Integrating Gravimetry Data with Thermal Infra-red Data from Satellites to Improve Efficiency of Operational Irrigation Advisory in South Asia

Indira Bose, Faisal Hossain, Hisham Eldardiry, Shahryar Ahmad and Nishan K. Biswas
Department of Civil and Environmental Engineering, University of Washington, Seattle, USA

Ahmad Zeeshan Bhatti
University of Prince Edward Island, Charlottetown, Prince Edward Island, Canada

Hyongki Lee
Department of Civil and Environmental Engineering, University of Houston, Houston, USA

Mazharul Aziz and Md. Shah Kamal Khan
Department of Agricultural Extension, Khamarbari, Farmgate, Dhaka, Bangladesh

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Corresponding Author:

Faisal Hossain

Department of Civil and Environmental Engineering, Seattle, WA 98195, USA

Email: fhossain@uw.edu

Abstract

The rapid decline of groundwater resources in South Asia due to excessive irrigation during dry season requires awareness of optimal on-field water requirements. Such information is currently provided on farmer cellphones through an operational Irrigation Advisory System (IAS). To minimize the cost of sending such irrigation advisory texts to farmers while maximizing impact of IAS on groundwater sustainability, we integrated Gravity Recovery and Climate Experiment (GRACE) data with Landsat Thermal Infrared (TIR) Imagery to target regions in greater need of the IAS service. We demonstrated the concept of an improved IAS over eight irrigation districts of the Ganges and Indus basins. The Surface Energy Balance Algorithm for Land (SEBAL) was used to monitor on-field water consumption (evapotranspiration-ET) over cropped areas using Landsat TIR data at plot-scale spatial resolution. Comparison of SEBAL ET with crop water demand from Penman-Monteith (FAO56) technique quantified the extent of over-irrigation at the plot scale and provided a tangible pathway to micro-target the IAS service only to farmers with the largest groundwater use footprint, thereby improving the impact of the IAS service further. Our results suggested that an operational IAS that integrates GRACE and Landsat TIR data on average can save about 85% (80 million m^3) of groundwater per dry season for irrigation districts of Northern India and 87% (or 150 million m^3) per year for irrigation districts of Eastern Pakistan.

Keywords: Irrigation, groundwater, Gravity Recovery and Climate Experiment (GRACE), Landsat, thermal infrared, evapotranspiration

1. Introduction

Groundwater, one of the most important freshwater resources, satisfies significant water demand required by irrigational (42%), domestic (36%), and industrial uses (23%) (Döll et al., 2012; Famiglietti, 2014; Taylor et al., 2013). It also sustains rivers during dry seasons, by providing base flow. However, a growing population requires increased agricultural productivity. This consequently triggers a significant and often unsustainable extraction of groundwater around the world (Siebert et al., 2015). The evident correlation of groundwater depletion with extensive irrigation activity is very distinct in South Asian countries where the monsoon weather system dominates the precipitation regime. The monsoon is a system with prevailing winds along a certain direction. It brings in bountiful amounts of rain (wet phase) followed by a reversal in wind direction resulting in no precipitation (dry phase) (Ramage, 1971). Each phase lasts at least 4-5 months and the dry phase is markedly non-precipitating with low streamflow and dry soils. During the dry phase of the monsoon, irrigation activities for food production can be sustained only from groundwater recharged by the rains from previous wet phase.

South, Southeast, and East Asia sustain extensive irrigation systems by relying mostly on groundwater pumped during the dry season, which is (hereafter) the period spanning from November to April (Hossain et al. 2017). Hence, the water and food security in South Asia is deeply rooted in groundwater resources of the transboundary aquifer system of Indus-Ganges-Brahmaputra-Meghna (IGBM) rivers that supports a net cropping area of 1.14 million km^2 (Malakar et al., 2020; Mukherjee et al., 2015). For South and East Asia, the total annual water withdrawal is roughly 1981 km^3, which is about 50 percent of world total (FAO, 2016). Agriculture requires around 82 percent of the total freshwater withdrawal in Asia, which is much higher than global agricultural water withdrawal (70 percent) (FAO, 2016). The highest water withdrawal in

South Asia is reported in India comprising of about 10400 m^3/ha (1040000 m^3/km^2) of irrigated land (FAO, 2016). As a result of this high groundwater withdrawals, South Asia today experiences rapid groundwater depletion, predominantly in North-West (Ganges Basin) and South-East (Bengal basin) India, upper Indus Basin in Pakistan and Meghna basin in Bangladesh (MacDonald et al., 2016). Such extensive withdrawal of groundwater jeopardizes the water sustainability for the millions of farmers in South-Asia whose livelihood depends on crops produced during the dry season.

Rodell et al. (2018) identified the rate of depletion of total water storage (TWS) to be 19.2 ± 1.1 km^3/year (half the storage capacity of Three Gorges Dam in China) in Northern India resulting from groundwater irrigation. From 1996 to 2017 an increasing trend of groundwater storage loss has been reported over the lower Ganges basin varying from -48.83 to -2.27 cm/year during winter (or dry) seasons (November to April) (Rahman et al., 2020). According to GRACE TWS analysis, Indus basin has been losing groundwater storage at a rate of 1.5 km^3/year even after accounting for monsoonal recharge (Iqbal et al., 2017, 2016). Piezometer-based investigations indicated a smaller but nevertheless non-negligible loss rate of 0.54 km^3/year (Iqbal et al., 2016). However, the overall trend remains alarmingly unsustainable irrespective of data source or method used (Iqbal et al., 2016). A recent study also reported a net loss of about 1 cm/year groundwater storage from 2010 to 2017 in the upper Indus plain (Salam et al., 2020).

