https://doi.org/10.5194/essd-2021-420
Preprint. Discussion started: 23 December 2021
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A Hydrologic Monitoring Dataset for Food and Water Security Applications in Central Asia

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https://doi.org/10.5194/essd-2021-420
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Abstract

From the Hindu Kush Mountains to the Registan desert, Afghanistan is a diverse landscape where droughts, floods, conflict, and economic market accessibility pose challenges for agricultural livelihoods and food security. The ability to remotely monitor environmental conditions is critical to support decision making for humanitarian assistance. The FEWS NET Land Data Assimilation System (FLDAS) global and Central Asia data streams described here combine meteorological reanalysis datasets and land surface models to generate routine estimates of snow-covered fraction, snow water equivalent, soil moisture, runoff and other variables representing the water and energy balance. This approach allows us to fill the gap created by the lack of in situ hydrologic data in the region. First, we describe the configuration of the FLDAS and the two resultant data streams: one, global, at ~1 month latency, provides monthly average outputs on a 10 km^2 grid from 1982-present. The second data stream, Central Asia, at ~1 day latency, provides daily average outputs on a 1 km^2 grid from 2001-present. We describe our verification of these data that are compared to other remotely sensed estimates as well as qualitative field reports. These data and value-added products (e.g., anomalies and interactive time series) are hosted by NASA and USGS data portals for public use. The global data stream with a longer record, is useful for exploring interannual variability, relationships with atmospheric-oceanic teleconnections (e.g., ENSO), trends over time, and monitoring drought. Meanwhile, the higher spatial resolution Central Asia data stream, with lower latency, is useful for simulating snow-hydrologic dynamics in complex topography for monitoring snowpack and flood risk.

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1 Introduction

1.1 Central Asia Weather and Climate

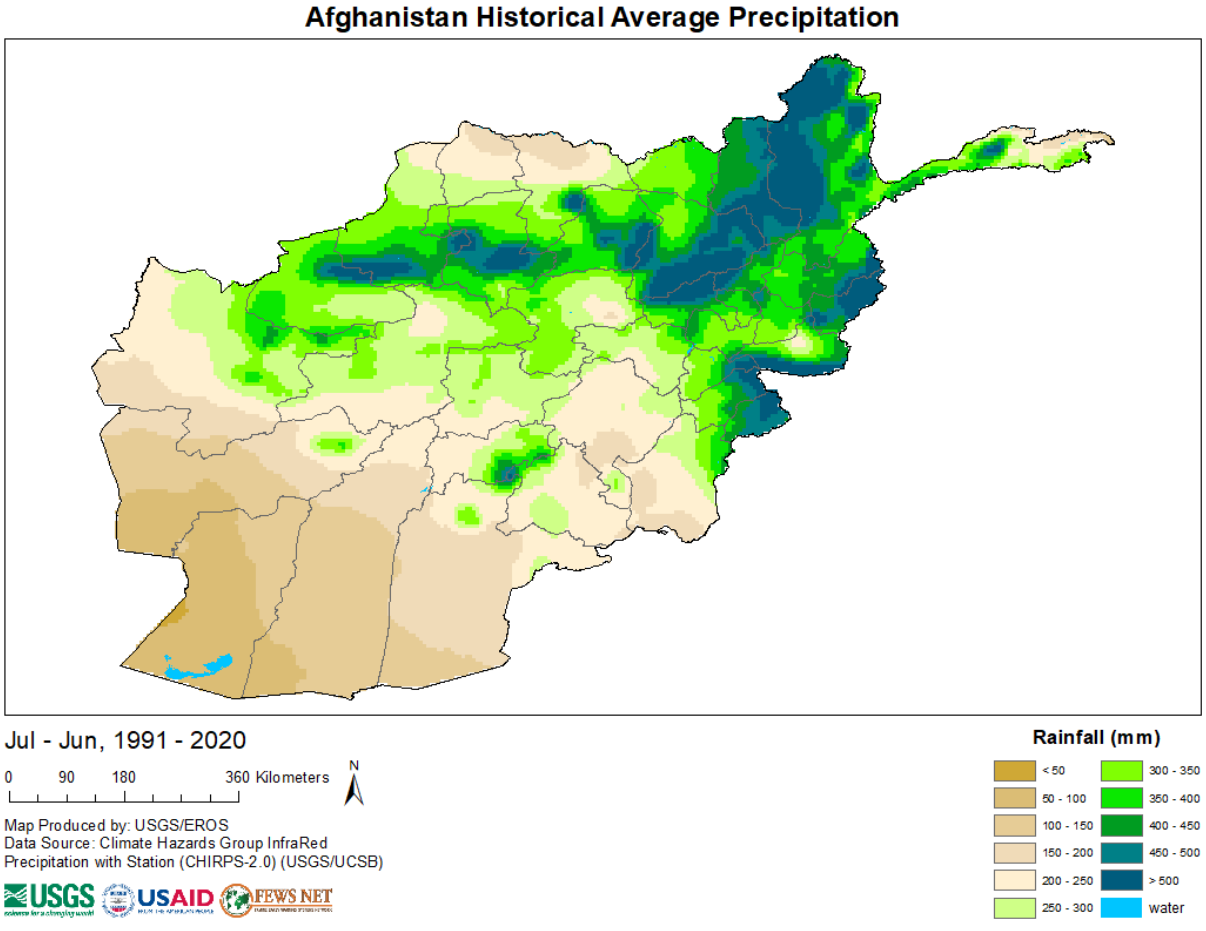

Figure 1a. Mean annual precipitation in Afghanistan from 1991-2020, overlayed on province boundaries. Map (USGS Knowelge Base, 2021) with data from Funk et al. (2015).

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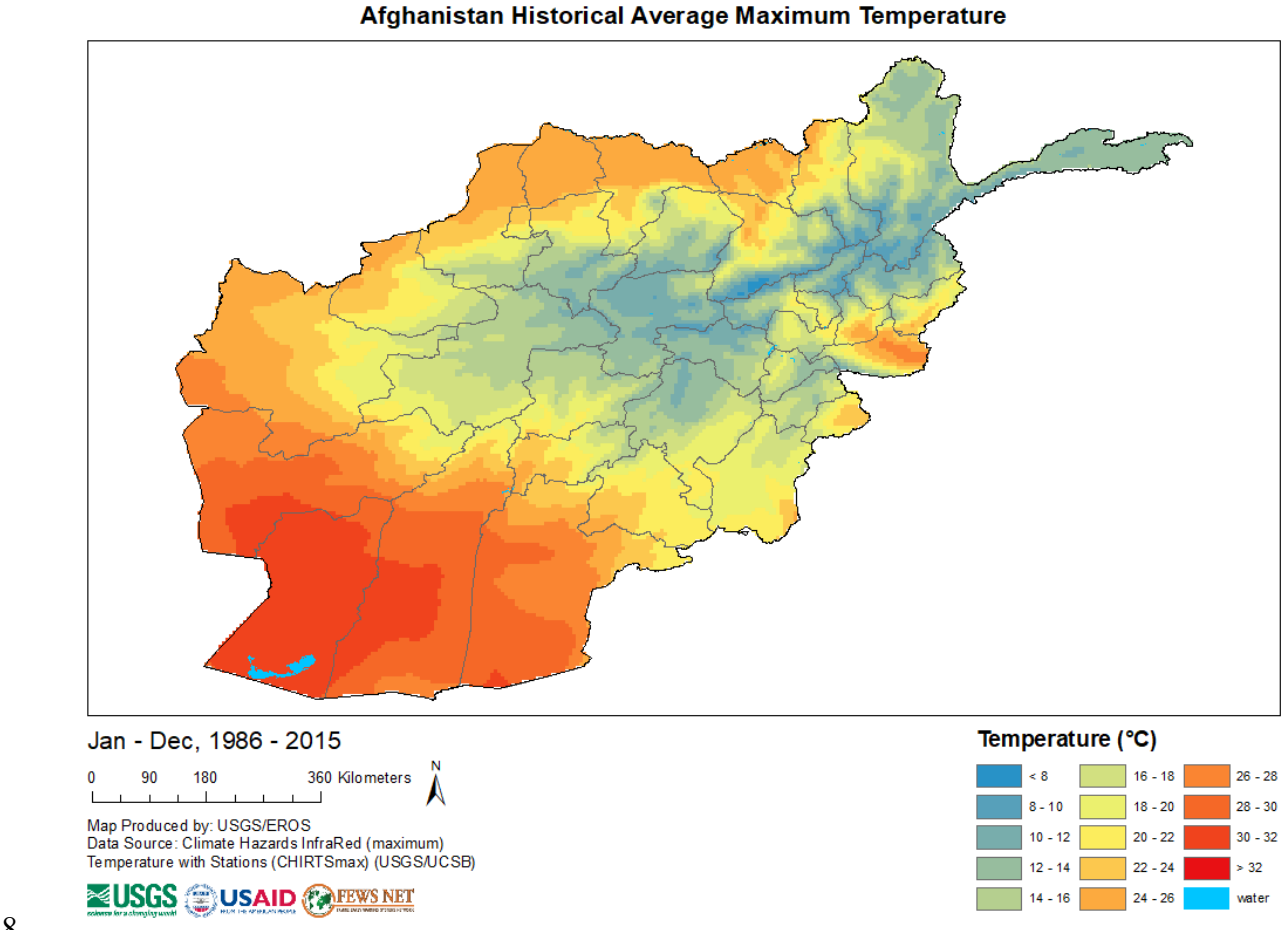

Figure 1b. Average maximum monthly temperature from (1986-2015), overlayed on province boundaries. Map (USGS Knowelge Base, 2021) with data from Verdin et al. (2020).

