaP), Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), and the Global Land Data Assimilation System (GLDAS) compared to ground-level weather information for 14 different indicators for the case of Uzbekistan. Our analysis indicates that those sources may provide the necessary data for an accessible and adequate climate service. However, a considerable risk of overestimation and underestimation depending on the source of satellite data may exist, especially for precipitation data in the conditions of Central Asia. Among the tested datasets, GSMaP showed a relatively better performance than CHIRPS in precipitation estimation for drought and flood detection. In order to reduce detection inaccuracy, the application of satellite weather products for index insurance is possible when temporal aggregation (e.g., monthly, seasonal) is considered. Globally available climate data could serve as a good source to establish index insurance products in Central Asia; however, a careful selection of source and index is required.

Practical implications

In contrast to traditional indemnity-based insurance, which requires field visits to verify actual harvest losses, index insurance allows for the identification of yield losses on the basis of a pre-determined index (e.g., rainfall, temperature, soil moisture). Index insurance has a number of further significant advantages compared to traditional insurances, such as low transaction and administrative costs, as well as the prevention of moral hazard and adverse selection (Fisher et al., 2019; World Bank, 2015). Despite the promising potential of index insurance, dissemination is slow due to a lack of climate services, which would support the practical operation of index insurance products (Coleman et al., 2018; Hazell et al., 2010). The strongest impediment against the

practical implementation is lacking access to reliable and sufficient long-term weather data, which is lacking in most of the developing countries (Barnett and Mahul, 2007; Collier et al., 2009). Meanwhile, insurance infrastructure may be one of the potential areas that may support further dissemination of climate services, benefitting agricultural clients beyond the risk sharing function of insurance. Due to the large intrinsic interest of insurance companies, the insurance sector could also be one of the areas where dissemination of climate information is utilized by private companies (Surminsk et al., 2019).

This study aims to analyze the suitability of globally available satellite data, namely the Global Satellite Mapping of Precipitation (GSMaP), Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), as well as the Global Land Data Assimilation System (GLDAS), as a potential source of weather data for developing and implementing index insurance in Central Asia. The

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prominent advantage of using this data is that it allows implementing index insurance programs even in countries with weak climate services. Thus, the development of index insurance markets would also enable access to climate services, which could be used not only for financial instruments but also other, broader purposes (Prasada, 2020).

In order to identify the suitability of the open data, we compared the satellite-based weather data with in-situ weather information using 14 different statistical indicators for the case of Uzbekistan. Moreover, to verify the ability of satellite-based weather products to detect and monitor the drought and flood events, we calculated and compared the Meteorological Drought Indices (MDI) based on both satellite and in-situ weather data. MDIs are suggested as one potential method to design index insurance in cases of low availability of historical yield data, which applies to most developing countries (Bobojonov et al., 2014; Okpara et al., 2017). According to our results, all satellite-based weather products exhibit satisfactory accuracy in measuring weather parameters and detecting drought/flood events in semi-arid and arid zones of Central Asia. Meanwhile, GSMaP on its own and in combination with GLDAS, as an MDI, demonstrated better performance than CHIRPS. Moreover, all satellite-based weather products achieved slightly higher accuracy during rainy and wet seasons.

After determining the suitability of these products, we created an open access platform that would provide climate services to a wide range of users. While the variety and quality of the satellite-based weather products has significantly increased over the last decades, most of them are accessible only to qualified specialists in the field of remote sensing. The developed climate service platform bridges the gap between raw data and end users by creating visualized and regional weather products on a user-friendly, automatic and real time web-platform named “Satellite Weather Data Extractor” (<https://www.klimalez.org/srs-export>). This extractor provides easy access to satellite-based precipitation and temperature data and might serve as a source for individuals and organizations to make climate smart decisions worldwide.

Introduction

Agricultural insurance is a risk management tool that can assist in coping with climate risks in agricultural areas by protecting assets, opening access to credits, mitigating risk, maintaining the resilience of farmers, and supporting food security. However, because of high costs, moral hazard and adverse selection, traditional agricultural insurance, known as “loss-indemnifying” insurance has not yet effectively assisted and mitigated all of the risks for farmers in developing countries. Index-based insurance has been proposed and recommended as a solution by various organizations and scholars as a means for developing countries to overcome the challenges of traditional insurance (Bobojonov et al., 2014; Coleman et al., 2018; World Bank, 2011). The most common and widely used form of index insurance is weather index insurance, which makes use of the typically high correlation between weather data and crop yields (Bobojonov et al., 2014; Chantarat et al., 2007; Coleman et al., 2018; World Bank, 2011). For the case of index-based insurance, indemnity payments are determined by an index that is neither affected by farm-individual production decisions nor vulnerable to manipulation by third parties. This approach is aimed at reducing adverse selection and problems of moral hazard, which are frequent issues in traditional agricultural insurances (Fisher et al., 2019; World Bank, 2015).

Meanwhile, there are several challenges in the implementation of index insurance under real-life conditions. One of the largest challenges is the availability of historical weather data for implementing such an insurance (Barnett et al., 2008; Kath et al., 2019). In many developing and transition economies, a complete lack or the poor quality of long-term daily climate data with all the necessary parameters hinders large scale dissemination (Barnett and Mahul, 2007; Collier et al., 2009).

Moreover, requesting and obtaining weather data from data holders might be challenging, time consuming and costly; in many developing countries, high-quality data has been commercialized.

Additionally, an insufficient density of meteorological stations (the term “station” will be used from here onwards) in agricultural areas significantly affects the reliability of insurance products. Because of micro-climatic factors, weather parameters may differ even between locations in close proximity (Tadesse et al., 2015). Existing studies have shown that using station data for index insurance leads to a very high basis risk (i.e., the correlation between index and yields is very low) when the station is located >20–25 kms away (Gommes and Göbel, 2013; Osgood et al., 2007). Consequently, Hazell et al. (2010) have suggested keeping a distance of 10–20 km between the station and farms in order to decrease basis risk.

Fig. 1 illustrates the challenge of sufficient station density for the case of Central Asia. Here, stations are installed and regulated by governmental agencies, but also recognized by the World Meteorological Organization (WMO) and included in the dataset of the Global Historical Climatology Network (GHCN) (NCEI, 2021). As presented by the spatial analysis in Fig. 1, >94% of farmland in Central Asia is located beyond a distance of 20 km from the nearest station. Only 6% of the region’s cropland (highlighted in dark green) is situated close enough to a weather station to allow for reliable yield estimation along the weather station data. Any area that is not classified as cropland is shown as a transparent area (see also Fig. SM 1.1 in supplementary material (SM) 1).

In many high-income countries, the installation of new weather stations at the farm level is promoted as a potential solution. However, starting from the above conclusion that accurate data for weather indices requires a density of one station every 10–20 km, both the installation and maintenance of these stations would considerably increase the price of products relying on this data, which is a problem for extensive or low-yield production. Furthermore, the lack of historical records for these new stations will pose an additional problem for product design.

Under these conditions, satellite remote sensing data (the term “satellite data” will be used from here onwards) is increasingly used for designing and operating index insurance programs. Numerous recent studies have investigated and proposed the use of agronomically suitable Meteorological Drought Indices (MDI) that do not require yield data for designing and implementing index-based insurance, as yield data is often inaccurate or difficult to obtain at sufficient resolution (Bezdan et al., 2019; Bobojonov et al., 2014; Ghamghami et al., 2017; Okpara et al., 2017; Tarnavsky et al., 2018). Many studies have found a significant correlation between MDIs and crop yields (Elhag and Zhang, 2018; Gunst et al., 2015; Salehnia et al., 2018; Todisco et al., 2008; Vicente-Serrano et al., 2012). Moreover, Musshoff et al. (2011) and Odening et al. (2007), found a higher risk reduction potential of index insurance based on MDIs rather than cumulative rainfall.

Meanwhile, each of the available satellites differs in terms of resolution, coverage, quality and frequency of data collection. Therefore, one can expect differences in accuracy of the produced data for measuring weather parameters for each particular region. However, the question of how accurate the various satellite products actually are has not been studied to a sufficient extent in the region. Our study therefore provides two distinct contributions to the literature: First, the accuracy of two important satellite-based weather products, as Global Satellite Mapping of Precipitation (GSMaP) and Global Land Data Assimilation System (GLDAS)¹ have never been scientifically tested in the context of index insurance. This study undertakes the investigation of the accuracy of these, along with CHIRPS data, for various classification, quantitative and agreement statistic metrics. Secondly, this is the first attempt at

¹ Details about the selected satellite-based weather products will be discussed in the following chapters.