In addition to the boom of groundwater-dependent irrigation, wastage of water by irrigating more than the crop water demand also contributes to this unsustainable groundwater depletion. For instance, the water requirements for rice in Punjab and Sindh Provinces of Pakistan are approximately 600 and 1400 mm, respectively; but the farmers routinely apply around 2200 mm resulting in a significant loss of groundwater, and an increase in fuel cost due to pumping from deeper layers (Hossain et al. 2017). Therefore, a proper management of groundwater resources for agricultural uses is critical for a sustainable balance between groundwater supply and demand to ensure food security in the coming decades for South Asia (Malakar et al., 2020; Rahman et al., 2020). A recent study by the Central Groundwater Board of India has reported that Western India is likely to run out of its groundwater in another 20 years (Singh, 2020).

Optimizing irrigation according to crop water need can play an important role in ensuring a more sustainable use of ground water. By ensuring that farmers pump groundwater during the dry season according to the demand for crop growth rather than the archaic wasteful practice of flood irrigation, an Irrigation Advisory Service (IAS) should be able to minimize the current and rampant groundwater wastage. There has already been anecdotal evidence that an operational IAS can achieve this based on recent implementation in Indus basin since 2016 (http://www.pcrwr.gov.pk/advisory.php and http://www.pak-ias.org) and more recently in India (Hossain et al., 2020; http://www.i-pani.com), and Bangladesh (http://pani.hmrcweb.com).

To conserve groundwater and improve crop yield, one of the well-known IAS services for Pakistan Council of Research in Water Resources (PCRWR; http://www.pcrwr.gov.pk/advisory.php and http://www.pak-ias.org) was developed by Sustainability, Satellites, Water, and Environment (SASWE) research group of University of Washington (UW) in August 2016 (Hossain et al. 2017). This IAS is coined as "smart" irrigation service and was operationalized for advising farmers on how much and when to irrigate based on crop water demand or evapotranspiration (ET) and forecast of precipitation and weather conditions. A proxy measure of the reference evapotranspiration rate (ETo), the crop water requirement for a crop, was computed using a method from Allen et al. (1998) which is known as Penman-Monteith (FAO 56) method. This technique was basically an alteration of a well-known equation reported in Monteith and Unsworth (1990) using temperature, humidity, wind speed, and solar radiation as inputs. The model outputs are nowcasts and forecasts of the need of irrigation and precipitation for each week. The input to the model is obtained from a Global Numerical Weather Prediction (NWP) modeling system known as the Global Forecast System (GFS) (see here: https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forcast-system-gfs). The nowcast weather variables from GFS produce nowcast of crop water demand, precipitation, and other farming-relevant conditions such as humidity, windspeed and temperature. Similarly, the forecast weather variables from GFS help produce forecast of the same variables. Lysimeter-based ET data were used by PCRWR to validate the nowcast inputs to indicate that the FAO56 based crop water demand (forecast and nowcast) was skillful enough to be used in IAS for farmers.

In this operationalized IAS, when supply (rainfall/recent irrigation) exceeds crop water demand, the farmers get advisory on their cellphones to skip or reduce irrigation. Similarly, when crop demand exceeds supply, farmers get the advisory to apply or increase irrigation. Such an IAS has also been successfully piloted over Kanpur in India under the name of Provision for Advisory on Necessary Irrigation (PANI) (Hossain et al., 2020; http://www.i-pani.com). PANI was launched at the start of the winter wheat season of October 2018 and irrigation and weather advisory services were provided to farmers until harvest in March 2019. After harvest, the survey reported that out of the 150 farmers, 128 (85 percent) provided valuable feedback on the effectiveness of PANI. (USAID Agrilinks, 2020). Most recently, the IAS has seen expansion to Bangladesh in 2019 on a pilot scale with 165 farmers (http://pani.hmrcweb.com). Starting with 700 farmers in Pakistan in 2016, tens of thousands of farmers are now beneficiary of the services of IAS in these monsoonaffected South Asian nations who are known to waste groundwater during the dry season when food production is critical.

According to a survey of randomly selected farmers carried out by PCRWR, it is speculated that the IAS can potentially save about 2.5 km^3 of groundwater a year per 100,000 farmers in Pakistan (IAS, 2018). This is equivalent to 40% potential savings in irrigation water. In recent years, IAS had positive impacts on increase in yield of wheat in Pakistan and India of up to 500 kg/ha for wheat with 80%, 85% and 78% usage rate by farmers in Pakistan, India, and Bangladesh, respectively (IAS, 2018). Many other countries have also adopted crop water demand-based irrigation advisory such as IAS. Examples are Castilla-La Mancha in Spain, Baixo Acaraú irrigation district in Brazil, and Australia. (Car et al., 2012; Corcoles et al., 2016; Ortega et al., 2005). An assessment report on water use efficiency (WUE) of IAS in Spain was published for corn yield by comparing crop coefficients from regional IAS (demand) and satellite products (consumed). It evaluated the irrigation deficit and over-irrigation based on WUE and reported deficient irrigation during dry season and full or over-irrigation during wet season over their selected irrigation districts (Segovia-Cardozo et al., 2019).

Despite the benefits, there is always room for improvement as IAS is a public service with an operational cost. In South Asian countries, this cost is maintained by governments, and therefore only a finite fraction of farmers can receive this service at the moment. These countries are not yet ready for a viable and universal service that is accessible to every single of the 130 million or more farmers of South Asia (Dixon et. al., 2001). Hence, one area of improvement for IAS is to optimize the targeting of the service exclusively to regions and farmers where groundwater consumption for irrigation needs to be more urgently managed so that the overall impact on sustainability is larger for the same limited service.

The objective of this study is to improve the existing IAS by integrating Gravity Recovery and Climate Experiment (GRACE) TWS anomaly data with Thermal Infrared (TIR) imagery from Landsat by prioritizing advisory texts only to over-irrigating farmers in rapidly depleting groundwater regions. The use of Landsat TIR data for tracking on-field agricultural water consumption is now well established (this is discussed in more detail in section 4). Large scale identification of groundwater depleted zones using GRACE TWS data have been reported in many studies (Bhanja et al., 2020; Castellazzi et al., 2018, 2016; Gao et al., 2020; Li et al., 2019; Richey et al., 2015; Rodell et al., 2018, 2009; Salam et al., 2020; Sarkar et al., 2020; Voss et al., 2013). Also, local scale investigation of groundwater level changes has been reported by Sun (2013) by downscaling GRACE TWS data. However, to the best of our knowledge, none of these studies incorporated groundwater depleted zone identification from GRACE data and integrated with Landsat TIR data for an operational IAS Resource-constrained nations in South Asia have limited capacity to maintain an irrigation advisory as a free service for all their farmers until a proper business model is developed. Thus, it is timely to investigate how the integration of satellite gravimetry with satellite TIR data can improve the efficiency of the IAS in terms of maximizing impact for the same outreach to farmers.