Central Asia, a region that includes Afghanistan, is water-scarce receiving roughly 75% of its annual precipitation during November–April (Oki and Kanae, S., 2006). In Afghanistan, rainfall is highest in the northeast Hindu Kush Mountains and decreases toward the arid southwest Registan Desert (Fig. 1a). Temperature follows a similar pattern with cooler temperatures in the high elevation and wetter northeast and warmer temperature in the south, and southwest (Fig. 1b). Regional precipitation is strongly influenced by the El Niño-Southern Oscillation (ENSO). La Niña condition are associated with below average precipitation (FEWS NET, 2020b) and El Niño conditions associated with above average precipitation (Barlow et al., 2016; Hoell et al., 2017; Rana et al., 2018; Hoell et al., 2018, 2020; FEWS NET, 2020a). Other dynamical factors with an important influence on precipitation include orography, storm tracks, and the Madden–Julian oscillation (MJO) (Barlow et al., 2005; Nazemosadat and Ghaedamini, 2010; Hoell et al., 2018). The last several years have experienced a number of ENSO events, with recent La Niña events in

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2016-17, 2017-18, and 2020-2021 (NOAA CPC ENSO Cold & Warm Episodes by Season, 2021) that corresponded to droughts (FEWS NET, 2017b, 2018c, 2021).

Despite Afghanistan's semi-arid climate, agriculture is an important sector, contributing 23% of the gross domestic product and employing 44% of the national labor force (CIA World Factbook). High mountain snowpack and snowmelt runoff are important for agricultural water supply, and according to the Famine Early Warning Systems Network (FEWS NET, 2018b) is responsible for "providing over 80% of irrigation water used. The timing and duration of the snowmelt is a key factor in determining the volume of irrigation water and the length of time that it is available, as well as its availability for use in marginal areas that experience [variable] rainfall." Therefore, routine hydrologic monitoring, with a particular emphasis on snow, is critical for tracking agricultural conditions and provides early warning for food insecurity.

1.2 Precipitation Data Availability in Afghanistan

Sparse in-situ precipitation observations lead to uncertainty in gridded and satellite-based precipitation estimates which are important for environmental monitoring and driving hydrologic models. Precipitation station observations are used for (a) bias correction of satellite estimates and (b) validation of gridded products. In terms of gridded dataset development, Hoell et al. (2015) describe lack of station observations in Afghanistan, Iraq and Pakistan and how complex topography in these locations makes this issue particularly problematic. Barlow et al. (2016) also highlight the station availability across the region and how that influences uncertainties in the Global Precipitation Climatology Center (GPCC) version 6 dataset over Central Asia (Fig. 2a) and specifically Afghanistan over time (Fig. 2b). Related to validation, Yoon et al. (2019) highlight that the representativeness of the sparse in-situ data is a serious limitation in their evaluation of precipitation over High Mountain Asia.

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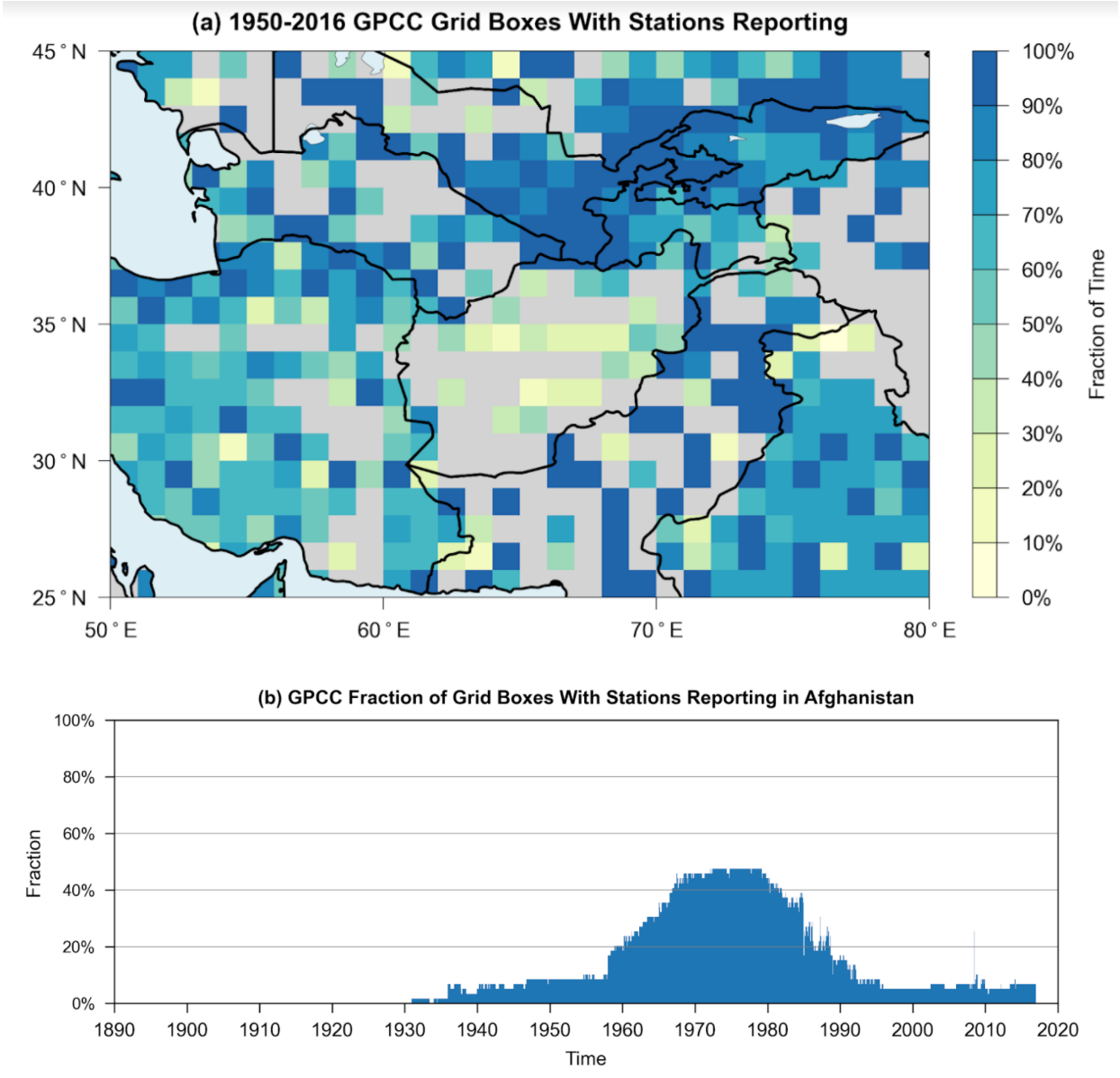

Figure 2. a) Station data availability underlying the GPCC version 6 dataset, for the 1951–2010 period, on the 0.5°-resolution grid over Central Asia. b) Number of Stations used as input to GPCC rainfall dataset in Afghanistan.

Despite uncertainties, Schiemann et al. (2008) find that gridded precipitation estimates can qualitatively identify large scale spatial distribution of precipitation, seasonal cycle and interannual variability (i.e., wet and dry years) across Central Asia. Long term estimates of rainfall from satellite derived products, as well as derived historic time series from hydrologic modelling, can be used as a baseline of "observations," from which we can have a sense of relative conditions, i.e., anomalies

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and variability. When this historical record is harmonized with a routine monitoring system, current conditions can be placed in historical context. Anomaly-based representation of hydrologic extremes can provide confidence in modeled estimates that have the potential to influence agricultural, water resources and food security outcomes.

In addition to reliance on the representation of relatively wet and dry conditions, a "convergence of evidence" approach that draws on (quasi-)independent sources of information is useful to understand actual conditions. For convergence of Earth observations, hydrologic models can generate ensembles of historic, current or future estimates of snow, streamflow, soil moisture, and evapotranspiration which can then be compared to satellite derived estimates of surface water (e.g. McNally et al., 2019), soil moisture (e.g. McNally et al., 2016), vegetation conditions and evapotranspiration (e.g. Pervez et al., 2021; Jung et al., 2019), snow cover (e.g. Arsenault et al., 2014), in situ stream flow (e.g. Jung et al., 2017) and others. Hydrologic estimates can also be compared to outcomes in crop production e.g. (McNally et al., 2015; Davenport et al., 2019; Shukla et al., 2020), and nutrition, health, and food security (e.g. Grace and Davenport, 2021) to provide a qualitative understanding of both hydrologic model performance and conditions on the ground. In this paper we provide an example of 2018 where drought conditions were associated with crisis levels of acute food insecurity over most of Afghanistan (FEWS NET, 2018c).

This paper describes the FLDAS hydrologic modeling system's global and Central Asia data streams, which are designed for food and water security applications. These data streams provide a long historic record for contextualizing estimates, as well as low latency data for timely decision support. These data streams can also support research and monitoring by the broader food and water security community. The purpose of this data descriptor is four-fold: (1) describe the development of the moderate resolution, low latency FLDAS system to inform hydrologic monitoring for Central Asia, specifically Afghanistan, (2) increase awareness of these data resources which are intended to be a public good, (3) demonstrate how our methods inform critical investigations that ultimately improve general understanding of water resources in this important region of the world, and (4) advocate for a convergence of evidence approach to hydrologic monitoring in locations where all sources of information contain some level of uncertainty. An outline of this data descriptor is as follows. First, in the Methods (section 2) we describe the hydrologic modeling system, parameters and meteorological inputs and model outputs. In the Results (section 3) we report comparisons to other precipitation estimates, as well as comparisons of modeled snow estimates to remotely sensed snow observations and find generally good agreement. Finally, we describe an application (section 4) of these data to the Afghanistan drought of 2018.