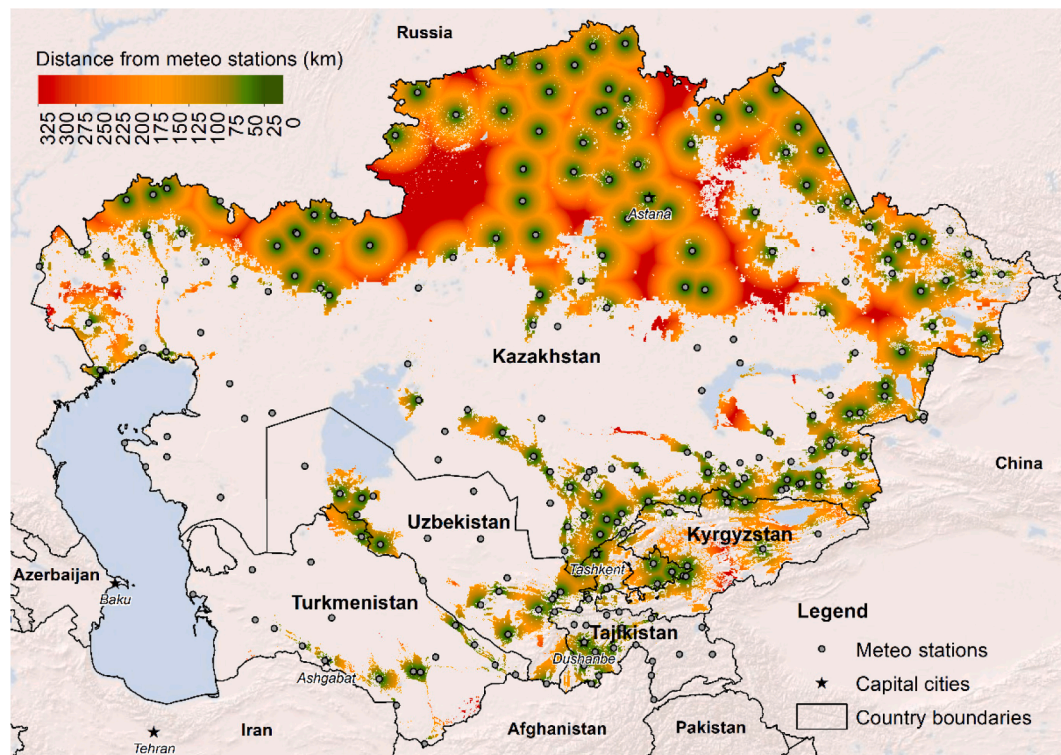


Fig. 1. Geographical distribution of meteorological stations in the croplands of Central Asia. Own presentation based on data from [Teluguntla et al. \(2015\)](#) and [NCEI \(2021\)](#).

undertaking an accuracy assessment of selected satellite-based temperature and precipitation data and calculation of MDIs based on satellite-based weather products for Central Asia. While region-specific climate challenges need to be taken into account, the results of this case study may also provide insights relevant for arid and semi-arid agricultural regions elsewhere in the world.

This paper is structured as follows: The second chapter provides a review of the literature on the application of satellite data on index insurance in various countries. The third chapter discusses opportunities for establishing index insurance in Central Asia, while the fourth chapter describes the process of in-situ and satellite-based data selection and acquisition. We report on methods selected for the accurate assessment of satellite-based weather data and selected MDIs that examine the ability of satellite-based weather data to detect droughts and floods. Chapter five provides the results from our analyses followed by a comprehensive discussion. We conclude with an outlook on opportunities and limitations of satellite-based data in the detection of drought and flood events.

Literature review of the application of satellite remote sensing data to index insurance

A number of studies in developing countries have investigated and proven significant accuracy, applicability and the potential of satellite data for index insurance in the agricultural sector at various temporal and spatial scales. [De Leeuw et al. \(2014\)](#) conducted a systematic search of the available literature to review the potential and uptake of remote sensing in the insurance industry, concluding that there is particular scope for the application of remote sensing by the index insurance industry. They have also concluded that satellite-based indices can be applied when there is a significant correlation with what is insured, as

such indices serve to lower the cost of the insurance product and create new insurance markets and services². Therefore, this literature review focuses on research papers published after [De Leeuw et al. \(2014\)](#).

Many existing research articles provide evidence of the suitability of satellite indices, such as the Normalized Difference Vegetation Index (NDVI); the Vegetation Condition Index (VCI); the Temperature Condition Index (TCI); and the Vegetation Health Index (VHI) (see [SM 2](#) for detailed information) or Satellite-based Precipitation Estimates (SPE), in selected countries and under various agro-climatic conditions ([Coleman et al., 2018](#); [World Bank, 2015](#); [World Bank, 2011](#)). Some studies have focused on assessing the accuracy of single indices: For example, [Black et al. \(2016a\)](#) and [Black et al. \(2016b\)](#) analyzed the applicability of the *Tropical Application of Meteorology Using Satellite Data* (TAMSAT) SPE to develop an index insurance for cotton fields in Zambia. They found a significant relationship between rainfall and soil moisture, and a strong association between cotton production losses and rainfall on a national scale. [Enenkel et al. \(2018\)](#) investigated the efficiency of using *Climate Hazards Group InfraRed Precipitation with Station* (CHIRPS) SPE for detecting drought and developing an advanced index insurance design in Ethiopia, Senegal and Zambia. By comparing drought years reported by farmers, they identified a high “hit rate”, albeit with some limitations when it came to detecting moderate drought events.

Other studies have conducted comparative analyses of two or more indices: [Coleman et al. \(2018\)](#) investigated the suitability of *NOAA-based African Rainfall Climatology Version 2* (ARC2) and TAMSAT SPE to detect drought events and develop a village-scale index insurance for groundnut, millet and maize in Senegal. [Tarnavsky et al. \(2018\)](#) tested three different SPE products, namely ARC2, CHIRPS and TAMSAT SPEs to monitor country-level maize production in Tanzania, and analyzed their applicability for designing an index insurance. They discovered a higher correlation between SPE and maize when CHIRPS SPE was

² A more detailed review of literature before 2014 can be found in [De Leeuw et al. \(2014\)](#).

employed and suggest that CHIRPS SPE is more suitable for the application of index insurance. Osgood et al. (2018) tested the link between village-level drought years in Ethiopia as reported by farmers and drought years detected by SPE products ARC2 and CHIRPS; they found evidence that events reported by farmers are independently reflected in satellite datasets. Brahm et al. (2019) conducted cross-correlation analyses with *Climate Hazards Group InfraRed Precipitation* (CHIRP), CHIRPS, *Tropical Rainfall Measuring Mission* (TRMM), *Multisatellite Precipitation Analysis* (TMPA) and MODIS-NDVI to test the accuracy of the newly released data source *Historical Database for Gridded Daily Precipitation Dataset over Latin America* (LatAmPrec). They also used a logistic regression approach with aggregated farmer-reported data to check the ability of the LatAmPrec to detect drought events across regions in Latin America. Their results show that LatAmPrec performs better than other satellite data sources in Latin America and is able to satisfactorily identify those yield losses that are relevant to insurances.

As can be seen in this summary, existing studies have not yet tested the applicability of the GSMaP and GLDAS datasets, both of which might be particularly suitable for developing and transformation countries, as their data is publicly available and free of charge. Moreover, none of the existing studies have tested the accuracy of precipitation estimates and the applicability of these to index insurance or other datasets for the Central Asian region.

Development of index insurance in Central Asia

Agricultural production has a substantial contribution to the economy and GDP of Central Asian countries. Between 20 and 50% of the population is employed in the agricultural sector (Bobojonov et al., 2019; Hamidov et al., 2016). In the meantime, systematic extreme weather events due to climate change in Central Asia have become more frequent, putting agricultural production at risk (Hamidov et al., 2016; Zhang et al., 2019). Based on information provided in Christmann et al. (2009), Bobojonov and Aw-Hassan (2014) reported that drought events during the critical period of rainfed crop growth in 2001 and 2008 had a great effect on crop production and the socio-economy of Central Asia, particularly in Tajikistan where more than a third of the cropping area was damaged, costing US\$63 million (Patrick, 2017). In the case of Kyrgyzstan, the gross agricultural output significantly decreased in 2009 due to droughts in preceding years that caused extreme climatic conditions and a deterioration of the economic situation. Generally, in Central Asia, the drought of 2001 was the most prolonged and widespread drought, resulting in below-average drops of 40–60% for rainfall levels and 35–40% for river flows. This drought event contributed to a loss of 80% of rural households' income, resulting in consequences of increased poverty rates and negative impacts on food security and public health (Patrick, 2017). In that year, the loss of agricultural production was estimated at US\$800 million for the whole region, which was a significant cost for all countries (World Bank, 2005). All of these implications indicate a need for improving risk management strategies and especially agricultural insurance.

Concerning the potential for the implementation of index insurance in Central Asia, the governments of Tajikistan and Kyrgyzstan have already initiated and developed a law regarding the use of index insurance in the agricultural sector. However, because of little interest from insurance companies and farmers, and a lack of weather data for designing the index insurance, these initiatives are not being taken up by local insurance industries even though both states aim to partially finance the insurance premiums (Broka et al., 2016a; Broka et al., 2016b). In Uzbekistan and Kazakhstan, there are no orders or initiatives at the state level for the implementation of index insurance, while both states support the implementation of traditional insurances with the help of various mechanisms. However, big challenges in the implementation of traditional insurances create a bottleneck for the development of an insurance market in these countries (Bobojonov et al., 2019; Broka et al., 2016c; Muradullayev et al., 2015). Several

international organizations have recommended the use of index insurance in the agricultural sector of Kazakhstan and Uzbekistan to solve existing challenges in the traditional insurance markets (Broka et al., 2016c; Sutton et al., 2013), and some feasibility studies and small scale piloting activities have started to emerge in recent years. For example, Bokusheva and Breustedt (2012) have proved the suitability of drought indices based on station data, while Bokusheva et al. (2016) have extended this analysis to the applicability of VCI and TCI in index insurance for wheat production in northern Kazakhstan. For the same location, Conradt et al. (2015) investigated the applicability of station-based cumulative rainfall data for designing an index insurance. Bobojonov et al. (2019) reported on the suitability of cumulative precipitation based on weather station data and MODIS-based NDVI to identify shortfalls in wheat yields and index design in the Gallaral district, Uzbekistan.

A number of international organizations and projects in cooperation with local governmental agencies are attempting to implement satellite-based index insurance in Kazakhstan, Uzbekistan and Kyrgyzstan. For example, the United Nations Development Programme (UNDP) and the Ministry of Agriculture of Kazakhstan (MAK) are introducing an NDVI-based index insurance for croplands and livestock in Kazakhstan (UNDP, 2016). Swiss insurance company SwissRE and Dutch company Vandersat, in cooperation with MAK, have been working on introducing a satellite soil-moisture-based index insurance since 2018 (Allinsurance, 2018). Moreover, the Leibniz Institute of Agricultural Development in Transition Economies (IAMO), together with local and international insurance companies, has been developing and piloting a satellite NDVI and precipitation-based index insurance for croplands in Uzbekistan and Kyrgyzstan since 2018 (Bobojonov et al., 2019).