In this study, we identified the groundwater depleted regions using GRACE TWS during dry season. We assessed the irrigation scenarios over those identified zones at a local/district scale. We compared the water consumed by plants over those districts with the crop water demand. To determine the actual water consumption, we computed ET using Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al., 1998a, 1998b) and the crop water demand was computed by estimating the ET based on Penman-Monteith (FAO-56) technique. Finally, from this comparison we identified the regions with excessive over-irrigation and evaluated the percent of ground water that could potentially be saved with proposed improved IAS. Finally, we proposed an improved IAS based on integration of GRACE gravimetry and Landsat TIR data for maximum reduction of groundwater waste for monsoon dominated regions around the world with extensive dry season irrigation practice.

The key questions this study asks are as follows:

1) What is the representative scale at which GRACE TWS data should be applied for integration with an operational IAS?
2) To what extent we can independently verify GRACE-identified regions where groundwater is potentially declining due to excess irrigation during dry season?
3) What is the potential impact of irrigation water saving with an IAS enhanced with GRACE and Landsat TIR satellite data?

The rest of the paper is organized as follows. We describe the selected study sites in section 2, data sources and methodology are introduced in sections 3 and 4, respectively and the results are discussed in section 5. Future direction of the work and conclusions are summarized in section 6.

2. Study Sites

The IGBM basin spreads across the lush plains in Pakistan, India, Bangladesh, and Nepal; one of the world's most important high yielding transboundary aquifer systems (Mukherjee et al., 2015). In this study, we considered the Ganges and Indus basins from IGBM. Rapid depletion of groundwater has been observed over Uttar Pradesh (Ganges, India) and Punjab (Indus, Pakistan). In Uttar Pradesh, the net area of irrigation dependent on groundwater is approximately 106,410 km^2 (FAO, 2016). Uttar Pradesh is divided into many irrigation districts. Based on depth to water table (DTW) analysis we selected Kanpur Nagar (3,155 km^2), Kanpur Dehat (3,021 km^2), Agra

(4,027 km^2), and Lucknow (2,530 km^2) as these regions are suffering most from water scarcity during dry season (Figure 1a). Here we define dry season as the period from November to April. In Kanpur Nagar, the DTW was 8 m in 2002, which has now dropped to 20 m in 2020. Similarly, in Kanpur Dehat, Agra, and Lucknow DTW dropped from 8 m to 17 m, from 15 m to 30 m and from 7 m to 20 m, respectively (WRIS India; see https://indiawris.gov.in/wris/).

In northeastern part of Punjab province in Pakistan, the declining groundwater tables are mostly noticed in areas with fresh groundwater (Mekonnen et al., 2016). Particularly, Eastern Punjab is a hotspot for groundwater depletion. The net irrigation area dependent on groundwater in Punjab province is about 42,930 km^2 (FAO, 2016). For our study we selected four most vulnerable areas comprised of Sargodha (5,854 km^2), Muzaffargarh (8,249 km^2), Layyah (6,291 km^2), and Sheikhupra (3,030 km^2) in Punjab based on DTW analysis (Figure 1b).

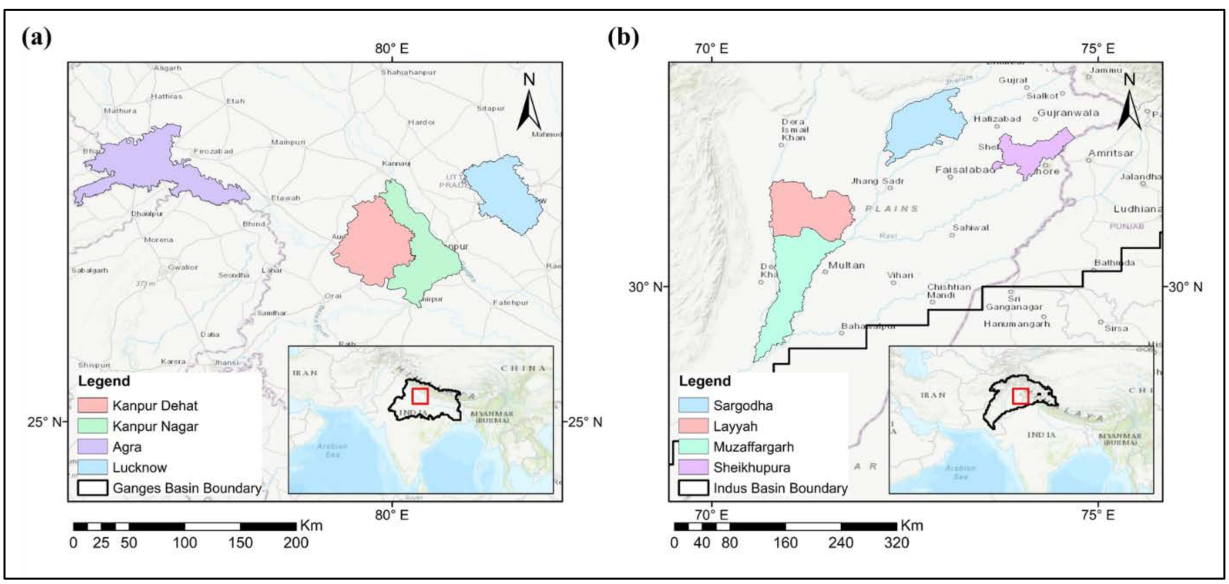


Figure 1: Study sites showcasing (a) four irrigation districts (Kanpur Nagar, Kanpur Dehat, Agra, and Lucknow) selected within Ganges basin and (b) four irrigation districts (Sargodha, Layyah, Muzaffargarh, and Sheikhupura) selected within Indus basin.