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2 Methods

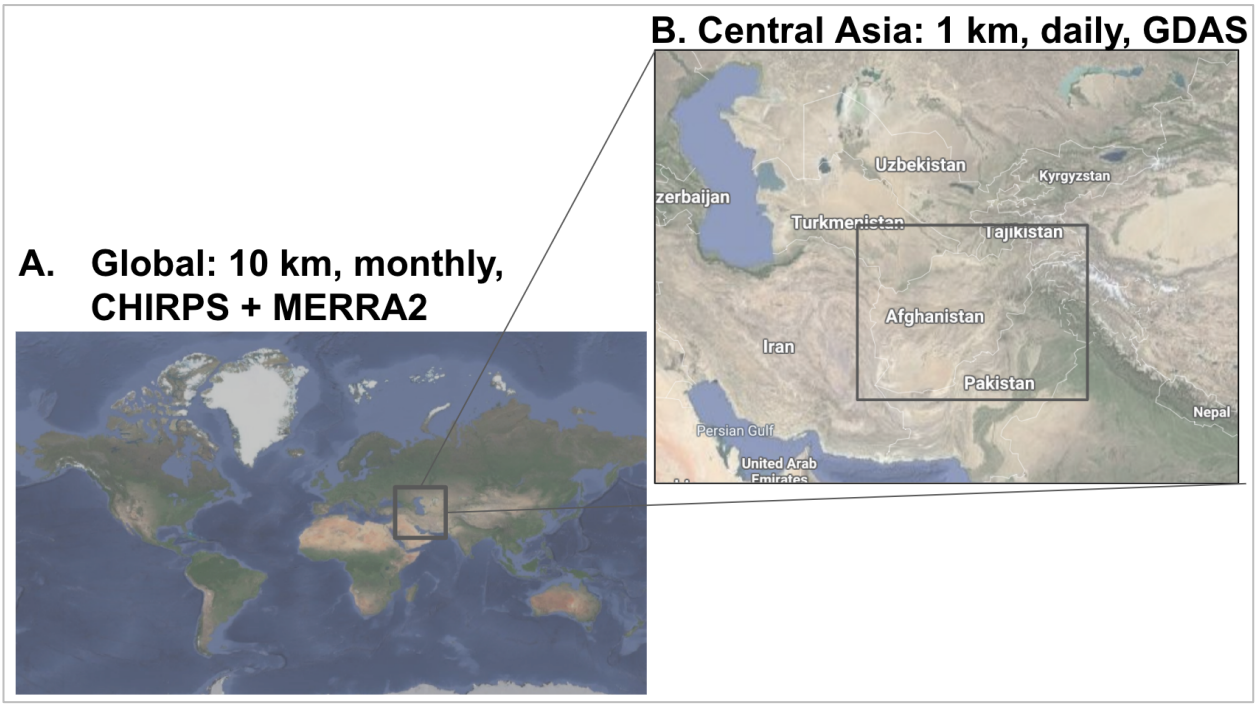

Figure 3. The FEWS NET Land Data Assimilation System (FLDAS) domains for (A) the global data stream at 10 km^2 spatial resolution, and ~1 month latency for monthly averaged hydrologic estimates and (B) the Central Asia data stream at 1 km^2 spatial resolution and ~1 day latency for daily averaged hydrologic estimates. Imagery 2021 TerraMetrics, Map data © Google.

2.1 Land Surface Modeling System & Parameters

Land surface models (LSMs) can provide spatially and temporally continuous information about the water and energy budgets of the land surface. This information is useful for food and water security applications in places where in situ measurements of rainfall, soil moisture, snow and runoff are sparse. This is particularly relevant in mountainous places like Afghanistan where heterogeneous geography limits the representativeness of sparse in situ measurements. We use NASA's Land Information System Framework (LISF), which is comprised of a pre-processor, the Land Data Toolkit (Arsenault et al., 2018), the Land Information System (Kumar et al., 2006; Peters-Lidard et al., 2007), and the Land Verification Toolkit (Kumar et al., 2012). To support the needs of FEWS NET we have developed a custom instance of the NASA LISF - the FEWS NET Land Data Assimilation System (FLDAS) (McNally et al., 2017). In this data descriptor we describe the two configurations of the FLDAS data streams used for Central Asia food and water security applications. It uses the Noah 3.6 Land Surface Model (Chen et al., 1996; Ek et al., 2003) and has two data streams. One, global, at ~1 month latency, provides monthly average outputs on a 10 km^2 grid from 1982-present. The second data stream, Central Asia, ~1 day latency, provides daily

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156 average outputs at 1 km^2 from 2001-present. While the two data stream specifications are largely the
157 same, there are some differences related to the input parameters and specifications (Table 1) and
158 model spin-up procedure.
159
160 Table 1. FEWS NET Land Data Assimilation System (FLDAS) specifications for (A) global data
161 stream, 10 km^2, monthly with CHIRPS+MERRA-2. (B) Central Asia data stream 1 km^2 daily with
162 GDAS.

	Global	Central Asia
Spatial Extent	179.95°W- 179.95°E, 59.95°S-89.95°N	30-100°E, 21-56°N
Landmask	Land Data Toolkit (LDT) generated from MODIS (Arsenault et al. 2018)	MOD44w (Carroll et al., 2017)
Landcover	IGBP landcover	IGBP landcover
Parameters	FAO Soils Reynolds et al (2000)	FAO Soils
Elevation	SRTM (NASA JPL, 2013)	SRTM
Albedo	NCEP albedo (Csiszar, I., and Gutman 1999)	NCEP albedo
Albedo	Native Max Snow Albedo; Barlage (2005)	Native Max Snow Albedo
Vegetation Parameters	NCEP greenness fraction (Gutman and Ignatov 1997)	NCEP greenness fraction
Non-Precipitation Meteorological Inputs	MERRA-2 meteorological variables	GDAS meteorological variables
Soil Texture	FAO STATSGO soil texture	FAO STATSGO soil texture
Precipitation Inputs	CHIRPS daily precipitation, downscaled to 3-hourly with LDT	GDAS 3-hourly precipitation
Specifications	Noah 3.6.1	Noah 3.6.1
Map Projection	Geographic Latitude-Longitude	Geographic Latitude-Longitude
Software Version	7.2	7.3
Spatial Resolution	0.1 degree	0.01 degree
Temporal Coverage	1982-01-01 to present	2001-10-01 to present
Model Timestep	30-min timestep	15-min timestep

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Met. Forcing Heights	2m Air Temperature (Tair), 10m Wind	2m Tair, 10m Wind
Soil layers (meters)	0-0.1; 0.1-0.4; 0.4-1.0; 1-2	0-0.1; 0.1-0.4; 0.4-1.0; 1-2
Features	radiation correction	radiation correction

The parameters and specifications listed in Table 1 are largely default settings defined by the Noah LSM community (NCAR Research Applications Library, 2021). One important feature, added by the NASA LISF software development team, is the radiation correction described in Kumar et al. (2013), which improves the representation of snow dynamics with respect to slope and aspect corrections on the downward solar radiation field. The precipitation and other meteorological forcing variables, the period of record, and the spatial resolution were all determined to best meet the target end-users' needs (i.e. FEWS NET) for routine agricultural and hydrologic monitoring.

Another noteworthy feature is the method of the Central Asia data stream restart (i.e., annual initialization based on climatology), which was developed to address an issue of excessive inter-annual snow accumulation found in the Noah LSM. First, a nine-year spin-up of the system was performed to produce stable snow and soil moisture conditions. Next, the resulting model states were compared with the Moderate Resolution Imaging Spectroradiometer (MODIS) Maximum Snow Extent data originally computed by NOAA National Operational Hydrologic Remote Sensing Center (Personal Communication Greg Fall, 2014). Then, the model estimated conditions were adjusted to produce a climatological model state for 1 October that is used to initialize each year. This approach ensures that the 'water year', beginning 1 October, is initialized with a reasonable amount of snowpack. While this method does effectively manage excessive inter-annual snow accumulation, the user should be aware that using the climatological model state will persist for ~1-2 months in the water and energy balance of the LSM until they are superseded by "observed" meteorological inputs for the current water year. Preliminary work indicates that this issue will be resolved in future updates. In contrast, the global data stream does not employ this 1 October initialization procedure.

2.2 Meteorological Forcing Inputs

Precipitation is the most important input to the FLDAS products. The lower-latency Central Asia data stream is a daily product, forced with NOAA's Global Data Assimilation System (GDAS) (Derber et al., 1991) 3-hourly precipitation, which is available from 2001-present at <1-day latency. Meanwhile, the global data stream is driven by the daily CHIRPS precipitation product, which is available from 1981 present at ~ 5-day latency for CHIRPS Preliminary and ~1.5-month latency for CHIRPS Final. As mentioned earlier, lack of rainfall stations for bias correction of satellite-derived estimates and evaluation poses a major challenge. However, we find that the GDAS rainfall product and the CHIRPS rainfall product are adequate for routine monitoring and, along with additional sources of remote sensed information, important for convergence of evidence when making a best guess at land surface states and fluxes.

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Before the daily CHIRPS rainfall can be used as input to the FLDAS models, the daily precipitation must be pre-processed to a sub-daily timestep, using the LDT component of the LIS software. LDT temporally disaggregates the daily CHIRPS rainfall, using an approach similar to the North American LDAS precipitation downscaling method (Cosgrove et al., 2003). For this approach, we use a finer timescale MERRA-2 precipitation as a reference dataset to represents an accurate diurnal cycle. Coarser scale meteorological forcings are spatially disaggregated to the output resolution (0.01, and 0.1 degree for Central Asia and global, respectively) in the LIS using bilinear interpolation.

The FLDAS models require additional meteorological inputs, including air temperature, humidity, radiation, and wind. The lower-latency Central Asia data stream uses GDAS 3-hourly meteorological inputs available from 2001-present at <1-day latency. For a longer historical record, the global data stream of FLDAS uses NASA's Modern Era Reanalysis for Research and Applications version 2 (MERRA-2) (Gelaro et al., 2017) (1979-present) 1-hourly products with a two-week latency.

2.3 Model Evaluation Statistics and Comparison Data

To assess the quality of our modeling outputs, we conduct comparisons between (1) FLDAS satellite rainfall inputs and other satellite precipitation estimates, and (2) model estimated snow cover fraction and satellite derived snow cover fraction estimates.