The above-mentioned studies and projects have not explored the accuracy of satellite-based weather data for index development in Central Asia. Since farming systems are heterogeneous and risks are diverse, weather data could be important for measuring various climate-related risks (a review on the need for satellite weather data usage in the region can be found in SM 3).

Methods and materials

Data sources

Meteorological data

Whenever station proximity, historical records and general data quality are provided, weather station data remains the most accurate source of information for the design of weather indices. Therefore, we chose the daily precipitation and temperature data of six meteorological stations located in Uzbekistan as a benchmark for our accuracy assessment. The selected weather stations provide information on a time period from January 1st, 2000 to December 31st, 2017, which is a sufficient time horizon for comparison. Furthermore, we only compared data from a satellite that was in direct proximity³ to the selected stations.

The meteorological data was provided by the Centre of Hydro-meteorological Service at the Ministry of Emergency Situations of the Republic of Uzbekistan (Uzhydromet), which is responsible for all national hydro-meteorological network stations (Uzhydromet, 2008). The Djizzakh, Gallaral and Lalmikor stations are located in the Djizzakh province. The Samarkand station is located in the Samarkand province, and the Karshi station is situated in the Kashkadarya province of Uzbekistan (Fig. 2) (see SM 4 for detailed information). Among the selected stations, only Djizzakh, Samarkand and Karshi stations were used during the calibration of all selected satellite-based weather products (CHC, 2021; Ji et al., 2015; Mega et al., 2019; NCEI, 2021).

³ Details about the spatial resolution of the selected satellite-based weather products will be discussed in following chapters

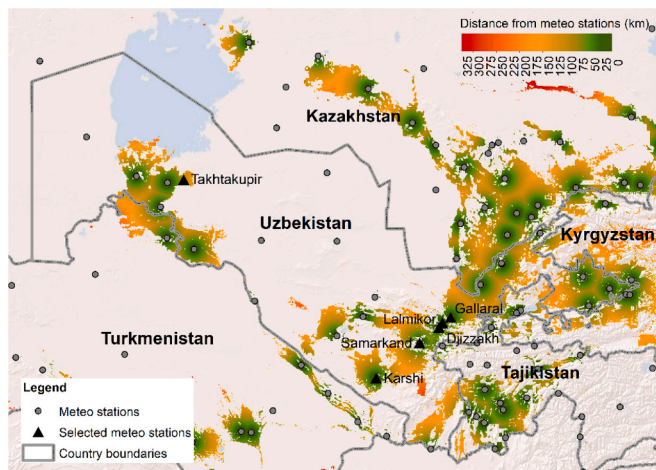


Fig. 2. Selected meteorological stations. Source: Authors' presentation based on data from Teluguntla et al. (2015) and NCEI (2021).

Satellite remote sensing precipitation and temperature data

After a systematic review of available satellite-based weather products (see SM 5 for a detailed review), we selected three satellite weather products for this study: Firstly CHIRPS, secondly GSMaP, and finally the satellite temperature product GLDAS. The selection was made based on the coverage area of the case study region, spatial and temporal performances in terms of suitability for index insurance development (e.g., extreme large resolution may not be suitable due to high basis risk), as well as data accessibility, which would also be relevant for the sustainable application to insurance products.

CHIRPS⁴ is a semi-global precipitation product, covering latitudes 50°S–50°N and all longitudes. The product is designed for drought monitoring and environmental analyses (Funk et al., 2015). CHIRPS data is available starting from 1981 to the near present, and the dataset consist of daily, pentadal, decadal and monthly temporal resolution data, which were completed and made available to the public in February 2015 by the Climate Hazards Group (CHC, 2015). CHIRPS integrates a $0.05^\circ \times 0.05^\circ$ spatial resolution of satellite images and data from stations to produce a gridded precipitation time series. A detailed description of the CHIRPS dataset has been published in Funk et al. (2015).

GSMaP is a semi-global precipitation product with $0.1^\circ \times 0.1^\circ$ spatial resolution and 1-hour temporal resolution that uses multi-band passive microwave and infrared radiometers from the GPM Core Observatory satellite and, with the assistance of a constellation of other satellites, covering latitudes 60°S–60°N and all longitudes. The product is designed for flood monitoring, meteorology and climatology analyses. GSMaP data is available starting from 2000 to the near present, and the dataset consist of hourly and daily data, which is available through the JAXA G-Portal (2019). This study uses a gauge-data (GG) band, which has adjusted precipitation rate to rain gauge. The dataset is processed using a GSMaP algorithm version 6 (product version 3).

GLDAS is a global 3-hourly climate product created by combining satellite and ground-based observation datasets, which apply multiple advanced land surface modelling and data assimilation methods to generate optimal fields of land surface states and fluxes (Rodell et al., 2004). For this study, we used the Tair_f_inst (air temperature) band from 2.1 version of the GLDAS. GLDAS 2.1 is analogous to previous versions with upgraded models, which integrate GDAS, GPCP and

AGRMET datasets. Data from the GLDAS 2.1 is available for the period from early 2000 to the near present. The spatial resolution of the product is $0.25^\circ \times 0.25^\circ$ (Chen et al., 2013). The GLDAS data is archived and freely available through GSFC DISC (2019).

In order to obtain daily updates on CHIRPS, GSMaP and GLDAS data, we developed an algorithm and programmed an automatic web platform (see SM 6 for details and information on the free data platform), which allows easy access to the related datasets. This web platform for data acquisition can be found under the following link: <https://www.klim.alez.org/srs-export>. A large number of existing studies that have assessed the accuracy of satellite products are characterized by decadal, monthly, seasonal and annual scales (e.g., Darand and Khandu (2020); Peng et al. (2020); Rivera et al. (2018); Yu et al. (2020)), especially studies in the field of index insurance design (e.g. Bobojonov et al. (2014); Odening et al. (2007); Osgood et al. (2007); Westerhold et al. (2018); Xu et al. (2008)). To comprehend the pattern of the satellite precipitation and temperature measurements at different time scales and locations, this study assessed the satellite data in decadal and monthly aggregation. The aggregation of hourly, 3-hourly and daily data into decadal and monthly values cancels out errors observable in short-term data, as mentioned for instance by Usman and Nichol (2020). Coleman et al. (2018) have stated that aggregated SPEs are more accurate than daily ones, as there is significant uncertainty in an individual precipitation measurement either by the satellite or the station.

Accuracy measures

To evaluate the accuracy of the GSMaP, CHIRPS and GLDAS data, we used a number of classification metrics, which are based on existing indices or adaptations of such as used in the existing research literature (Hu et al., 2013; Yu et al., 2020):

Frequency Bias (BIAS), Critical Success Index (CSI), also known as Threat Score, Probability of Detection (POD) and False Alarm Ratio (FAR) were used to demonstrate the ability of remote sensing to precisely measure decadal and monthly precipitation and temperature (Schaefer, 1990; Stephenson, 2000). BIAS measures the tendency of a satellite to underestimate or overestimate events. POD measures the probability of a satellite to detect precipitation events. FAR indicates the probability of a satellite-based precipitation event being detected by mistake. CSI represents the overall accuracy of a satellite in classifying precipitation events. CSI, POD and FAR are recommended and extensively used by the US National Weather Service to verify various weather events (Gerapetritis and Pelissier, 2004). The details of these statistics can be found in Table 1, where a represents correctly detected precipitation events by a satellite, b stands for precipitation events that are detected by the satellite but not confirmed by station data, and c denotes precipitation events that are not detected by satellite data but are observed by station data.

Furthermore, we employed a number of quantitative metrics. In detail, these are 1) Percentage Bias (PBIAS), which measures the average tendency of satellite estimates to be larger or smaller than the benchmark; 2) Mean Bias Error (MBE), which measures the average satellite estimate error; 3) Mean Absolute Error (MAE), which measures the average magnitude of a satellite's estimate; 4) Root Mean Square Error (RMSE), which measures the same as MBE but puts greater weight on higher errors than MBE.

We also applied some agreement metrics such as 1) Spearman's Rank-order Correlation Coefficient (SC), which measures the strength of a monotonic relationship between estimations and observations; 2) Pearson's Correlation Coefficient (PC), which measures the linear correlation between estimations and observations; 3) Determination Coefficient (R^2), which measures how well data points fit in a regression line, as well as the predictability level of the observation data from satellite data; 4) Index of Agreement (d), which solves certain problems associated with PC and R^2 and measures the degree to which satellite estimation is free of error; it also measures how well a satellite estimate

⁴ Climate Hazards Group Infrared Precipitation (CHIRP) was not considered for this study since we already included CHIRPS, which is the improved version of CHIRP, providing higher accuracy than its predecessor, as pointed out by (Dinku et al., 2018; Funk et al., 2015; Shen et al., 2020)

Table 1
Details of accuracy measures.