3. Data

3.1 GRACE TWS: Identifying groundwater depleted zones

To rapidly identify the unsustainable groundwater depleted regions (during dry season) for a more efficient IAS, GRACE TWS anomaly data for the period of 2002 to 2016 were retrieved from a cloud computing catalog (https://developers.google.com/earthengine/datasets/catalog/NASA_GRACE_MASS_GRIDS_LAND) hosted by Google Earth Engine (GEE) (Gorelick et al., 2017). GRACE Tellus (GRCTellus) Monthly Mass Grids provides monthly gravitational anomalies relative to a 2004-2010 time-mean baseline. The anomaly data confined in this dataset are units of "Equivalent Water Thickness" which represent the deviations of mass in terms of vertical extent of water in centimeters. The GRCTellus dataset is produced by three centers: the Center for Space Research at the University of Texas at Austin (CSR MASCON), NASA Jet Propulsion Laboratory (JPL) and German Space Agency (Geoforschungszentrum, GFZ). Each center is a part of the GRACE Ground System and generates Level-2 data (spherical harmonic fields) which are resampled to 1 degree in the GEE catalog. Here we used the CSR MASCON product with a resolution of 1 degree (~100 km).

3.2 Landsat-7 Thermal IR Data: Estimation of ET

To monitor water consumption of plants (ET), land surface temperature is an important component, which we can derive from satellite remote sensing data, specially where no ground data is available. For computing ET, we used TIR data from Landsat-7 ETM+ (Tier 1) as top of the atmosphere (TOA) radiation because TIR bands have a high spatial resolution of 60-100 m with bi-weekly temporal resolution (Senay et al., 2016). Among various ET estimation methods, in this study we used the SEBAL method for monitoring water consumption of plants (discussed later in methodology). We imported Landsat-7 ETM+ (Tier 1) TOA TIR radiation and visible/near-infrared reflectance data from GEE which were radiometrically corrected following the procedure from Chander et. al. (2009). We did not perform further ambient atmospheric corrections for the TIR radiation, as our focus was exclusively on the dry season with very low atmospheric moisture content. We used an interpolation algorithm in GEE taking mean of pixels in a square kernel of radius 1 or mean of 2 pixels in neighborhood to fill the gaps in Landsat 7 images. This interpolation technique did not impact the results as spatial variation of temperature or wind speed is not significantly different between two adjacent pixels of Landsat. The Blue (0.45 - 0.52 µm), Red (0.63 - 0.69 µm), Near Infrared (0.77 - 0.90 µm), Shortwave Infrared (1.55 - 1.75 µm) bands were acquired at a resolution of 30 m and TIR band data (10.40 to 12.50 µm) was acquired at a resolution of 60 m (see https://developers.google.com/earthengine/datasets/catalog/LANDSAT_LE07_C01_T1_TOA).

3.3 Meteorological Forcings

For developing models to estimate crop water consumption and crop water demand, one of the important datasets is the meteorological forcing data. In this study we used the dataset from Global Land Data Assimilation System (GLDAS) (available at: https://developers.google.com/earthengine/datasets/catalog/NASA_GLDAS_V021_NOAH_G025_T3H). GLDAS combines satellite and ground based observed data; creates optimal fields of land surface states and fluxes. It provides 3 hourly data with a spatial resolution of 0.25 degree (~25 km). The GLDAS component inputs for both models (SEBAL and Penman-Monteith) were air temperature at 2 m, wind speed at 10 m, specific humidity, and pressure. For our purposes, using GEE, we aggregated 3 hourly data to daily data.

3.4 Precipitation products and In-situ well data

For precipitation, which is a key component of water budget model, we used three different products; Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), Tropical Rainfall Measuring Mission (TRMM) and Copernicus ERA5. CHIRPS is a 35+ year quasi-global rainfall data set, spanning 50°S-50°N (and all longitudes). It provides daily data at 0.05 degree (~5 km) spatial resolution (see here: https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY) . TRMM 3B42 dataset provides a 3 hourly rainfall estimates at 0.25-degree (~25 km) resolution (see here: https://developers.google.com/earth-engine/datasets/catalog/TRMM_3B42). ERA5 dataset provides an atmospheric reanalysis of the global climate, a fifth-generation product of European Centre for Medium-Range Weather Forecasts (ECMWF). The reanalysis integrates the model data with complete and consistent observations from across the world into a global dataset. The daily total precipitation values in ERA5 are given as daily sums with a spatial resolution 0.25 degree (~25 km) (see here: https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5_DAILY). We downscaled all three precipitation products to 100 m for spatial aggregation using bilinear resampling technique. We summed up the precipitation values of each dataset for getting the monthly accumulations. For example, in case of TRMM, we first aggregated the three-hourly precipitation to obtain the daily data. Next, we aggregated the daily precipitation values to obtain the monthly accumulated precipitation. Note that, these products were used separately without merging into a single product.

To understand if on-farm water consumption according to SEBAL ET during dry season is a proxy for groundwater withdrawals, we used in-situ DTW data. For irrigation districts within Ganges basin, we used a data portal named Water Resources Information System of India (WRIS

India; see https://indiawris.gov.in/wris/) that uses data from Central Ground Water Board of India. For irrigation districts within Indus basin, we used sampled piezometer data provided by PCRWR (Iqbal et al., 2017).