For the precipitation analysis, we compare CHIRPS and GDAS inputs to the Integrated Multi-satellite Retrievals for the Global Precipitation Mission (IMERG), a NASA precipitation product that integrates passive microwave and infrared satellite data with surface station observations (Huffman et al., 2020). The IMERG Final Run precipitation product, available at ~ 2-month latency (thus not suitable for our monitoring applications) has been used in numerous verification studies, including studies over Africa (Dezfuli et al., 2017), South America (Gadelha et al., 2019; Manz et al., 2017) and the mid-Atlantic region of the United States (Tan et al., 2016). These studies demonstrated that IMERG Final was able to capture large spatial patterns and seasonal and interannual patterns of rainfall. However, fewer studies have explored the performance of the lower latency IMERG Late Runs (DOI: 10.5067/GPM/IMERGDL/DAY/06) product that we use here. Kirshbaum et al. (2016) include a qualitative comparison for CHIRPS Final and IMERG Late for the Southern Africa start-of-season 2015. IMERG Late appears to perform similarly to the 1.5-month latency CHIRPS Final and outperform the 1-day latency NOAA Rainfall Estimate version 2 (RFE2) product (Xie and Arkin, 1996). Differences in the daily rainfall distribution patterns between IMERG Final and CHIRPS Final have also been shown to impact the resulting hydrological modeled output in simulations done using the NASA LIS framework (Sarmiento et al., 2021).

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For the Snow Cover Fraction (SCF) analysis, we compare the global and Central Asia data streams with the MODIS daily SCF product, MOD10A1 Collection 6 (Hall and Riggs, 2016). MOD10A1 data is available at 500 m spatial resolution from February 2000 to the present. SCF is generated using the Normalized Difference Snow Index (NDSI) and additional filters to reduce error and flag uncertainty. Routine qualitative comparisons, which can be viewed on the NASA LIS FEWS NET project website generally show agreement between the model and MODIS SCF, as well as occurrence of cloud cover (https://ldas.gsfc.nasa.gov/fldas/models/central-asia). Following Arsenault et al. (2014) we aggregated pixels to 0.01 degree to reduce error related to sensor viewing angles and gridding artifacts. For this analysis, using MODIS SCF as "truth", we determined True Positives (TP), True Negatives (TN), False Negatives (FN) and False Positives (FP). We then computed probability of detection (POD) where POD = (TP/(TP + FN)) and False Alarm Rate (FAR) where FAR = (FP/(FP + TN)). We computed these for the total area of Afghanistan, as well as by basin (Fig. 3 a & b). This paper does not compare modeled snow water equivalent (SWE) to independent snow observations because, as noted by Yoon et al. (2019), direct evaluation of snow mass and snow water equivalent (SWE) is difficult over Central Asia due to poor coverage of accurate snow observations. We follow the Yoon et al. (2019) recommendation to conduct quantitative SCF comparisons and provide qualitative SWE analysis in Applications, Section 4.

3 Results

3.1 Gridded Rainfall Comparison

For Central Asia applications we have two data streams with different precipitation inputs: the global data stream with CHIRPS precipitation at 10 km^2 spatial resolution provides a long consistent data record, and the Central Asia data stream with GDAS precipitation at 1 km^2 provides near real time, finer spatial resolution updates. These two data streams have their respective errors and allow data users to apply a convergence of evidence approach for food and water security applications. In this section we present a comparison of these precipitation inputs. We also include IMERG Late for comparison as a high quality, low latency product. Future work will incorporate the IMERG precipitation inputs into FLDAS simulations. We also include MERRA-2 precipitation for comparison. Pair-wise correlation are shown in Table 2. CHIRPS Final, IMERG Late and GDAS ($R \geq 0.90$) are well correlated in terms of average daily precipitation (mm/day) at the monthly and annual (i.e., water year) timestep. MERRA-2 correlations with these datasets are lower at the monthly timestep ($0.75 \leq R \leq 0.81$) and annual timestep ($0.64 \leq R \leq 0.69$). Fig. 4 shows the time series of the precipitation products for their overlapping period of record (2001-2020), which illustrates how they co-vary and some general patterns in terms of relative mm/day: GDAS (red) and IMERG Late (dashed-black) tend to have the highest average precipitation per day, CHIRPS (blue) has lower mm/day, but higher than MERRA-2 (dashed green) which tends to have the lowest average precipitation per day, until 2019 when it is notably higher than the other products.

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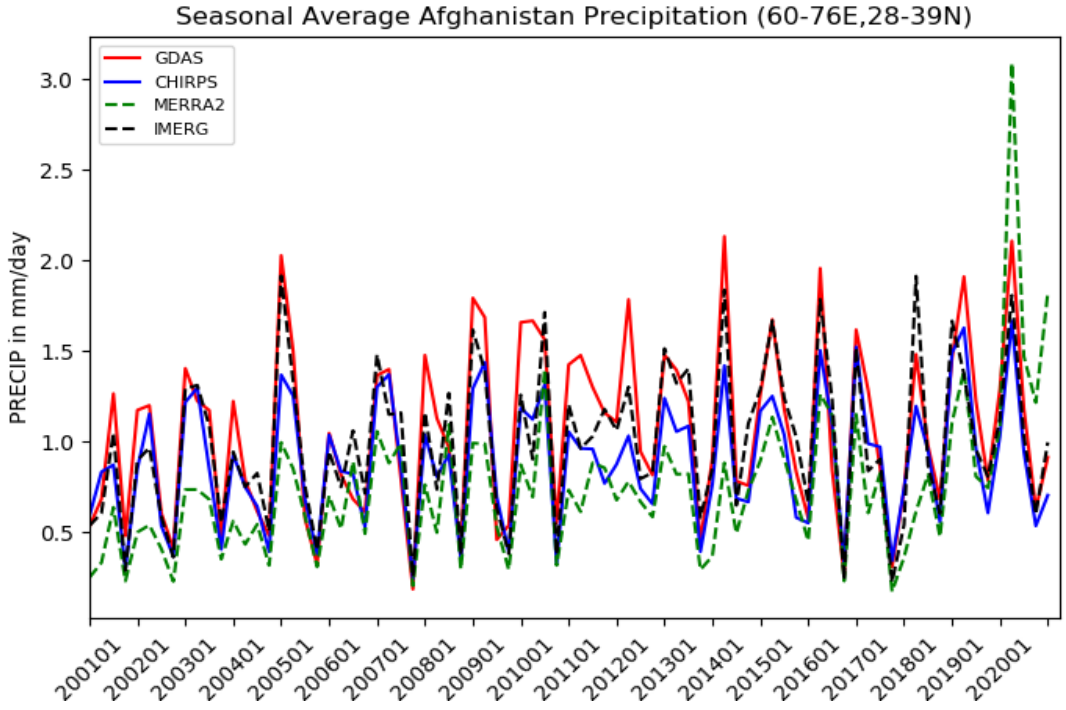

Figure 4. Afghanistan country-wide average, annual average mm/day time series for CHIRPS, GDAS, IMERG Late, and MERRA-2. At the annual time step, Spearman rank correlations range from 0.64 (GDAS vs. MERRA-2) to 0.92 (GDAS vs. CHIRPS).

Table 2. Afghanistan spatial average Spearman Rank Correlation of monthly (annual) precipitation 2001-2020

	GDAS	CHIRPS Final	IMERG Late
GDAS	x	-	-
CHIRPS Final	0.91 (0.92)	x	-
IMERG Late	0.91 (0.89)	0.92 (0.90)	x
MERRA-2	0.75 (0.64)	0.78 (0.68)	0.81(0.69)

3.2 Remotely Sensed and Modeled Snow comparisons

The estimation of snow is important for Afghanistan and Central Asia because it is an important contributor to water resources and irrigated agriculture. Here, we compare mean SCF (Fig. 5a), POD, and FAR statistics (Fig. 5b) relative to MODIS SCF over eight hydrologic basins in Afghanistan.

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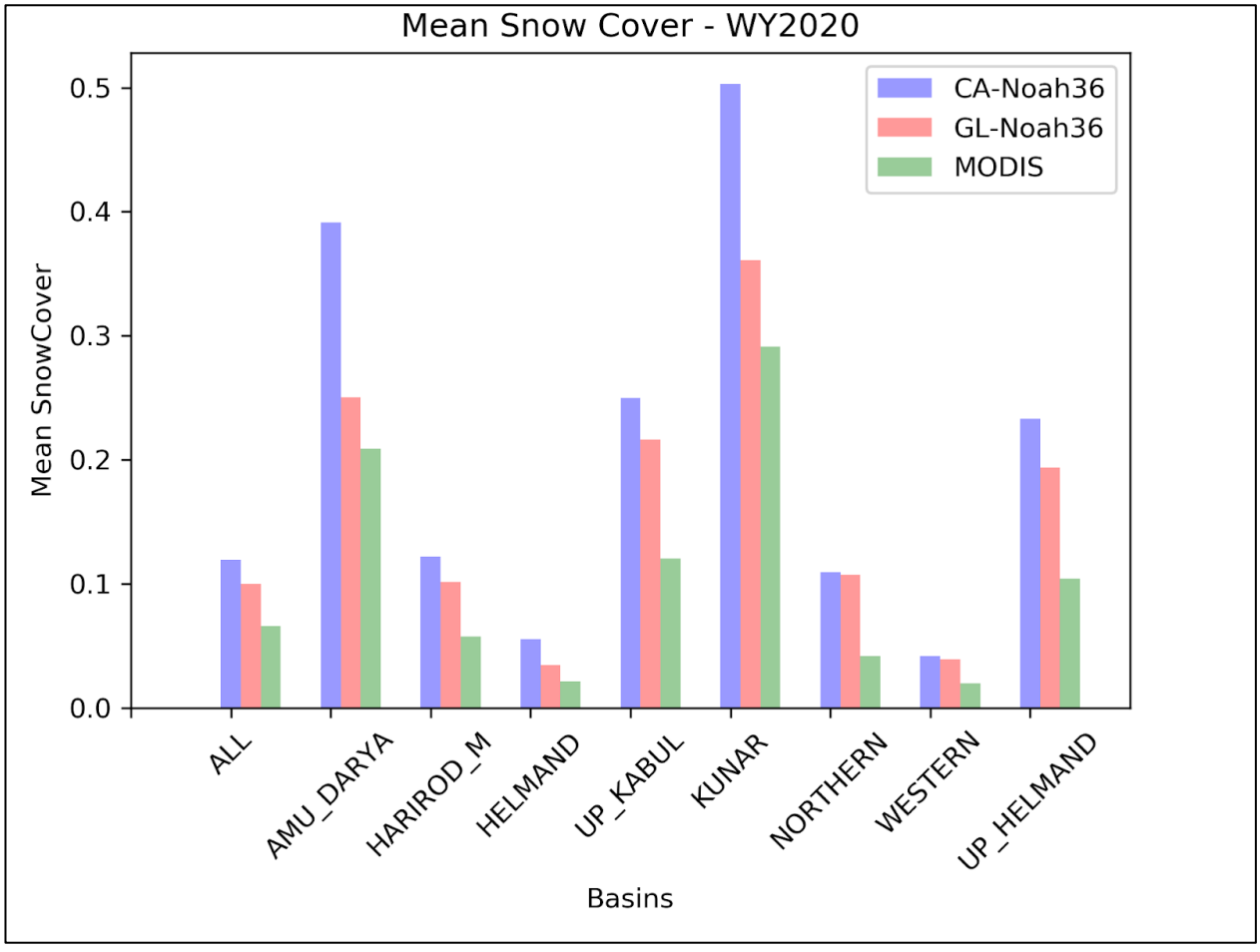