Statistics	Formula	Range	Unit	Perfect Value
Frequency Bias	$BIAS = \frac{a+b}{a+c}$	0 to ∞	None	1
Critical Success Index	$CSI = \frac{a}{a+b+c}$	0 to 1	None	1
Probability of Detection	$POD = \frac{a}{a+c}$	0 to 1	None	1
False Alarm Ratio	$FAR = \frac{b}{a+b}$	0 to 1	None	0
Percentage Bias	$PBIAS = \frac{\sum_{i=1}^n (E_i - O_i)}{\sum_{i=1}^n (O_i)} \times 100\%$	$-\infty$ to ∞	%	0
Mean Bias Error	$MBE = \sum_{i=1}^n (E_i - O_i)$	$-\infty$ to ∞	mm or C°	0
Mean Absolute Error	$MAE = \frac{1}{n} \sum_{i=1}^n E_i - O_i $	0 to ∞	mm or C°	0
Root Mean Square Error	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (E_i - O_i)^2}$	0 to ∞	mm or C°	0
Linear Error in Probability Space	$LEPS = \frac{1}{n} \sum_{i=1}^n CDF_o(E_i) - CDF_o(O_i) $	0 to 1	None	0
Spearman's Correlation	$SC = \frac{\frac{1}{n} \sum_{i=1}^n (O_i - \bar{O})(E_i - \bar{E})}{\sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\frac{1}{n} \sum_{i=1}^n (E_i - \bar{E})^2}}$	-1 to 1	None	1
Pearson's Correlation	$PC = \frac{\sum_{i=1}^n (O_i - \bar{O})(E_i - \bar{E})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (E_i - \bar{E})^2}}$	-1 to 1	None	1
Determination Coefficient	$R^2 = 1 - \frac{\sum_{i=1}^n (E_i - \bar{O})^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$	-1 to 1	None	1
Index of Agreement	$d = 1 - \frac{\sum_{i=1}^n (O_i - E_i)^2}{\sum_{i=1}^n (E_i - \bar{O} + O_i - \bar{O})^2}$	0 to 1	None	1
Nash-Sutcliffe Efficiency	$NSE = 1 - \frac{\sum_{i=1}^n (O_i - E_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$	$-\infty$ to 1	None	1

simulates station data (Willmott, 1981); 5) Linear Error in Probability Space (LEPS), which measures the mean absolute difference between the estimated cumulative distribution value and the observation (Potts et al., 1996); 6) Nash-Sutcliffe Efficiency (NSE), which was first proposed by Nash and Sutcliffe (1970) and originally used for assessing the predictive power of hydrological models, but was later widely used for quantity accuracy assessment of various models. However, NSE is highly sensitive for data that has a high temporal volatility. Therefore, NSE has been used only for accuracy assessment of the temperature data. The details of these statistical indices can be found in Table 1, where E_i and O_i are satellite and station observations, respectively, at a specific time i ; \bar{O} is the average of the observed precipitation/temperature.

Additionally, we used Ordinary Least Squares (OLS) regression and Quantile Regression (QR) to measure the relationship between decadal and monthly weather measurements by station and satellite. QR was used to assess the satellite decadal and monthly weather data in various quantiles of the station precipitation measurements, which is not possible in traditional regression methods. QR has a number of advantages for measuring the relationship between variables compared to traditional regression methods. QR measures the relationship between minimum and maximum response and provides a more detailed overview of the relationship (Cade and Noon, 2003). QR minimizes the sum of absolute residuals and is robust to outliers (Li, 2015). In our study, we focused on all lower, median and upper tile quantiles 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95 to check the ability of SPE during drought/flood periods. All statistical calculations and figures were developed using the R project (R Development Core Team, 2018) and just the results of the QR analysis were generated with STATA 15 (StataCorp, 2019).

Meteorological drought indices and anomaly detection

In order to check the ability of satellite-based MDIs to detect weather shocks during the vegetation period of rainfed crops (March-May) and irrigated crops (May, September, October), we calculated MDIs using both in-situ weather and satellite data and applied correlation analyses. For the analyses, we selected two drought indices, namely the

Standardized Precipitation Index (SPI) and the Standardized Precipitation-Evapotranspiration Index (SPEI). According to Wanders et al. (2017), the SPI and SPEI are among the most frequently used drought indices worldwide. Ghamghami et al. (2017) and Okpara et al. (2017) have found the SPI well-suited for index insurance purposes. SPI is based on the conversion of precipitation data into probabilities using gamma distribution. The negative output value of SPI represents drought intensity, with the following categories: > 0 is no drought, 0 to -0.99 is mild drought, -1.00 to -1.49 is moderate drought, -1.50 to -1.99 is severe drought and ≤ -2.00 is extreme drought (McKee et al., 1993). The main advantages of the SPI are a simple calculation that uses only precipitation data and its multi-temporal character. Meanwhile, the SPI measures only the water supply and does not take into account any temperature changes over the given period, thus ignoring the problem of evapotranspiration. In this regard, SPEI is an improvement of SPI, by taking into account both precipitation and Potential Evapotranspiration (PET) in defining drought (Vicente-Serrano et al., 2010). Bezdan et al. (2019) have proposed the use of SPEI in decision-making at both national and regional levels and in the agricultural insurance sector. In our calculations, the PET have been calculated according to the Hargreaves and Samani (1982) method, which has an option of calculating the PET using only Tmax and Tmin data. Categories of output values are similar to the SPI. A detailed explanation of the SPI index calculation can be found in McKee et al. (1993), and for SPEI calculation in Vicente-Serrano et al. (2010). SPI and SPEI were calculated using the R package developed by Beguería and Mainater (2017), who are the authors of SPEI itself.

Additionally, we tested the ability of SPEs to detect the extreme weather events by using the percentiles as a threshold for anomaly detection. We applied <10 th and <20 th percentiles for drought (March, April and May) and >80 th and >90 th percentiles for flood events (May, September, October) detection. Classification accuracy measures listed in Table 1 were applied to examine the performance of products.

Results

Accuracy of satellite precipitation data

Fig. 3 provides a comparison of decadal and monthly precipitation levels as measured by satellites at the Djizzakh station in the period of March–December 2017. A similar visualization for the remaining five stations can be found in SM 7.1 and 7.2. While both satellites did record the local precipitation events, we noticed that monthly precipitation, in comparison with our benchmark stations, was overestimated by CHIRPS, while it was underestimated by GSMaP.

To quantify this difference in precipitation data, Table 2 and SM 8.1 provide the results of classification, quantitative and agreement statistics of continuous decadal and monthly precipitation for all six stations. The results obtained from BIAS show that GSMaP slightly overestimate the precipitation events while CHIRPS underestimates; mean values are equal to 1.12 and 0.91 for monthly scale and 1.24 and 0.91 for decadal scale, respectively. According to POD, GSMaP has almost perfect values and significantly better probability to detect precipitation events than CHIRPS. Meanwhile, based on FAR results, CHIRPS has a lower probability of false positives in terms of precipitation events than GSMaP. The values of CSI, which measures comprehensive detection probability of satellite to precipitation events, vary from 0.78 to 0.91 on a monthly scale and from 0.71 and 0.86 on a decadal scale for GSMaP; and from 0.82 to 0.89 on a monthly scale and from 0.82 to 0.98 for CHIRPS.

According to results from PBIAS and MBE in both temporal aggregations, GSMaP underestimates precipitation in all locations while CHIRPS overestimates. MBE and RMSE shows that GSMaP has a lower difference from benchmark measurements and a higher accuracy compared to CHIRPS in all locations. Results of SC, PC, R^2 , d and LEPS for GSMaP are close to perfect values in all locations, except for the Takhtakupir station, which is located in an arid zone. Meanwhile, these agreement metrics are also high for CHIRPS but slightly lower than GSMaP. As shown in Table 2 and SM 8.1, the results of all statistical metrics for the Takhtakupir station are slightly lower in both SPEs. Overall, the results of all statistical metrics for all stations are on a satisfactorily accurate level. GSMaP showed a stronger ability to measure precipitation variance than CHIRPS in terms of most statistical metrics.

In both SPE products for the decadal and monthly scales, the quantile coefficients and their 95% confidence intervals do not lie within the 95% confidence interval (Fig. 4, SM 9.3 and 9.5); furthermore, there is a significant difference between coefficients in the upper and lower quantiles compared to OLS (Table 3, SM 9.2 and 9.4). This indicates a different relationship between precipitation by station and SPE along the quantiles, showing that the OLS regression slope is not sufficient to describe this relationship. Both Fig. 4 and Table 3 show that the magnitude of coefficients is increasing as they approach the upper quantiles of the distribution of station precipitation. Coefficients of GSMaP in the lowest quantiles (low precipitation decades and months) are below one, as opposed to the quarter quantiles coefficients, which exceed one. Correspondingly, GSMaP overestimates the precipitation in

lower quantiles, but starts underestimating after quarter quantiles. Structurally, the results for CHIRPS are similar; however, CHIRPS overestimates the precipitation until about the median, after which it starts underestimating precipitation. Overall, both SPE products have a significant correlation with station precipitation measures, according to both OLS and quantile regression.

SM 8.3 and Fig. 5 illustrate the average results from all six stations for classification, quantitative and agreement accuracy metrics of the decadal and monthly precipitation records for each period from March 2000 to December 2017. This means that each month offers 18 periodic precipitation observations for analysis, except January to March, for which there are 17 periodic precipitation observations. According to the averaged results, GSMaP shows a significantly higher accuracy than CHIRPS in most decades and months in all accuracy metrics. The values of classification accuracy metrics (BIAS, CSI, POD and FAR) for GSMaP are close to a perfect value in all months excluding the dry season (June to September), which indicates a higher classification accuracy for GSMaP in wet seasons (winter, spring and fall). Meanwhile, the classification accuracy metrics for CHIRPS are lower than GSMaP, while CHIRPS also has a significantly lower classification accuracy in the summer season, as compared to other seasons. Based on these results, the average values of PBIAS and MBE confirm that GSMaP underestimated precipitation levels in the vast majority of decades and months; meanwhile, CHIRPS overestimated the amount of precipitation in decades and months from January to May and from October to December, even though for both satellite products, the MAE and RMSE in summer season are significantly lower than in other seasons. GSMaP has higher and moderately close to perfect values in SC, PC, R^2 , d and LEPS than CHIRPS provides in all months, and a decrease of quantitative and agreement accuracy can be observed during the summer season for both products. Overall, GSMaP has a significantly higher accuracy in terms of all statistics than CHIRPS, which can be observed from both continuous decadal and monthly precipitation analyses and analyses for each decades' and months' precipitation.