4. Methodology

First, we identified the regions of rapid groundwater depletion by analyzing spatial and temporal trend of GRACE TWS anomaly from 2002-2016. Next, to find the appropriate scale for rapid zone identification, we compared GRACE TWS anomaly with water budget model derived TWS. Then, as mentioned earlier, we analyzed four irrigation districts each within Ganges and Indus basins. Given that wheat is the dominant crop during the dry season in those districts, for wheat we compared the actual water consumption and crop water demand using SEBAL and FAO 56 Penman-Monteith method, respectively and assessed the nature of ambient irrigation (under or over) in the selected irrigation districts. A scenario of over-irrigation was identified when actual water consumption (SEBAL ET) was found to be greater than the crop water demand (Penman-Monteith ET). Similarly, when actual water consumption was found to be less than the crop water demand, the scenario was flagged as under-irrigation. Finally, we calculated the percent of over or under irrigation over those regions and calculated how much irrigated water can be potentially saved with an improved IAS during dry season. Figure 2 schematically summarizes the approaches followed to address our following objectives.

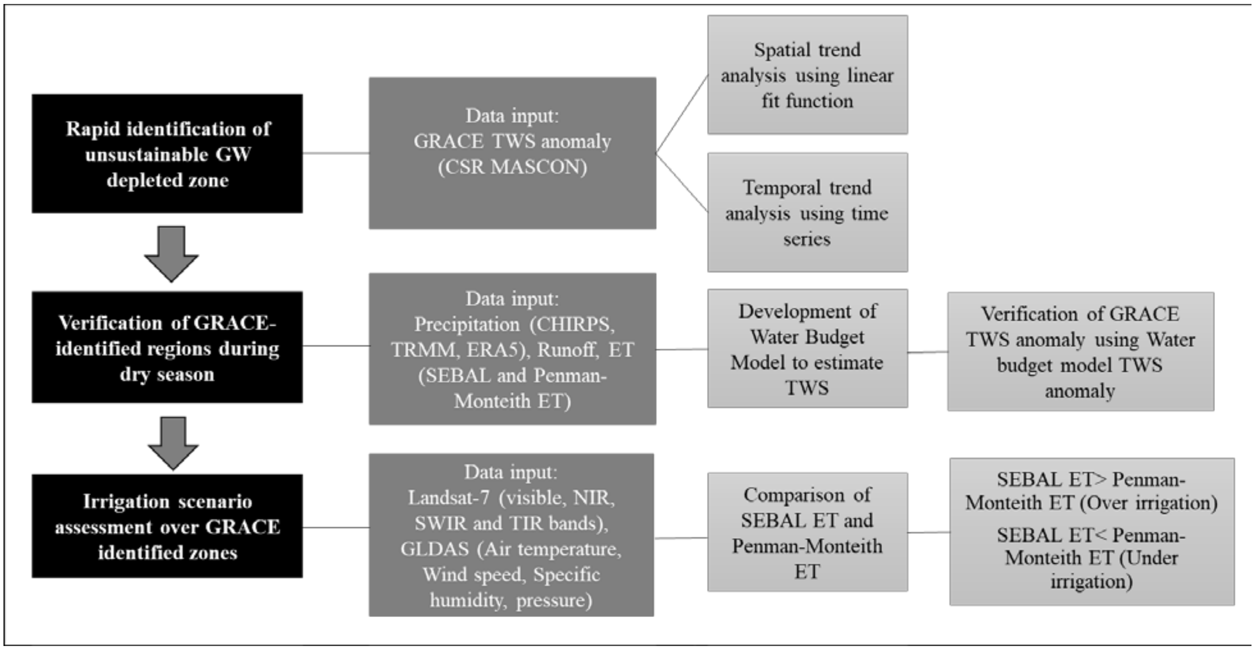


Figure 2: Schematic summary of steps followed in methodology

4.1 SEBAL ET

For quantifying actual water consumption (ET) variability where availability of ground-based data is a constraint, various satellite-based methods are reported in literature. SEBAL and METRIC (Mapping Evapotranspiration at High Resolution and with Internalized Calibration) are such two widely-used techniques (Liou and Kar, 2014). In our study we implemented SEBAL which has already been effectively implemented in many studies to assess actual ET using satellite images (Ghaderi et al., 2020; Senay et al., 2016). SEBAL model solves the surface energy balance to compute ET using satellite images and weather data. Since the satellite image provides information for the overpass time only, SEBAL computes an instantaneous ET flux for the image time. A series of equations are incorporated in SEBAL model that compute net surface radiation, soil heat flux, and sensible heat flux to the air. The residual energy flux is then calculated by subtracting the soil and sensible heat fluxes from the net radiation at the surface. This residual energy (latent heat) enables liquid water to phase transition to water vapor, *i.e.*, evapotranspiration.

Thus, for each pixel of the image, the ET flux is calculated as a residual of the surface energy budget equation:

$$\lambda ET = Rn - G - H \tag{1}$$

where λET is the latent heat flux (W/m^2), Rn is the net radiation flux at the surface (W/m^2), G is the soil heat flux (W/m^2), and H is the sensible heat flux (W/m^2).

We computed daily or 24-hour ET by assuming that the variations in instantaneous ET are not significant over the 24-hour period (Allen et. al. 2007). For monthly ET calculation, we calculated ET on the day of Landsat acquisition, and we considered same steady-state ET for 16 days from that day to the day of next Landsat image availability. Next, we summed up the ET values for getting the monthly ET. This assumption of considering ET same for 16 days is feasible for crop water demand calculation as ET values are much stable during each growth stage of crops that lasts more than 15 days. Also, irrigation decisions in South Asia are often made according to growth stage variations or at weekly to bi-weekly timescales rather than sub-weekly.