Figure 5a. Mean snow cover fraction for the entire area and by basin for MODIS Snow Cover Fraction (SCF), Central Asia and global data streams.

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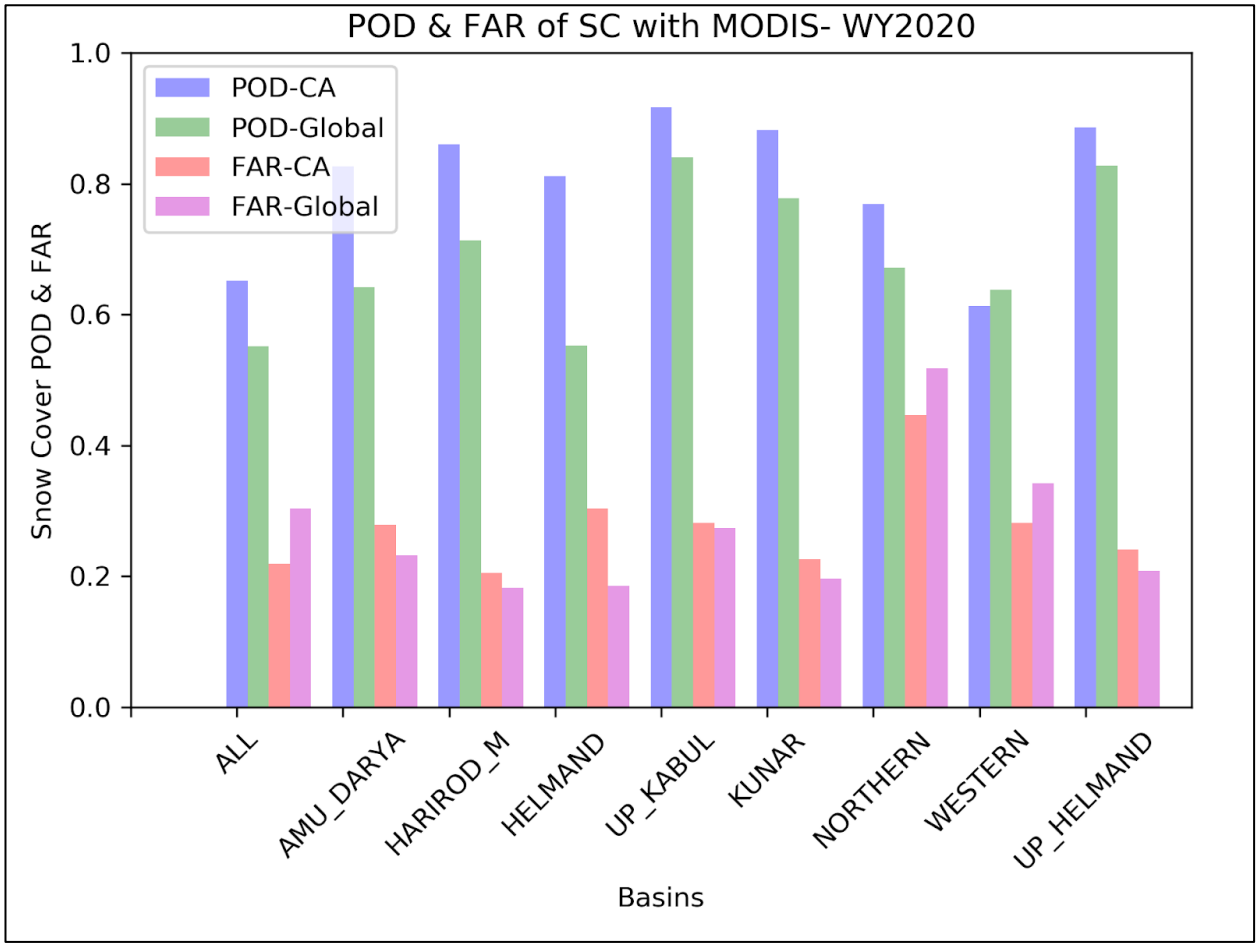

Figure 5b. Probability of Detection (POD) of snow presence, and False Alarm Rate (FAR) for the Central Asia (CA) and global data streams relative to the MODIS SCF.

Overall, both model runs estimate greater mean SCF than the MODIS SCF product. The Central Asia (CA) data stream has consistently higher mean snow cover for all basins compared to MODIS SCF estimates and the global data stream. Perhaps not surprisingly then it performs consistently better in POD (by basin = ~80%) except for the Western [Helmand] Basin. Similarly, the FAR of the CA is higher where POD is higher except for the Northern Basin. The difference in statistics may be related to the different inputs forcing or the higher spatial resolution of the Central Asia data stream. Kumar et al. (2013) note that higher spatial resolution was important for snow dominated basins. We also note the likely importance of the MERRA-2 and GDAS temperature forcing between the global data stream and the Central Asia data stream, respectively. The panels in Fig. 6 provide additional insight into the differences between MODIS SCF and the two FLDAS runs for water year 2020. The green line (Central Asia) is consistently higher than the red, MODIS SCF estimates, and the blue, global data stream estimates. Both the models estimate higher SCF during peak coverage in the Upper Kabul and Kunar basins. The time series plots also illustrate

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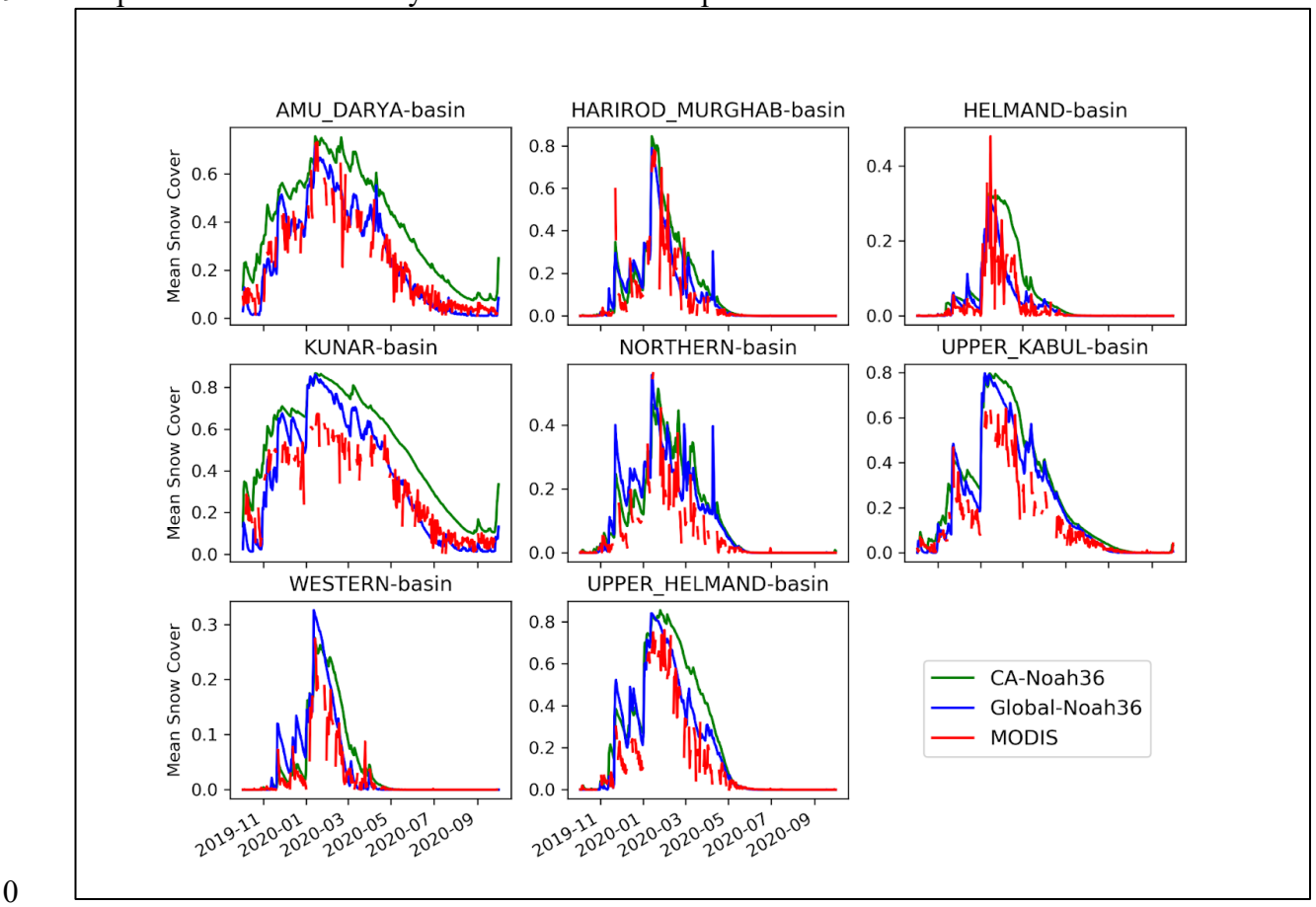

Figure 6. Basin-averaged SCF for Water Year 2020 as estimated by global and Central Asia (CA) data streams, and MODIS SCF. Time series show generally a similar pattern with the CA typically having higher SCF values. These plots also demonstrate discontinuities in the MODIS SCF data that reduce the quality of quantitative comparisons but provide qualitative confirmation of adequate model performance.