Accuracy of satellite temperature data

Using the Djizzakh station as an example, Fig. 6 demonstrates the decadal and monthly average Tmax and Tmin estimates by GLDAS and the stations between January 2000 and December 2017. A similar visualization for the remaining five stations can be found in SM 7.3 and 7.4. According to results, GLDAS has a high ability to detect average Tmax and Tmin, and performs extremely accurate measurements at the 1% level in both temporal aggregation for all periods and all locations.

SM 8.1 and Table 4 illustrate the results of classification, quantitative and agreement statistics of continuous decadal and monthly Tmax and Tmin in all six station locations between January 2000 and December 2017, all in all 642 decades and 214 months. According to this data, GLDAS has perfect classification accuracy in all indices, which means that GLDAS captured Tmax and Tmin in all decades and months of the study period in selected locations.

The obtained results from the quantitative statistic metrics

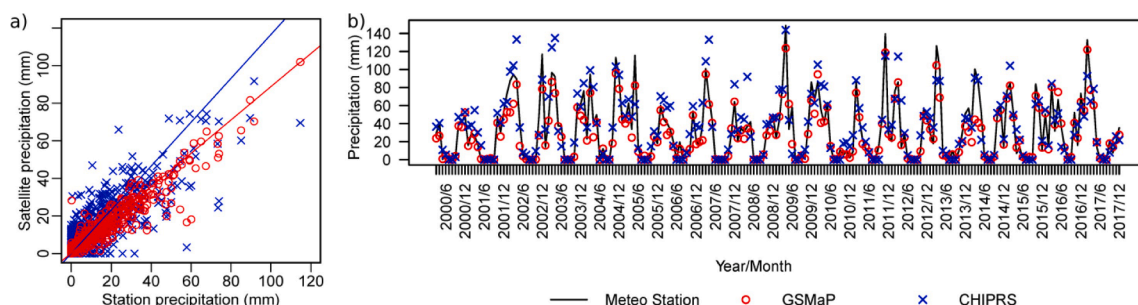
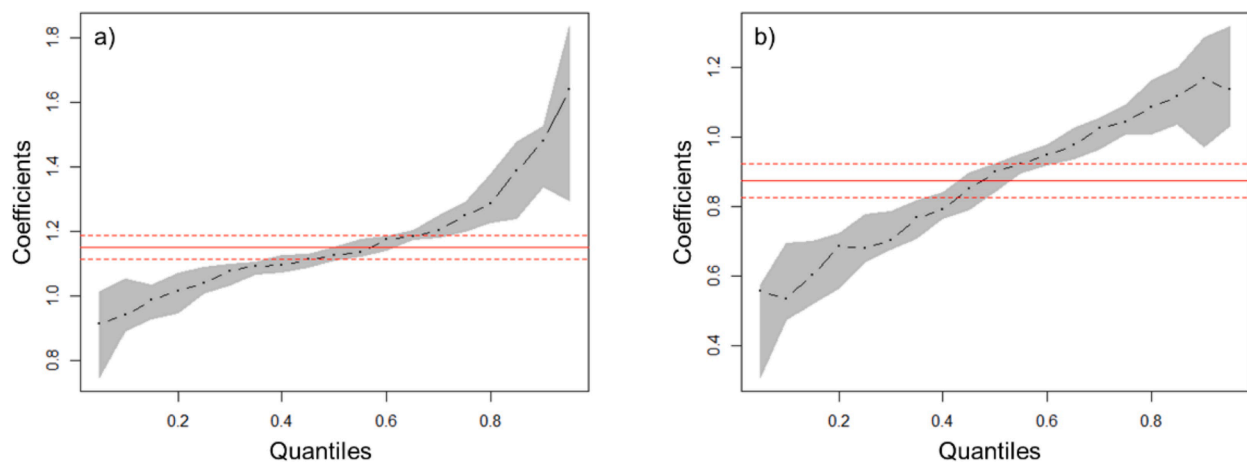


Fig. 3. Decadal (a) and monthly (b) precipitation by stations, GSMaP and CHIRPS at the Djizzakh station.

Table 2

Accuracy assessment of continuous monthly precipitation in selected locations (March 2000–December 2017).

	Djizzakh		Gallalar		Lalmikor		Samarkand		Karshi		Takhtakupir		Average	
	GSMaP	CHIRPS	GSMaP	CHIRPS	GSMaP	CHIRPS	GSMaP	CHIRPS	GSMaP	CHIRPS	GSMaP	CHIRPS	GSMaP	CHIRPS
BIAS	1.09	0.89	1.11	0.90	1.08	0.88	1.10	0.87	1.28	1.02	1.08	0.91	1.12	0.91
CSI	0.91	0.89	0.90	0.86	0.91	0.86	0.91	0.86	0.78	0.91	0.89	0.82	0.88	0.87
POD	0.99	0.89	1.00	0.88	0.99	0.87	1.00	0.87	1.00	0.97	0.98	0.86	0.99	0.89
FAR	0.08	0.00	0.10	0.02	0.08	0.01	0.09	0.01	0.22	0.05	0.09	0.05	0.11	0.02
PBIAS	−14.20	10.60	−9.10	18.00	−18.90	4.00	−12.90	4.90	−6.80	28.50	−13.90	9.50	−12.63	12.58
MBE	−4.68	3.50	−2.79	5.52	−6.48	1.37	−3.81	1.46	−1.22	5.11	−1.41	0.96	−3.40	2.99
MAE	6.45	10.37	7.77	11.74	9.25	10.93	6.27	8.33	3.69	6.97	4.15	4.86	6.26	8.87
RMSE	11.13	15.76	12.37	16.98	14.11	15.71	10.64	12.77	6.59	11.57	7.58	7.26	10.40	13.34
SC	0.97	0.92	0.94	0.91	0.95	0.91	0.98	0.94	0.96	0.95	0.84	0.84	0.94	0.91
PC	0.96	0.90	0.93	0.88	0.93	0.89	0.95	0.92	0.96	0.91	0.79	0.80	0.92	0.88
R ²	0.93	0.81	0.86	0.78	0.87	0.79	0.91	0.84	0.92	0.84	0.63	0.65	0.85	0.79
p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
d	0.97	0.94	0.96	0.93	0.95	0.94	0.97	0.96	0.97	0.94	0.88	0.88	0.95	0.93
LEPS	0.05	0.08	0.06	0.09	0.07	0.09	0.04	0.07	0.04	0.06	0.10	0.13	0.06	0.09

**Fig. 4.** Estimated results of quantile regressions for monthly scale precipitation by (a) GSMaP and (b) CHIRPS in Djizzakh station (a similar visualization for the remaining five stations can be found in [SM 9.1](#) and for decadal scale in [SM 9.3](#)).**Table 3**Quantile regression results of satellite-based monthly precipitation estimates for the Djizzakh station ($n = 214$). A similar table for the remaining five stations can be found in [SM 9.2](#) and for decadal scale in [SM 9.4](#).

		OLS	QR0.5	QR 0.1	QR 0.25	QR 0.5	QR 0.75	QR 0.9	QR 0.95
Djizzakh-GSMaP	Coef.	1.150***	0.914***	0.940***	1.039***	1.126***	1.249***	1.480***	1.640***
	SE	0.022	0.054	0.022	0.022	0.013	0.029	0.066	0.159
	R2/pR2	0.925	0.605	0.6708	0.7529	0.8046	0.7897	0.7531	0.711
Djizzakh-CHIRPS	Coef.	0.876***	0.558***	0.535***	0.681***	0.900***	1.044***	1.168***	1.137***
	SE	0.029	0.048	0.033	0.034	0.026	0.034	0.077	0.106
	R2/pR2	0.807	0.3273	0.4044	0.5469	0.6408	0.6534	0.6123	0.5873

Coef. = Coefficient; SE = standard error; R2 = R-square for OLS; pR2 = pseudo R-square for quantiles; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

demonstrate a satisfactory accuracy of both Tmax and Tmin measurements by GLDAS in both temporal aggregations according to [Yu et al. \(2020\)](#). According to PBIAS and MBE values, GLDAS slightly overestimated Tmax in four locations and underestimated in two locations. Similarly, GLDAS overestimated Tmin in five locations and underestimated in one location. Meanwhile, the results of MAE and RMSE values show that these over-/underestimations, as well as the difference between station and GLDAS measurements, can be disregarded. Overall, results of SC, PC, R2, d, LEPS and NSE for Tmax and Tmin are near to the perfect value of zero or one, respectively, which indicates the strong ability of GLDAS to measure variance of decadal and monthly mean Tmax and Tmin, even though agreement statistical metrics of Tmax are slightly and insignificantly higher than Tmin.

[SM 9.3](#) and [Fig. 7](#) show that OLS is sufficient to describe the

relationship between temperature (decadal and monthly) measurements by satellite and station. The quantile slope estimates are not statistically different from the OLS estimate. Therefore, we conducted only OLS regression for satellite temperature data (see [Table 5](#)). The average R2 of Tmax is 0.99, ranging from 0.98 to 0.99, and Tmin varies from 0.95 to 0.98, with a mean of 0.97. P-values in all locations are below 0.001, which means the results are statistically significant at the 1 % level. Coefficients of GLDAS Tmax in all locations are less than one, as opposed to GLDAS Tmin, which reach higher than one. Correspondingly, GLDAS slightly overestimates the decadal and monthly mean Tmax and underestimates the Tmin. Overall, both GLDAS Tmax and Tmin in all locations have a significant correlation with station temperature measurements according to both OLSs.