4.2 Penman-Monteith ET

Penman-Monteith ETo, which is a proxy to potential water demand for reference crop, was calculated over the same time period and districts following the steps from Allen et al., (1998). The equation for ETo is as follows:

$$ET_o = \frac{0.408\,\Delta\,(R_n - G) + \gamma\,\frac{900}{T+273}\,u_2\,(e_s - e_a)}{\Delta + \gamma\,(1 + 0.34\,u_2)} \tag{2}$$

where, ET_o is reference evapotranspiration (mm/day)

R_n is net radiation (MJ m^{-2} day^{-1})

G is ground heat flux (MJ m^{-2} day^{-1}), considered negligible (i.e., 0) here

T is mean air temperature at 2 m height (˚C)

u_2 is wind speed at 2 m height (m/s)

e_s saturation vapor pressure (kPa)

e_a actual vapor pressure (kPa)

Δ is slope of saturation vapor pressure (kPa $˚C^{-1}$)

γ is psychrometric constant (kPa $˚C^{-1}$)

ETo calculated using equation 2 is for a reference crop (grass of 0.12 m height) which is then converted for the actual crop growing in the selected districts. For this we considered the crop type, development stage, and the relative soil saturation (or stress). As wheat was the dominant crop in our study regions, we used the corresponding crop coefficient (Kc) referred in FAO, 2020 and assumed soil water stress coefficient (Ks) of 0.5, which in our experience is representative of stress conditions during the dry season. We multiplied Kc and Ks with ETo to derive the crop water demand for wheat over the study regions.

4.3 Spatial and temporal trend of GRACE TWS anomaly

To understand the trends in groundwater storage from 2002 to 2016, we fit a linear model. Considering January to December for CSR MASCON product of GRACE TWS anomaly over the entire time period, we developed a linear regression model. Here, we assumed that GRACE TWS anomaly is a strong proxy for groundwater storage change during dry season in monsoon climates based on the water budget equation as follows:

$$\Delta S = P - Q - ET \quad (3)$$

In above equation 3, ΔS, P, Q and ET are total/terrestrial water storage change, precipitation, surface run-off and evapotranspiration, respectively. The total storage change can be further broken down into the following four components.

$$\Delta S = \Delta GWS + \Delta SM + \Delta SWE + \Delta SW \quad (4)$$

Here, ΔGWS, ΔSM, ΔSWE, and ΔSW are storage change components for groundwater, soil moisture, snow water equivalent, and surface water, respectively.

During dry season in South Asian countries, there is negligible precipitation or surface run-off. Hence, P and Q are near-zero and thus, ΔSM and ΔSW are also negligible. Rodell et. al. (2009) stated that the contribution of Himalayan glacier mass loss to GRACE TWS anomaly trend is minor. Given no snow-covered areas in the Gangetic and Indus plains of South Asian countries, ΔSWE is also equivalent to zero. Therefore, we are left with the simplified form for equation 4 for South Asia during dry season, i.e., ΔS = ΔGWS. This is the basis of our hypothesis for using GRACE TWS anomaly as a proxy for groundwater storage change during dry season, which we later demonstrate as having a sound basis.

4.4Representative GRACE data scale for identification of groundwater depleted zones

For identifying the representative scale at which GRACE can be used to rapidly identify the fast depleting zones, we compared GRACE TWS anomaly against the water budget model derived TWS anomaly. First, we divided the entire Ganges basin into 5 sub-basins based on the stream orders as shown in Figure 3. We defined the stream order based on Strahler's classification. The higher ordered sub-basins included all the lower order sub-basins. After sub-basin delineation, we developed the water budget model from 2002-2014 using equation 3 and implemented over each sub-basin followed by estimating TWS. For model inputs, three different precipitation products (CHIRPS, TRMM and ERA5) were used to address the uncertainty embedded with satellite products, run-off from Variable Infiltration Capacity (VIC) (Liang et al., 1996; Siddique-E-Akbor et al., 2014) model, and ET from SEBAL model (equation 1).

For the ET component of the water budget model (equation 3), we applied SEBAL using Landsat-7 satellite images. The SEBAL model also required the meteorological data including wind speed, surface pressure, specific humidity, and air temperature as inputs for solving the surface energy balance calculation (equation 1). We used GLDAS outputs as meteorological forcing input for the SEBAL model. To avoid the non-cropped areas, we used the crop map from Global Food Security Support Analysis Data (GFSAD) Crop Dominance Global 1 kilometer (km) (can be accessed here: https://lpdaac.usgs.gov/products/gfsad1kcmv001/).

It is worth mentioning that there are alternate approaches for satellite-based ET estimation. For example, the VI-Ts method has been used to compute actual ET or crop water consumption (Tang et al., 2009). The spatial and temporal resolutions (250 to 1,000 m and 3 to 7 days, respectively) in that study were afforded by Moderate Resolution Imaging Spectroradiometer (MODIS). MODIS is a key instrument aboard the Terra (originally known as EOS AM-1) and Aqua (originally known as EOS PM-1) satellites (see: https://modis.gsfc.nasa.gov/about/). Tang et al. (2009) used different MODIS parameters to compute the crop water consumption and verified the results by modifying METRIC algorithm based on SEBAL. In our study, we used Landsat images (temporal frequency 16 days) which are not as frequent as MODIS. However, for the objective of our study, the spatial resolution (from Landsat) is more important than temporal frequency in general because farmers do not need to make irrigation decisions about their crops every day or week, especially for wheat.

Next, water budget derived TWS and GRACE TWS datasets was compared over each individual sub-basin. The desired scale was selected after analyzing the bias, root mean square error (RMSE), and Spearman's rank coefficient between water budget derived TWS and GRACE TWS anomaly.

4.5 Irrigation scenario assessment

We quantified actual (on-farm) irrigation scenario over the selected regions to find if over-irrigation was triggering groundwater depletion. First, we performed supervised classification technique (random forest classification scheme) to differentiate cropped and uncropped regions