3.3 Discussion of results compared to previous studies

Despite the lack of ground-based observations, our analysis shows that the remotely sensed estimates and the models have good correspondence with other sources of evidence in terms of seasonal timing and performance. This provides analysts with confidence when using the FLDAS snow estimates, in tandem with other sources, as an input to food security analysis. Our approach is supported by other studies that have explored the challenges of evaluating hydrologic estimates over the region (Yoon et al., 2019; Ghatak et al., 2018; Immerzeel et al., 2015; Qamer et al., 2019). With a study domain shifted to the east, Yoon et al. (2019) evaluate rainfall and near surface temperature estimates over the High Mountain Asia domain, including most of Afghanistan. They review how

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these results compare to other studies (e.g. precipitation trends (Nguyen et al., 2018; Rodell et al., 2018)), and their results suggest that the uncertainty in the meteorologic forcing is the dominant factor in the terrestrial water budget estimates. This is consistent with our results showing differences between the GDAS and CHIRPS+MERRA-2 driven outputs. Also consistent with our results, Yoon et al. (2019) show that their LSM ensembles of SCF have an average POD of 72% and FAR of 36%, which is within the range of our POD and FAR statistics (60-80% POD; 20-40% FAR) compared to MODIS SCF. Without a clear "winner" in their multi-model and multi-forcing experiments, Yoon et al. conclude that improvements in the meteorological boundary conditions would be needed to reduce the uncertainty in the terrestrial budget estimates. These sentiments are echoed in Qamer et al. (2019).

One recent attempt to improve meteorological inputs in the region is from Ma et al. (2020) with the development of the AIMERG dataset that combines IMERG Final with APHRODITE (Asian Precipitation - Highly-Resolved Observational Data Integration Toward Evaluation) rain-gauge derived product (Yatagai et al., 2012). Ultimately, it would be beneficial to have a global modeling system that used the best available inputs from each region. In the meantime, multi-forcing and multi-model ensembles, and convergence of evidence with other remotely sensed data and field reports, are a viable approach for providing hydrologic estimates for various applications.

3.4 Summary of differences between the model runs

Given the need for multiple data streams for convergence of evidence, we have summarized the pros and cons of the Central Asia and global data streams in Table 3.

Table 3. Pros and cons of the two data streams

	Central Asia: Noah 3.6 with GDAS (2000-present)	**Global: Noah 3.6 with CHIRPS+MERRA-2 (1982-present)**
PROS	1 km^2	less computationally intensive
	1 day latency, daily timestep	longer time record
	Snow estimates available in USGS Early Warning eXplorer	CHIRPS & MERRA-2 forcing spatial resolution does not change over time (stable climatology)
		Water and Energy balance available in NASA GIOVANNI, Google Earth Engine, Climate Engine
CONS	more computationally intensive	lower resolution (10 km^2)

https://doi.org/10.5194/essd-2021-420
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	shorter time record	~30-day latency
	GDAS forcing resolution changes over time (unstable climatology) NOAA NCEP https://www.emc.ncep.noaa.gov/gmb/STATS/html/model_changes.html)	not publicly available at daily timestep
	large data volume, difficult to move	

4 Applications

These data from global and Central Asia data streams are routinely used in several FEWS NET information products listed in Table 4. There is a weekly briefing from NOAA's Climate Prediction Center (CPC) International Desks on the past week's weather conditions and 1– 2-week forecasts for FEW NET regions of interest, including Central Asia. There is also a monthly FEWS NET Seasonal Monitor and a monthly Seasonal Forecast Review for which these data provide information on the current state of the snowpack, soil moisture and runoff. These "observed conditions" can then be qualitatively combined with forecasts ranging from 1 week to 3 months to assess potential hydro-meteorological hazards. To demonstrate the role of these data in the early warning process, at different points in the season, we provide an example of the 2017-2018 wet season in Afghanistan during a La Niña event.

Table 4. Routine Applications of FLDAS Central Asia's Afghanistan hydrologic data.

Routine application of these data	Weblink to updates	Notes
FEWS NET Global Weather Hazards Summary produced by NOAA CPC	https://fews.net/global/global-weather-hazards/ https://www.cpc.ncep.noaa.gov/products/international/index.shtml	shapefiles https://ftp.cpc.ncep.noaa.gov/fews/weather_hazards/
USGS Seasonal Monitor	https://earlywarning.usgs.gov/fews/search/Asia/Central%20Asia/Afghanistan Archives: https://fews.net/sectors-topics/sectors/agroclimatology	Updated monthly from October - May, during the precipitation season.

https://doi.org/10.5194/essd-2021-420
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FEWS NET Food Security Outlook Brief	https://fews.net/central-asia/afghanistan	Information on snow or other hydrology included if applicable
Crop Monitor for Early Warning	https://cropmonitor.org/index.php/cmreports/early warning-report/	Information on early warning and crop conditions

4.1 Snow monitoring & Seasonal Outlooks

As previously mentioned, and as shown in Fig. 7**,** Afghanistan and the broader region is strongly influenced by La Niña, which tends to increase the likelihood of dry events (Barlow et al., 2016; FEWS NET, 2020b). Depending on other factors, this may also increase the probability of negative snowpack anomalies, reduce springtime streamflow, and flood risk, and reduce summer irrigation availability and potentially crop yields.

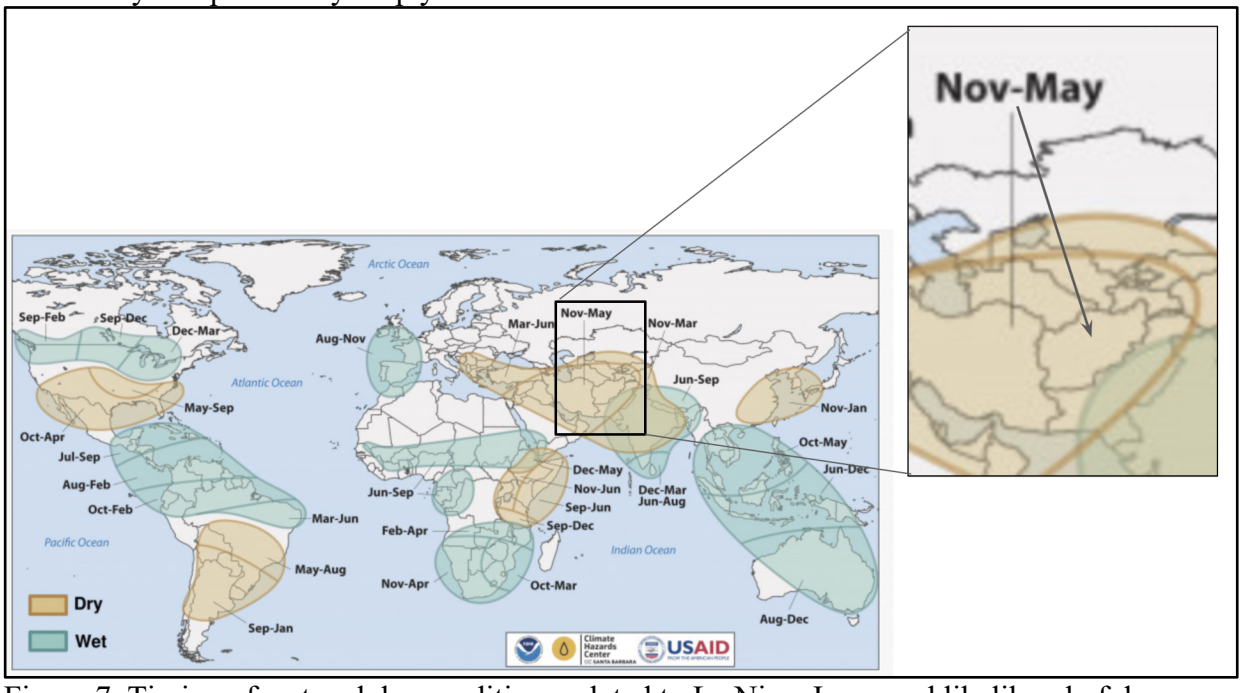

Figure 7. Timing of wet and dry conditions related to La Nina. Increased likelihood of dry conditions from Nov-May for Afghanistan during La Niña events.