[SM 8.3](#) and [Fig. 8](#) illustrate the average results (from six stations) of

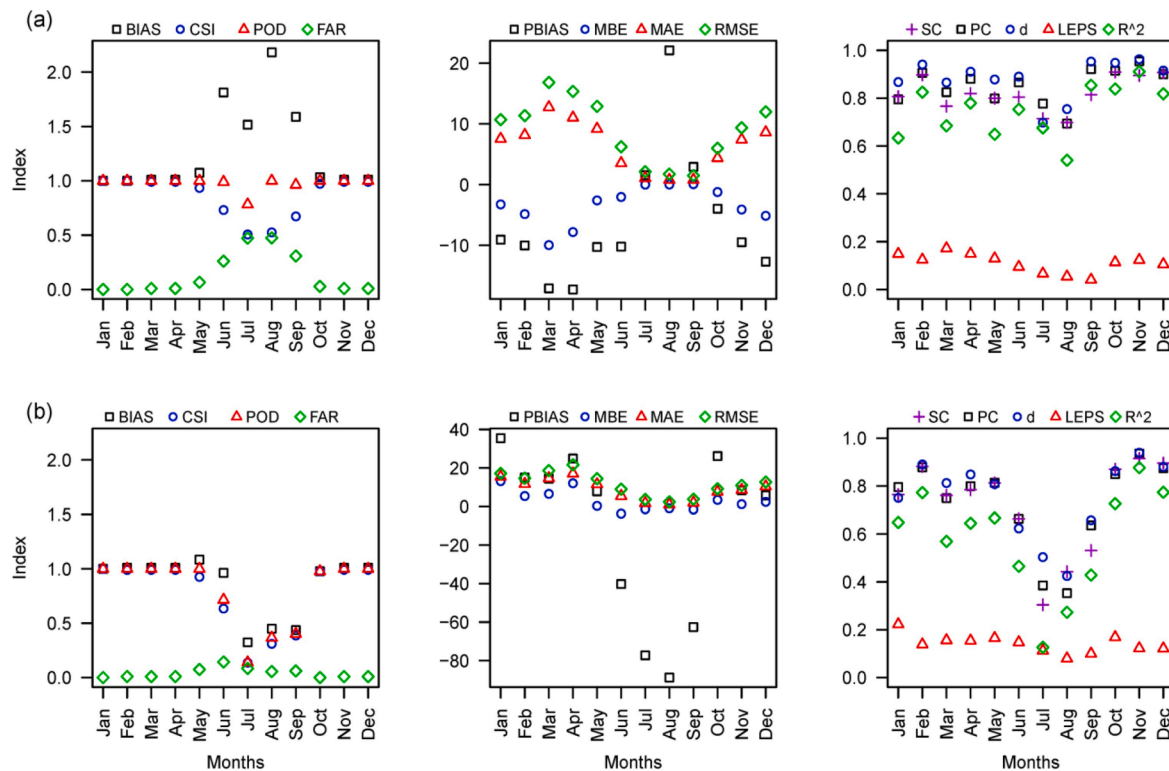


Fig. 5. Average results of classification, quantitative and agreement accuracy metrics of monthly precipitation for all stations, by (a) GSMap and (b) CHIRPS (a similar visualization of results for decadal scale can be found in [SM 8.1](#)).

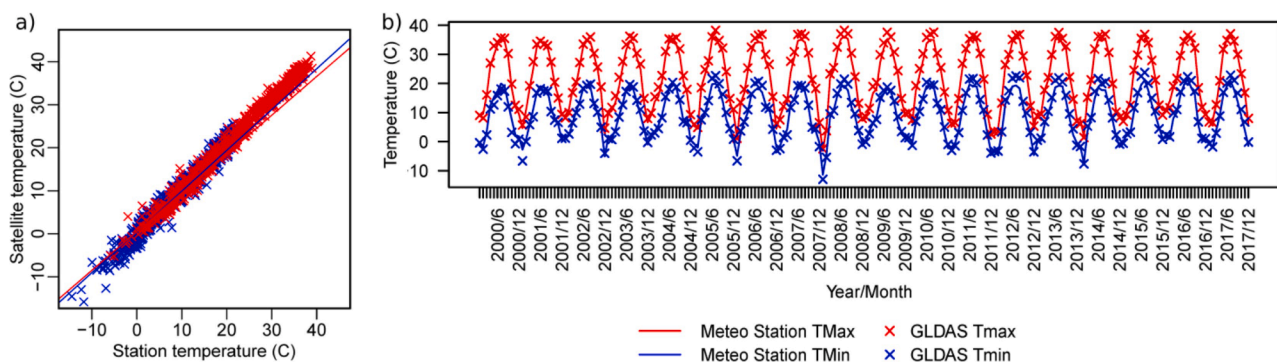


Fig. 6. Decadal (a) and monthly (b) average Tmax and Tmin by stations and GLDAS for the Djizzakh station.

classification, quantitative and agreement accuracy metrics of decadal and monthly temperature records for each period between January 2000 and December 2017, which means each month has 18 periodic temperature data measurements. Both Tmax and Tmin have perfect values for all classification accuracy metrics in all decades and months, which means that GLDAS is capturing all decadal and monthly temperature events and there is no data missing in any of the locations. In quantitative and agreement accuracy metrics, Tmax has a slightly higher accuracy than Tmin in most periods. PBIASs of Tmax and Tmin are significantly higher during the winter season, as average Tmax and Tmin during the winter season are very close to zero, and a slight difference between measurements might cause high PBIAS values. The PBIAS values are 107.55% in January and -7.75% in February for Tmax. The PBIAS values of Tmin are 19.06%, 102.85%, 45.6%, 14.43%, 35.83% and -203.85% in January, February, March, September, October and December, respectively. Despite this, the MBE, MAE and RMSE values of Tmax and Tmin during the winter season are lower than in other seasons, which demonstrates the low relevance of high PBIAS values to the

overall quantitative and agreement accuracy. As shown in the figure, Tmax has higher and closer to perfect values in SC, PC, R^2 , d and LEPS than Tmin in the majority of decades and months. Even though the SC, PC, d , LEPS and R^2 values are lower in summer seasons, those do not significantly affect the MBE, MAE and RMSE. Overall, both Tmax and Tmin have significant classification, quantitative and agreement accuracy, which can be observed from both continuous decadal and monthly temperature analyses and analyses for each decades' and months' temperature.

Additionally, accuracy comparisons were performed over the seasonal scale for the Djizzakh station only and results can be found in [SM 10](#).

Meteorological drought indices and anomaly detection

In the previous two sections, we have assessed the accuracy of satellite-based weather data. Our findings indicate the occurrence of considerable over- and underestimations. The following analysis

Table 4

Accuracy assessment of continuous monthly average temperature in selected locations (January 2000–December 2017). A similar table for the decadal scale analyses can be found in [SM 8.1](#).

	Djizzakh		Gallaral		Lalmikor		Samarkand		Karshi		Takhtakupir		Average	
	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin	Tmax	Tmin
BIAS	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CSI	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
POD	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
FAR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PBIAS	3.40	4.60	2.80	28.60	1.30	−11.60	−3.70	2.30	0.10	11.60	−0.70	58.80	0.53	15.72
MBE	0.73	0.43	0.58	1.86	0.25	−1.03	−0.81	0.21	0.03	1.21	−0.13	3.39	0.11	1.01
MAE	1.11	1.13	0.95	2.14	0.89	1.42	1.34	1.02	0.88	1.95	0.72	3.40	0.98	1.84
RMSE	1.36	1.42	1.20	2.68	1.16	1.87	1.72	1.35	1.14	2.31	0.95	3.88	1.26	2.25
SC	0.99	0.99	0.99	0.97	0.99	0.98	0.99	0.99	0.99	0.97	1.00	0.98	0.99	0.98
PC	1.00	0.99	1.00	0.97	0.99	0.98	0.99	0.99	1.00	0.98	1.00	0.98	1.00	0.98
R2	0.99	0.98	0.99	0.95	0.99	0.96	0.98	0.98	0.99	0.95	0.99	0.97	0.99	0.97
p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
d	1.00	0.99	1.00	0.97	1.00	0.99	0.99	0.99	1.00	0.98	1.00	0.97	1.00	0.98
LEPS	0.04	0.05	0.03	0.07	0.03	0.06	0.05	0.04	0.03	0.07	0.02	0.09	0.03	0.06
NSE	0.98	0.97	0.99	0.88	0.99	0.95	0.97	0.97	0.99	0.92	0.99	0.86	0.99	0.93

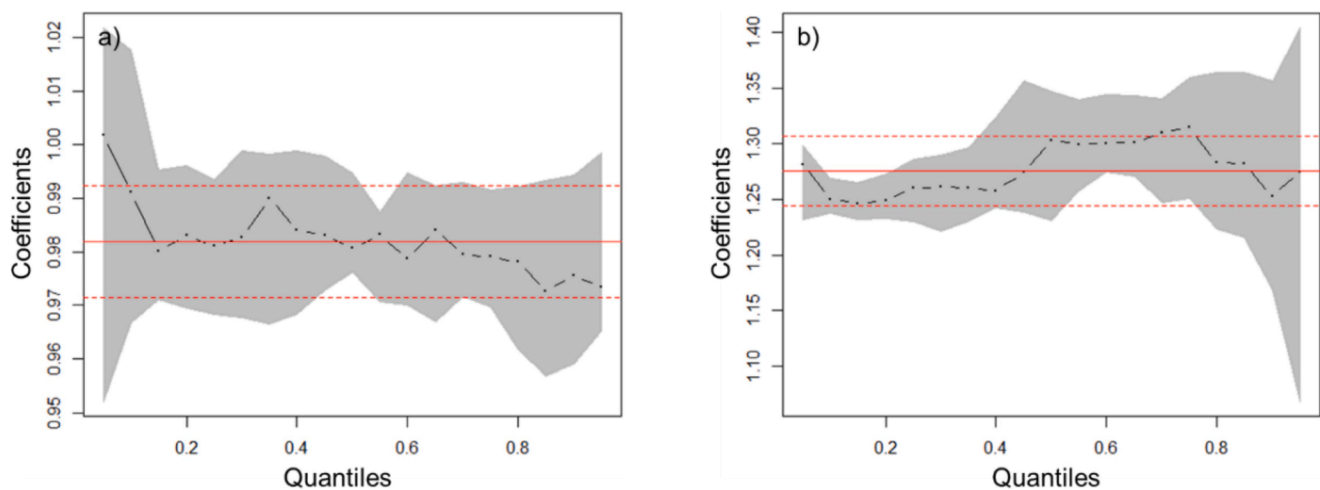


Fig. 7. Estimated results of quantile regressions for (a) GLDAS Tmax and (b) GLDAS Tmin in Djizzakh station (a similar visualization for the remaining five stations can be found in [SM 9.1](#) and for decadal scale in [SM 9.3](#)).