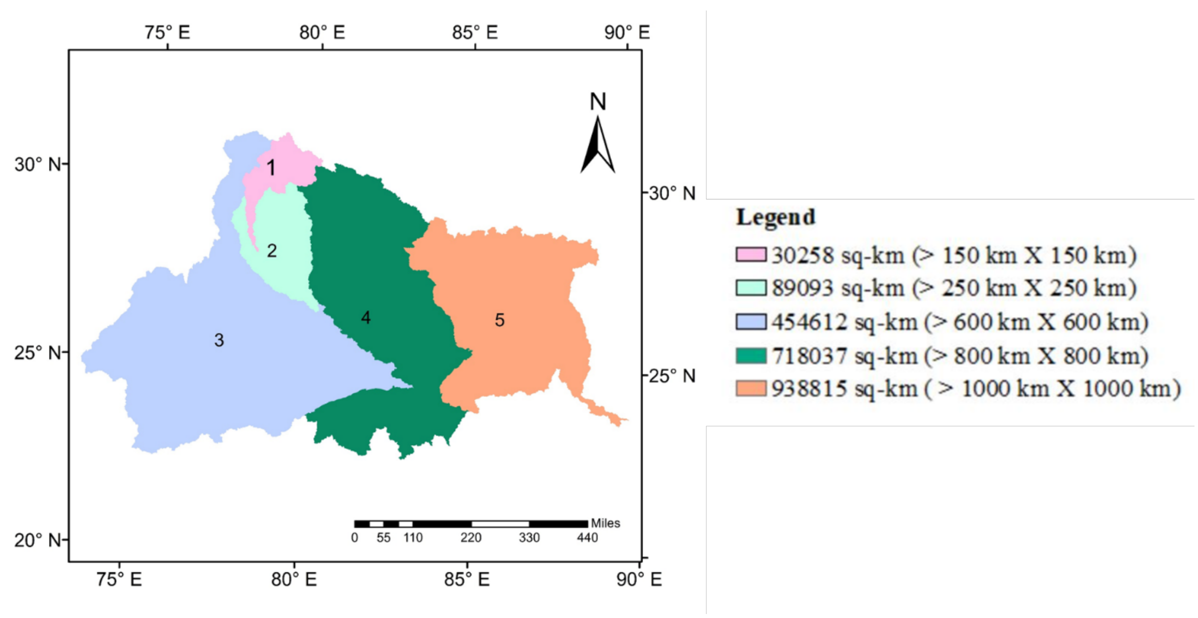


Figure 3: Delineation of sub-basins based on stream orders for water budget model development over Ganges basin. On the right, different colors incorporate to corresponding areas and respective scales of each sub-basin.

within the selected irrigation districts. We used Landsat-7 images and trained the classification model using four land covers; crop, forest, water, and urban to derive the land use with crops only (the latter three were grouped as uncropped) as shown in Figures 4 and 5. Wheat being the dominant crop from November to April (FAO, 2020) in the selected districts, we considered wheat growing over the entire cropped regions and proceeded with further analysis.

Next, we applied SEBAL and Penman-Monteith methods on the cropped regions from 2002 to 2014 to obtain the actual water consumed by plants and water required, respectively. Finally, we used equation 5 to obtain the percentage of over or under irrigation happening over the selected districts comparing two sets of ETs.

Percent of over/under irrigation =

$$\frac{\text{Actual water consumed (SEBAL ET)} - \text{Water Needed(Penman} - \text{Monteith ET)}}{\text{Water Needed (Penman} - \text{Monteith ET)}} \times 100 \qquad (5)$$

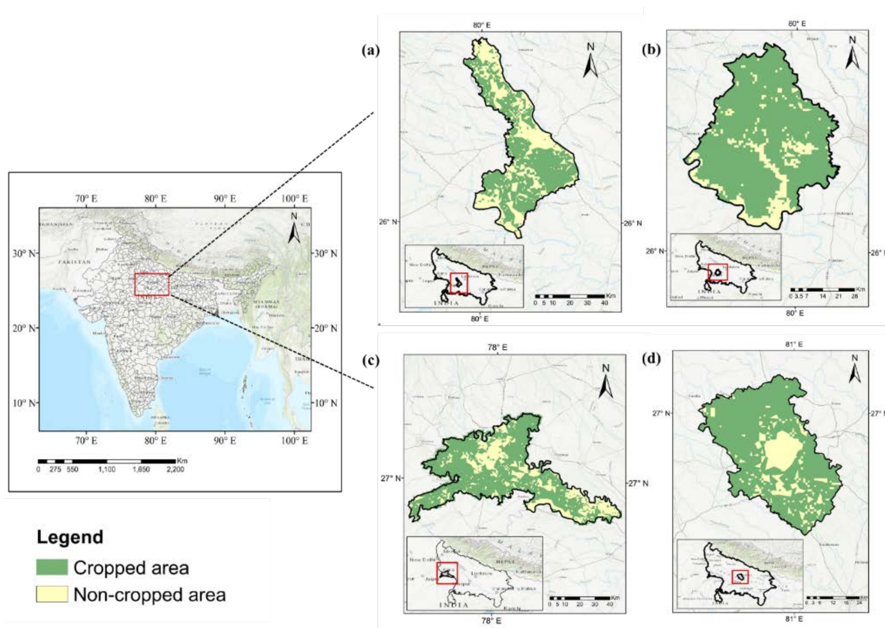


Figure 4: Crop maps over (a) Kanpur Nagar, (b) Kanpur Dehat, (c) Agra, and (d) Lucknow. Here, Green legend corresponds to the cropped areas.

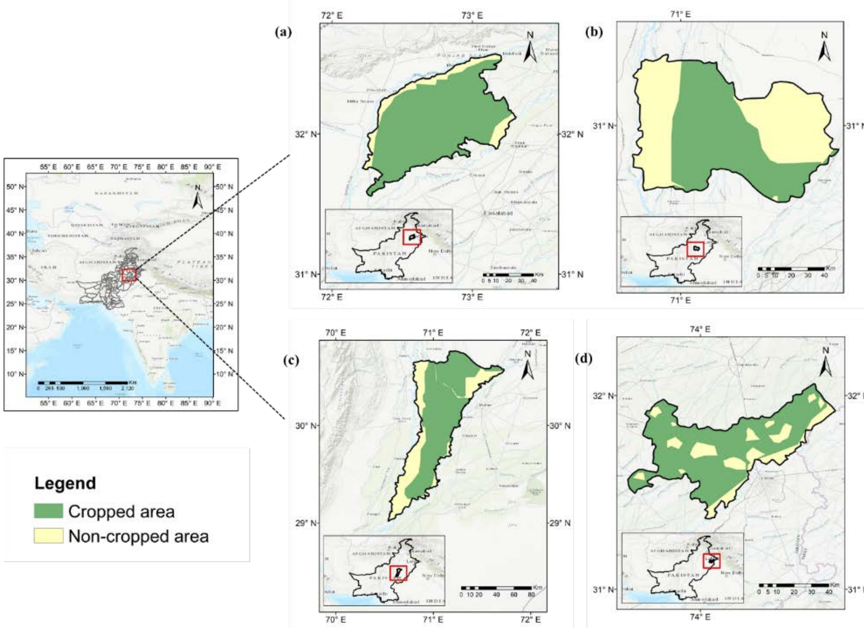


Figure 5: Crop maps over (a) Sargodha, (b) Layyah, (c) Muzaffargarh, and (d) Sheikhupura. Here, Green legend corresponds to the cropped areas.