A La Niña Watch was issued by NOAA in September 2017 (NOAA, 2017). The FEWS NET October 2017 Food Security Outlook (FEWS NET, 2017a) stated that La Niña conditions were expected throughout the northern hemisphere fall and winter and that below-average precipitation was likely over much of Central Asia, including Afghanistan, during the 2017-2018 wet season. With the expectation of below average rainfall coupled with above average temperature forecasts, FEWS NET anticipated that snowpack would most likely be below average. In the context of food

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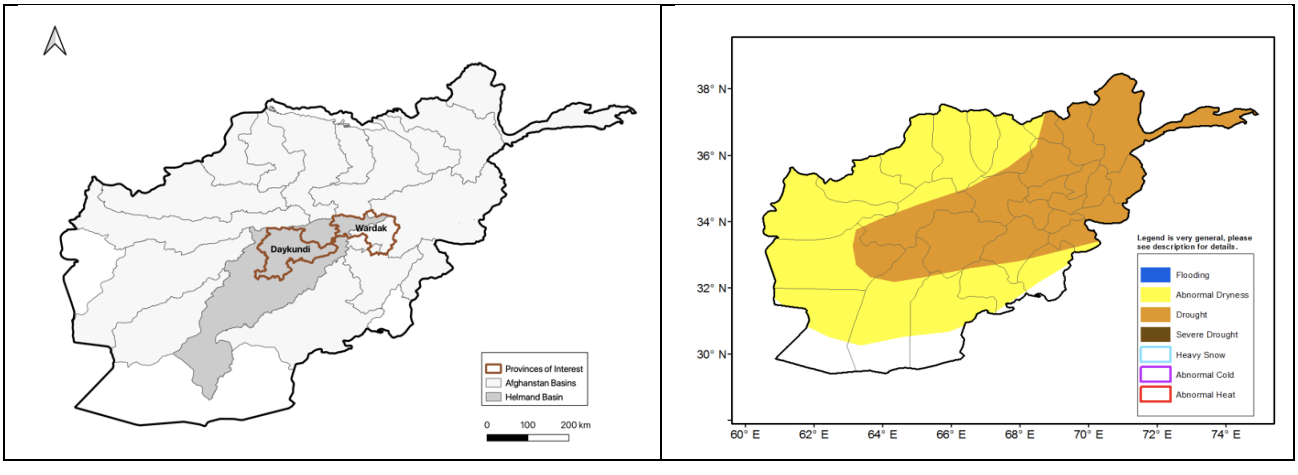
security outcomes, it was assumed that areas planted with winter wheat were likely to be lower than usual, reducing land preparation activities and associated demand for labor. Two provinces of particular concern were Daykundi and Wardak (Fig. 8a brown borders), both located in the Helmand River Basin (Fig. 8a; grey shading). Precipitation deficits in these provinces would lead to poor rangeland resources and pasture availability and would likely result in decreased livestock productivity and milk production through May. However, given that October was the very start of the wet season, there remained a large spread of possible outcomes: spatial and temporal rainfall distributions, and snowpack totals necessitating routine updates to assumptions.

Monitoring continued onward in the season from October, tracking observations from remote sensing, models, and field reports as well as weather, sub-seasonal and seasonal forecasts. This information was used to regularly update expectations of end of season outcomes. Using the FLDAS Central Asia data stream, a December 21, 2017, NOAA CPC Weather Hazards Brief reported that parts of northern and central Afghanistan remained atypically snow free, and north-eastern high elevation areas exhibited snow water equivalent (SWE) deficits. SWE is a commonly used measurement of the amount of liquid water contained within the snowpack, and an indicator of the amount of water that will be released from the snowpack when it melts. By January 17, 2018, an abnormal dryness polygon was placed over northeast Afghanistan, the central highlands of Afghanistan based on below average snow water equivalent values from the FLDAS Central Asia estimates. Abnormal dryness is defined for an area that has registered cumulative 4-week precipitation and soil moisture ranking less than the 30th percentile, with a Standardized Precipitation Index (SPI) of 0.4 standard deviation below the mean. In addition, it is required that forecasts indicate below-average precipitation (less than 80% of normal) for that area during the 1-week outlook period. By late February 2018, precipitation deficits and related SWE (Fig. 9) increased and met the criteria for “drought” (Fig. 8b). Drought is defined as an area that has previously been defined as “Abnormal Dryness” and has continued to register seasonal precipitation and soil moisture deficits since the beginning of the rainfall season. Specifically, an eight-week cumulative precipitation, soil moisture, and runoff below the 20th percentile rank, and an SPI of 0.8 standard deviation below the mean are classification guidelines.



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Preprint. Discussion started: 23 December 2021
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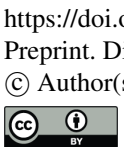

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Figure 8. (a) Map showing hydrological basins, with Helmand Basin in darker grey and location of Daykundi and Wardak provinces where food security conditions were of particular concern (b) NOAA CPC Afghanistan Hazard Report February 22-28, 2018 (CPC NOAA, 2018), map showing widespread abnormal dryness and drought, defined by 90-day precipitation deficits and extremely low snow water equivalent.

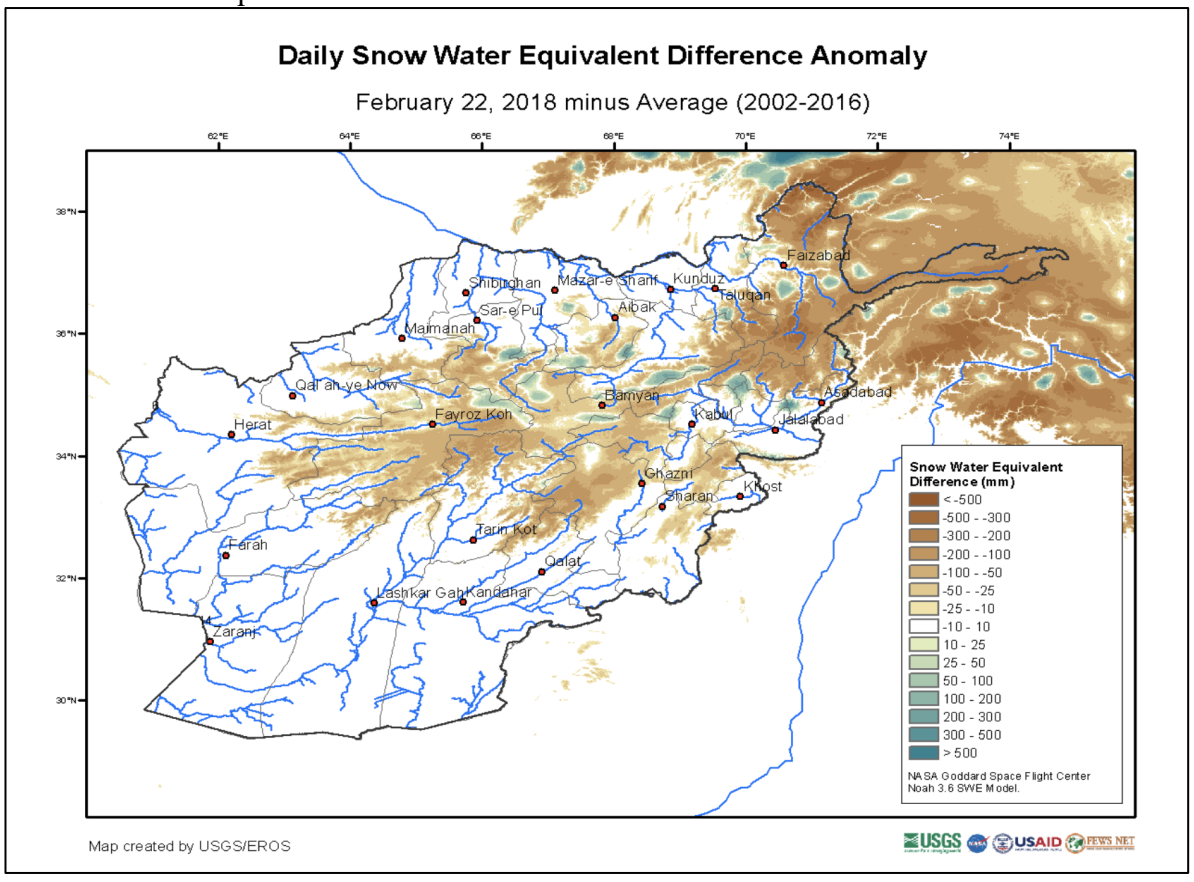

Figure 9. FLDAS Central Asia snow water equivalent (SWE) estimates for February 22, 2018. SWE deficits of >300 mm were widespread at this time.

The February 2018 Food Security Outlook (FEWS NET, 2018b) provided the following updates, based on the CPC Hazards Reports and Seasonal Monitors: “Snow accumulation and cumulative precipitation were well below average for the season through February 2018, with some basins at or near record low snowpack, with data since 2002….These factors will likely have an adverse impact on staple production in marginal irrigated areas and in many rainfed areas. [Moreover, with] forecasts for above-average temperatures during the spring and summer, rangeland conditions are expected to be poor during the period of analysis through September 2018. This could have an adverse impact on pastoralists and agro-pastoralists, particularly in areas where livestock movements are limited by conflict.” The Crop Monitor for Early Warning February and March 2018

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reports (GEOGLAM, 2018a, b) also cited reduced snowpack in Afghanistan and the negative impacts on winter wheat crops as well as irrigation water availability in the Spring. The story was also highlighted in NASA Earth Observatory March 2018 “Record Low Snowpack in Afghanistan” (Record Low Snowpack in Afghanistan, 2018).

The USGS’s Early Warning eXplorer (Shukla et al., 2021) allows analysts to look at maps and time series for a variety of variables and specific provinces and river basins. Plots from EWX in Fig. 10 show below average precipitation in provinces in the Helmand Basin for January and February. CHIRPS cumulative rainfall for 2017-18 vs the 18-year average for Day Kundi (a.k.a. Daykundi) Province showed near average conditions until December. From January cumulative rainfall remained below the 2000-2018 average throughout the rest of the season ending in May; the same pattern occurred in nearby Uruzgan Province. In neighboring Maydan Wardak (a.k.a Wardak) Province below average conditions were experienced in January and February but recovered in March to remain slightly above average. Day Kundi (Fig. 10a) and Wardak (Fig. 10b) are provinces located in the upper reaches of the Helmand Basin. Fig. 10d shows SWE averaged across the entire Helmand basin. The grey shading indicates the range of the minimum and maximum values, and the dashed blue line is the average. Initial snow conditions start above average until December when SWE deficits are near record low values through the beginning of February, and then persist at below-average levels.