Table 5

Estimated results of OLS regressions for monthly GLDAS Tmax and GLDAS Tmin in all locations. A similar table for the remaining five stations can be found in [9.2](#) and for decadal scale in [SM 9.4](#).

	Djizzakh		Gallaral		Lalmikor		Samarkand		Karshi		Takhtakupir	
	GLDAS Tmax	GLDAS Tmin	GLDAS Tmax	GLDAS Tmin	GLDAS Tmax	GLDAS Tmin	GLDAS Tmax	GLDAS Tmin	GLDAS Tmax	GLDAS Tmin	GLDAS Tmax	GLDAS Tmin
Coef.	0.947***	1.255***	0.982***	1.276***	0.979***	1.253***	0.934***	1.188***	0.945***	1.155***	1.016***	1.249***
SE	0.006	0.014	0.006	0.019	0.007	0.019	0.009	0.015	0.006	0.017	0.005	0.015
R-sq	0.991	0.973	0.991	0.953	0.989	0.954	0.981	0.967	0.992	0.954	0.995	0.972

Coef. = Coefficient; SE = standard error; R-square; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

illustrates the impact of these deficiencies on drought indices, as they might find application in index-based insurance products. In this chapter we focused on drought during the vegetation period of rainfed crops (March–May), on flood during the seeding of irrigated crops (May) and on flood during the harvesting of irrigated crops (September–October). [Fig. 9](#) compares the SPI values during March, April, May, September and October based on precipitation data from stations, GSMaP and CHIRPS for the Djizzakh station (a similar visualization for the remaining five stations can be found in [SM 11.1](#)). In general, SPI values from both SPEs are able to detect drought and flood, and performed reasonably accurate measurements in most locations. The PC between GSMaP-SPI and station-SPI is slightly higher than CHIRPS-SPI in all cases. Another

finding is that the agreement between SPIs located in the semi-arid agro-climatic zone was higher than in the arid agro-climatic zone.

Moreover, [Fig. 9](#) illustrates the calculated SPEI values based on the data combinations station & station (M & M), GSMaP & GLDAS (G & G) and CHIRPS & GLDAS (C & G) for the months of March, April, May, September and October for the Djizzakh station (a similar visualization for the remaining five stations can be found in [SM 11.2](#)). Generally, SPEI values from satellite precipitation and temperature products are able to detect drought and gave reasonably accurate measurements in most locations. This was confirmed by the SPEI results. The weather data combination involving GSMaP has a slightly higher agreement than the C&G combination. In addition, the PC of SPEIs located in the semi-arid

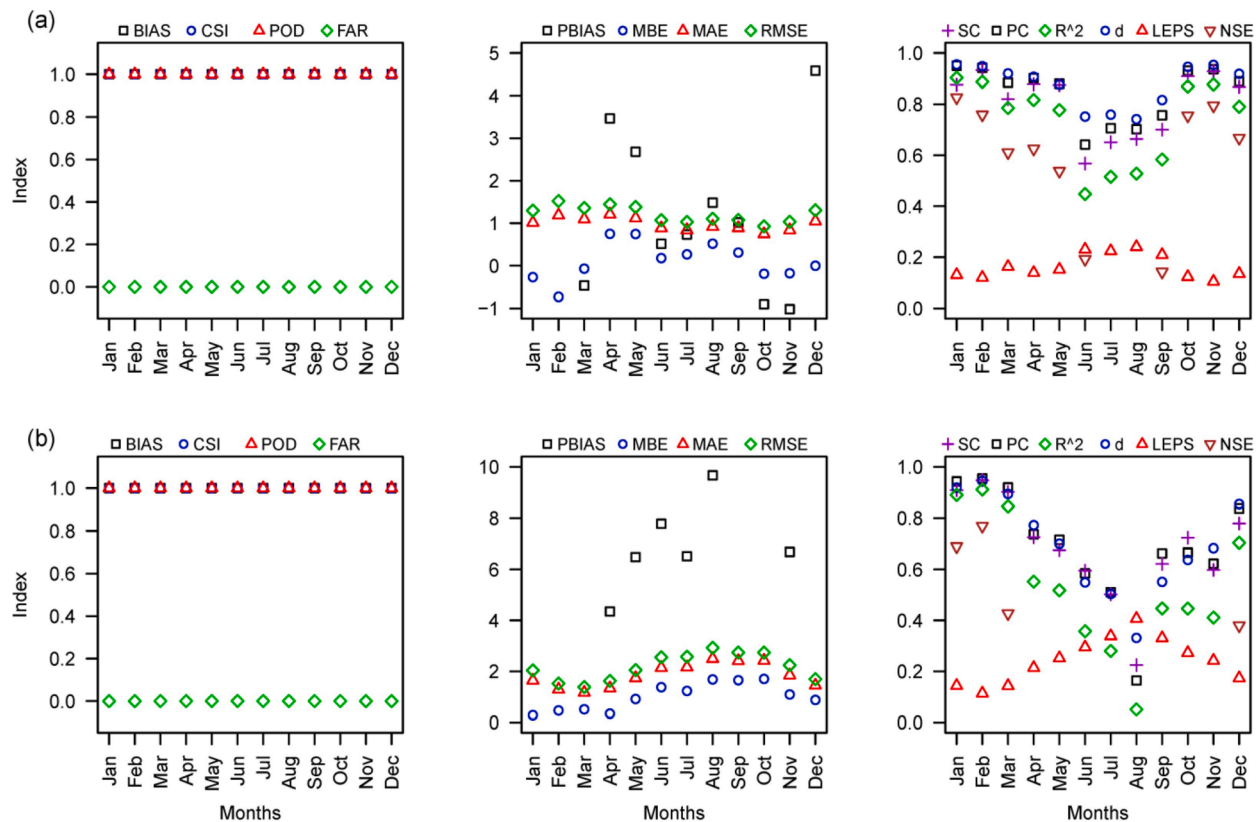


Fig. 8. Average results of classification, quantitative and agreement accuracy metrics of monthly precipitation for all stations, for (a) GLDAS Tmax and (b) GLDAS Tmin (a similar visualization of results for the decadal scale can be found in [SM 8.2](#)).

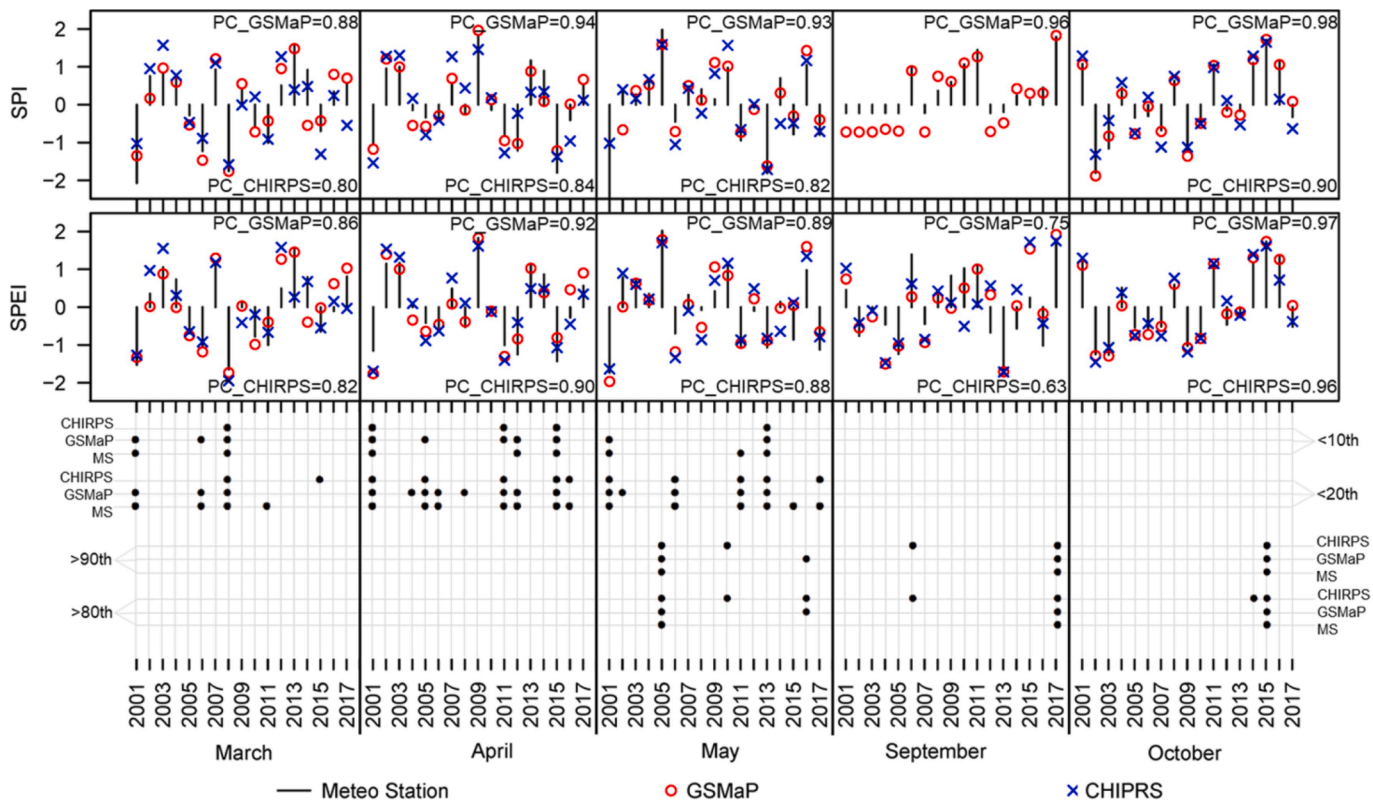


Fig. 9. Monthly values of Standardized Precipitation Index (SPI), Standardized Precipitation-Evapotranspiration Index (SPEI) and detected anomalies at 10th and 20th (March, April and May) percentiles for drought and 80th and 90th (May, September, October) percentiles for flood by stations, GSMaP and CHIRPS at the Djizzakh station (CHIRPS-SPI for September was not calculated due to a lack of measurements in this month).

agro-climatic zone was higher than that in the arid agro-climatic zone, in line with SPI results.

In addition, Fig. 9, SM 11.3 and SM 11.4 illustrate the capacity of GSMaP and CHIRPS to detect precipitation anomalies at < 10th and < 20th (March, April and May) percentiles for droughts as well as > 80th and > 90th (May, September, October) percentiles for floods. The results show that in the vast majority cases, SPEs detected the anomalies correctly, but there are minor false alarms and gaps that exist in both products. The capacity of SPEs to detect drought is slightly better than flood detection. In both types of extreme events and temporal aggregations, the GSMaP showed slightly better performance than CHIRPS, which is clearly evident from Fig. 9, SM 11.3 and SM 11.4. Regarding the accuracy of the applied temporal scales, we obtained ambiguous results since the classification accuracy varies across months and percentiles.

Overall, both satellite-based MDIs and detected anomalies align with the station-based estimates, and have the potential to some extent to detect the drought and flood events in focused periods. However, MDIs provide a more clear picture of drought and flood events with its strength, which is not possible with an anomaly detection approach based on percentiles. It was reported that drought events during the critical period of rainfed crop growth in 2001 and 2008 had a significant effect on crop production and the socio-economy of the region (Bobojonov and Aw-Hassan, 2014). These drought events were also precisely detected by both station and satellite-based MDIs, as well as anomaly detection. GSMaP itself, and in combination with GLDAS as MDIs, performed slightly better than CHIRPS in detecting these events. According to Fig. 9, in 2001, drought was moderate in March and followed by more severe drought in April and May, while in 2008 severe drought in March was followed by mild drought in April and May. Also, we can see some months with drought in other years, but these drought events were not prolonged that mitigate the effect of them, which are not reported as extreme drought years in any publications.

Discussion and conclusion

The main aim of the study was to investigate the suitability of freely available satellite temperature and precipitation data for designing and implementing an index insurance in Central Asia by analyzing the satellites products' accuracy and ability to detect droughts or floods using MDIs. For this assessment, the study used weather data acquired from six stations located in arid and semi-arid agro-climatic zones between 2000 and 2017. An accuracy analysis was conducted for those locations in pixel scale. Fourteen classification, quantitative and agreement statistical metrics were used to evaluate the accuracy and applicability of the satellite products in decadal and monthly time-series as well as on a per-decade and per-month scale. Additionally, we investigated the ability of these satellite-based weather products to detect drought and flood using SPI and SPEI.

Our assessments of decadal and monthly precipitation data by GSMaP indicate a better accuracy for the selected locations than CHIRPS can offer. Additionally, GSMaP spatially covers the full region of Central Asia. Nevertheless, we found a number of limitations, such as underestimation of precipitation during wet/rainy seasons and overestimation in the dry season, which have also been investigated by Trinh-Tuan et al. (2019) in Vietnam, Reddy et al. (2019) in India and Fatkhuroyan and TrinhWati (2018) in Indonesia. Additionally, we observed a slight overestimation of precipitation events by GSMaP, caused by minor GSMaP precipitation records during the summer period that do not exist in station observations. Moreover, we found that GSMaP performs better SPE during wet/rainy seasons compared to the dry season, which is in line with Hu et al. (2013), Fu et al. (2011) and Thiemig et al. (2012). Nevertheless, in the region observed by us, GSMaP performs better measurements in the dry season compared to CHIRPS. A novel quantile regression analysis checking the relationship between SPE products and in-situ weather data in various tiles confirms that both SPE products overestimate precipitation during low precipitation periods and

underestimate it during high precipitation periods. GLDAS was in significant agreement with in-situ temperature data in both time series and per period scale in all locations. Similar to GSMaP and CHIRPS, we found lower accuracy results during the dry season for GLDAS temperature estimates, which have also been investigated by Wang et al. (2016) in China. Lower quantitative and agreement accuracy metrics for Tmax and Tmin by GLDAS during the summer season can be explained by a low diversity of average decadal and monthly Tmax and Tmin in the summer season. Overall, all three satellite products have shown slightly better accuracy in measuring weather parameters in the semi-arid zones than in the arid zones. Additionally, we observed similar accuracy and performance for each climatic zone despite the fact that not all studied stations were used during the development of selected satellite-based weather products.

After calculating various classifications, quantitative and agreement statistical metrics to test the accuracy of satellite-based weather data, we found this combination of metrics to be useful and worth testing. Some of them, however, we found more useful than others and sufficient to assess the accuracy of satellite-based weather data: these are BIAS, POD and FAR for classification metrics; MBE and RMSE for quantitative metrics; SC, PC and d for agreement metrics. This combination of metrics allows an assessment of the accuracy of event classification, bias and variation between station and satellite-based weather data. In addition, for the first time, we could show the potential of using QR to access the accuracy of satellite-based weather data: By applying QR we were able to observe the relationship between station and satellite-based weather data among various quantiles, which cannot be achieved by using OLS.

Over- and underestimations of SPEs observed from accuracy and QR analyses are likely to lead to missing triggers. Consequently, it introduces basis risk, which is when the developed index estimations do not match with actual losses of insured farmers. However, these limitations might be mitigated or eliminated by the application of bias correction methods. As Yeh et al. (2020) for GSMaP particularly and Kimani et al. (2018) for CHIRPS demonstrated, significant improvements of SPE measures can be obtained after the application of bias correction methods.

In general, the years with extreme events reported by publications and detected by satellite products are matching, where the frequency is around once in eight years. As long as moderate frequency of risk serves to lower prices and premiums, making it affordable for farmers (Hazzell et al., 2010), it may ease introducing index insurance in the region. Despite some limitations, GSMaP itself, and in a combination with GLDAS as MDIs and anomaly detection, performed better than CHIRPS not only in detecting drought but also in detecting floods during the vegetation period of rainfed and irrigated crops. Consequently, GSMaP data should increasingly be taken into account for index generation in Central Asia. Moreover, the obtained results demonstrate the potential of satellite-based weather data for designing and implementing index insurances focused on drought during the vegetation period of rainfed crops (March-May), on floods during the seeding of irrigated crops (May) and on floods during the harvesting of irrigated crops (September-October). Drought events from March-May (the critical period for rainfed vegetation), for instance, have a significant influence on wheat, barley and potato yields and quality. Extended wet spells in May (the beginning of the cotton vegetation period) hit and damage the cotton-seeds, significantly affecting cotton yields and requiring re-seeding, which means additional technical efforts and expenses are needed. Floods during the cotton harvesting period significantly decrease the quality of the harvested cotton, which affects the price paid by buyers.

Accuracy comparisons between decadal, monthly and seasonal precipitation measurements by GSMaP and CHIRPS show that the agreement among stations and SPE improved as higher aggregation was applied. This finding shows the reasonability of using precipitation measurements in larger time intervals for better accuracy. Overall, globally available climate data could serve as a good source for establishing index insurance products in Central Asia; however, a careful

selection of source and index is required.

Our study is limited to stations located in the arid and semi-arid climatic zones of Uzbekistan. It would be interesting to also investigate the accuracy of these and other satellite-based weather data at stations located in similar and other climatic zones of neighboring countries. Nevertheless, the vast majority of Central Asian countries are located in arid and semi-arid zones (Bobojonov et al., 2016). Moreover, there are limitations regarding crop quality, re-seeding and yield data. For that reason, we think it would also prove interesting to investigate the relationship between SPE/MDIs and various crop quality, re-seeding and yield data in the region.

Funding

This research was supported by the German Federal Ministry of Education and Research (BMBF) [FKZ 01LZ1705A].

CRediT authorship contribution statement

Sarvarbek Eltazarov: Investigation, Methodology, Formal analysis, Software, Writing – original draft. **Ihtiyor Bobojonov:** Conceptualization, Methodology, Writing - review & editing. **Lena Kuhn:** Validation, Resources, Writing - review & editing. **Thomas Glauben:** Writing - review & editing, Supervision, Funding acquisition.

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.

Acknowledgements

The authors wish to thank the team members of the project “Increasing Climate Resilience via Agricultural Insurance – Innovation Transfer for Sustainable Rural Development in Central Asia (KlimALEZ)”, implemented by the Leibniz-Institute for Agricultural Development in Transformation Economies (IAMO).

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cliser.2021.100251>.

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