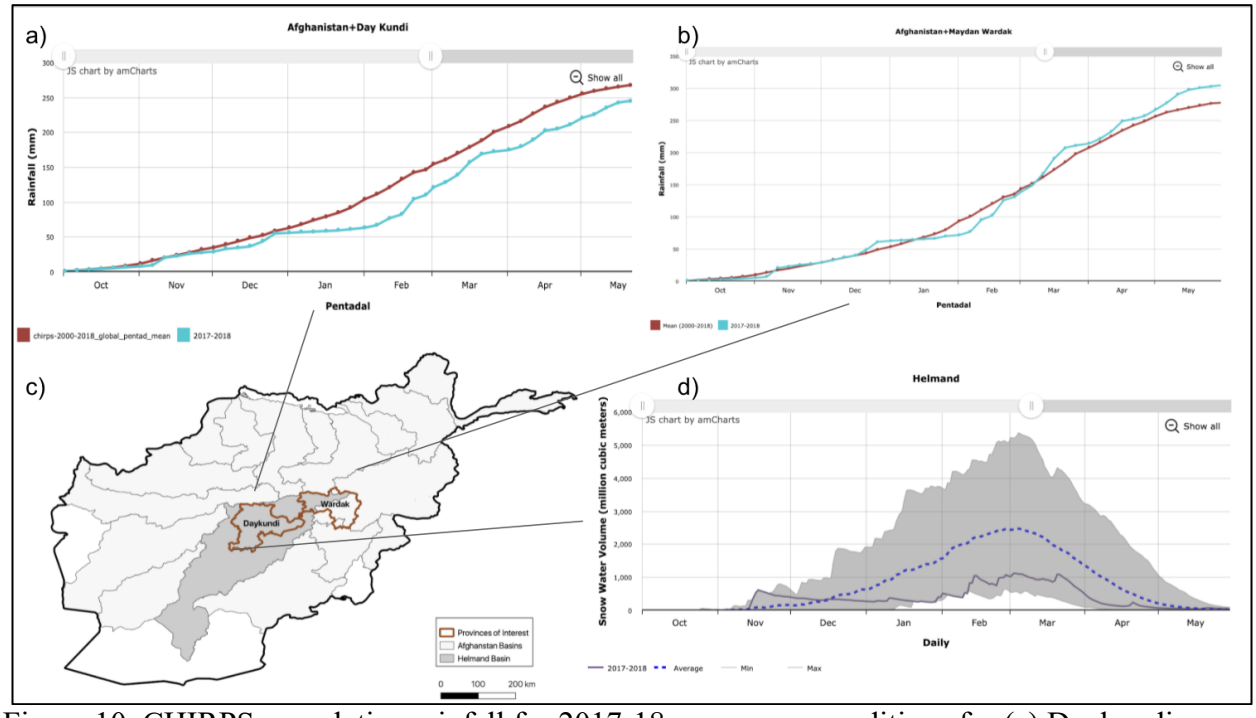

Figure 10. CHIRPS cumulative rainfall for 2017-18 vs average conditions for (a) Daykundi Province (b) Maydan Wardak Province. (c) Map showing location of Daykundi and Wardak provinces, and the Helmand Basin where food security conditions were of particular concern. (d)

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Helmand Basin snow water equivalent (SWE) from the Central Asia data stream. The grey shading indicates the range of the minimum and maximum values, dashed blue line is the average, and black line is 2017-18.

By the end of season in April 2018, FEWS NET (2018c) concluded that "below-average precipitation throughout most of the country during the October 2017 – May 2018 wet season has led to very low snowpack ...Low irrigation water availability is likely to have an adverse impact on yields for winter wheat and other ...barley, maize, and others.. particularly in downstream areas in regions with limited rainfall. ...The poor performance of the wet season and above average temperatures... exacerbated dry rangeland conditions in many areas, particularly in ..Sari Pul, [and surrounding] ...provinces. Pastoralists and agropastoralists in these areas will likely attempt to migrate to areas with better pasture and water availability or sell livestock at below-average prices." At the same time UNICEF reported in April 2018 (500,000 children affected by drought in Afghanistan – UNICEF, 2018) that among "the [drought] affected provinces, Baghis, Bamyan, Daykundi, Ghor, Helmand, ... and Uruzgan are of critical priority for nutrition and water, sanitation and hygiene assistance".

Several months after a season and harvest has ended more statistics become available for further verification of the drought outcomes. The FEWS NET October 2018 Food Security Outlook (2018a) reported that the 2017/18 drought had significant negative impacts on rainfed wheat production and livestock pasture and body conditions across the country. Reporting statistics from the Afghanistan Ministry of Agriculture, Irrigation, and Livestock, the total wheat production for the 2017/18 agriculture season was about 20% below average, where irrigated agriculture performed about average. However, rainfed agriculture production was only about 50% of average, most severely impacting households in in Badakhshan, Badhis, and Daykundi provinces where dry conditions, insecurity, poor incomes, and depleted assets were expected to continue to face emergency food insecurity though May 2019 characterized by large food consumption gaps reflected in acute malnutrition or are employing emergency coping strategies.

5. Data Availability

The Central Asia data described in this manuscript can be accessed at the NASA GES DISC repository under data doi 10.5067/VQ4CD3Y9YC0R. The data citation is the following:

Jacob, Jossy and Slinski, Kimberly (NASA/GSFC/HSL) (2021), FLDAS Noah Land Surface Model L4 Central Asia Daily 0.01 x 0.01 degree, Greenbelt, MD, USA, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed: **[*Data Access Date*]**, 10.5067/VQ4CD3Y9YC0R

The Global data described in this manuscript can be accessed at the NASA GES DISC repository under data doi 10.5067/5NHC22T9375G. The data citation is the following:

https://doi.org/10.5194/essd-2021-420
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McNally, Amy. NASA/GSFC/HSL (2018), FLDAS Noah Land Surface Model L4 Global Monthly 0.1 x 0.1 degree (MERRA-2 and CHIRPS), Greenbelt, MD, USA, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed: [Data Access Date], 10.5067/5NHC22T9375G

Currently the USGS EROS Center provides images from these data: https://earlywarning.usgs.gov/fews/search/Asia/Central%20Asia, as well as an interactive data viewer, the USGS Early Warning eXplorer (EWX) https://earlywarning.usgs.gov/fews/software-tools/1 (Shukla et al. 2021).

6. Code availability

The NASA Land Information System Framework (LISF) is publicly available and an open-source software. The software and technical support are available at https://github.com/NASA-LIS/LISF.

7. Conclusion

This paper describes a comprehensive hydrologic analysis system for food security monitoring in Central Asia, with analysis focusing on Afghanistan. Our intent is to provide the reader with substantial information regarding the configuration and specification of both the current global and Central Asia data streams. These data are publicly available and available at near-real time for food security decision support. An important note is that, as an on-going initiative, FLDAS model version and parameters are routinely updated, and the user should consult the version updates provided by the NASA GES DISC data provider and documentation on USGS Early Warning website. For example, efforts are currently underway to upgrade to the Noah with multi parameterizations (Noah-MP) (Niu et al., 2011) land surface model, which requires some changes in parameters for snow, glaciers and groundwater. This, and future changes will be informed by the strengths and weaknesses of the data stream configurations that we have discussed in this paper.

This paper also provides model-model and model-remote sensing comparisons, as well as a review of other research that highlights the challenges of quantitative evaluation of models and remote sensing in this region. A key challenge to hydrologic modeling is the considerable uncertainty in the meteorological forcing, particularly precipitation, available for this region. Advancements in remote sensing and modeling should help reduce these uncertainties. In addition, the current land surface modeling and river routing frameworks reflect natural conditions, i.e., they do not include representation of anthropogenic impacts such as human water abstractions (e.g., dams for flood control or irrigation, water diversions, groundwater pumping, etc.) or land application of abstracted water (i.e., irrigation). These factors impact streamflow (through abstraction and irrigation flows) as well as estimates of soil moisture, evapotranspiration, and sensible heat flux (land surface temperatures) in irrigated areas. Therefore, it is important to be aware of the limitations and combine with other products (e.g., Normalized Difference Vegetation Index (NDVI) or Actual

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Evapotranspiration (ETa) in irrigated areas) when exploring water and energy balance. Even with improvements to meteorological forcing and modeling parameterizations, errors will remain. Therefore, the 'convergence of evidence' approach that we advocate for here will continue to be important when assessing hydro-meteorological hazards and associated risks to food and water security. We hope that by making the data publicly available the broader food security and water resources communities will be able to provide insights that will lead to improvements in our understanding of the water and energy balance that will ultimately lead to improvements to food and water security decision support systems.

8. Author contribution

JJ runs the code, updates websites and archives routinely. DS maintains LIS code used in paper, JJ, KA, DS, SP conducted model evaluation AM, KS, CPL, SK contributed to design of evaluation. JR, MB, SP manage the data for USGS distribution. AH, JV provides feedback on data quality and interpterion. AM prepared the manuscript with contributions from all co-authors.

9. Acknowledgements

The authors wish to acknowledge the original version of the Central Asia snow modeling with LIS6 performed at NOAA National Operational Hydrologic Remote Sensing Center by Greg Fall and Logan Karsten. USGS work was performed under USGS contract 140G0119C0001. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government. KS, AH, DS, JJ, NASA work was performed under U.S. Agency for International Development, Bureau of Humanitarian Assistance PAPA AID-FFP-T-17-00001. KS, AH acknowledge support from the NASA Harvest Consortium (NASA Applied Sciences Grant No. 80NSSC17K0625). Computing resources have been provided by NASA's Center for Climate Simulation (NCCS). Distribution of data from the Goddard Earth Sciences Data and Information Services Center (GES DISC) is funded by NASA's Science Mission Directorate (SMD). We thank NOAA CPC International Desk for use of Figures. The NASA Land Information System Team for software support and development. The authors also thank the USGS reviewer for comments that improved the quality of the manuscript.

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