5. Results and Discussions

5.1 Spatial and temporal trend of GRACE TWS anomaly:

Understanding the spatial and temporal trends of groundwater depletion is key to finding the vulnerable zones for precision targeting for an improved IAS. The spatial trend of groundwater depletion observed using regression model over Ganges basin from 2002 to 2016 is depicted in figure 6 (a). The GRACE TWS anomaly, already noted as a proxy for groundwater change during dry season, showed a maximum negative trend of 1.99 cm/year equivalent height of water. This means the maximum rate of groundwater depletion over the Ganges basin is 1.99 cm/year. The most alarming finding is the overall descending trend suggesting a continuous depletion over the basin regardless of wet or dry seasons. That indicates, even with the wet season recharge phase, overall (net) groundwater storage continues to decline. We studied the temporal trend of averaged TWS anomaly over the basin and observed a declining trend of 1.2 cm/year (figure 6 b). We found a maximum positive trend/groundwater recharge of 0.52 cm/year over the lower part of the basin.

This increasing trend probably reflects natural variability (increasing trend) of rainfall. In addition, the lower part of the Ganges basin where we observed positive trend lies within Madhya Pradesh. Madhya Pradesh experiences less intensive irrigation and less dependency on ground water for irrigation than Uttar Pradesh (where negative trend is observed) (Dhawan, 2017). Variations in soil type, crop type, and farmers' behavior in different regions may have also led to the positive trend. Though we found a positive trend/groundwater recharge over the lower part of the basin, the overall temporal trend suggested a depletion for the entire basin (Figure 6).

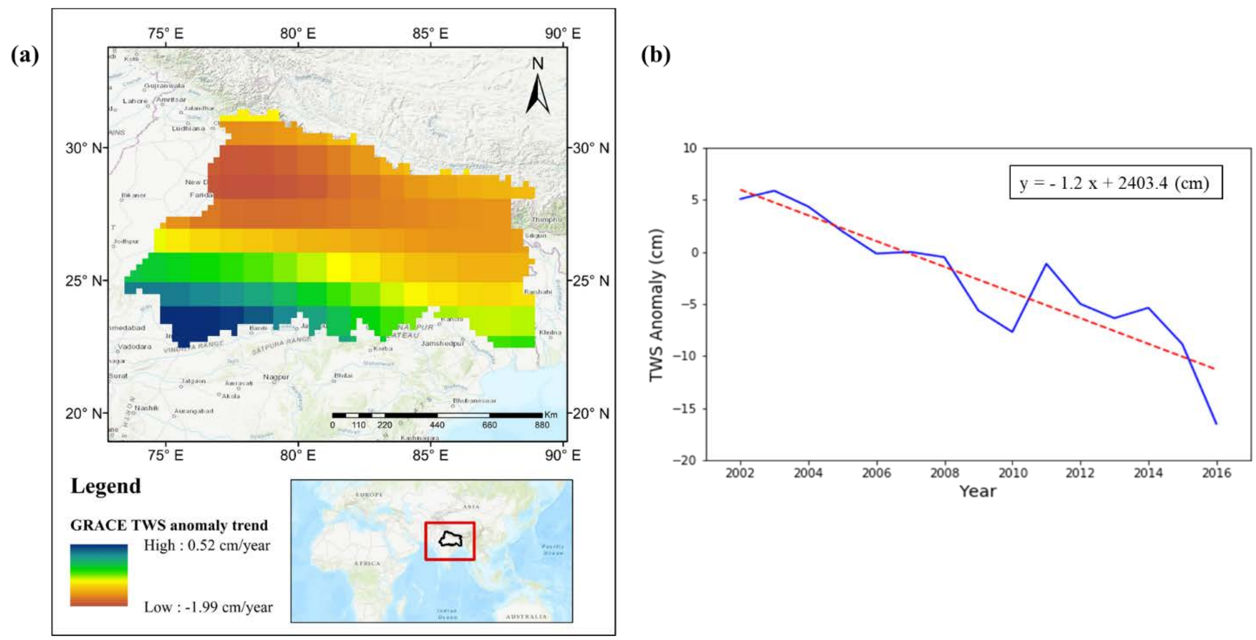


Figure 6: (a) Spatial and (b) temporal trend of GRACE TWS anomaly over Ganges basin from 2002 to 2016. The dark orange color in (a) represents the maximum negative rate of TWS anomaly (-1.99 cm/year) and the dark blue color represents the maximum positive rate of TWS anomaly (0.52 cm/year)

5.2 Identifying GRACE Spatial Scale of Analysis

Since we observed a negative trend of groundwater storage change over the Ganges basin (~80% area), we needed to find the scale at which GRACE can be incorporated to prioritize the zones for the improved IAS. We identified the representative scale by comparing GRACE TWS anomaly against the water budget model derived TWS anomaly derived from independent datasets (mentioned earlier in section 4.2). To compare these two sets of data, we used bias, RMSE, and Spearman's ranked coefficient as described in figure 7. Our results suggested that from sub-basin 3 (scale 600 km X 600 km), GRACE TWS anomaly matches closely with TWS from an independent water budget model. For example, the bias between the two TWS for sub-basins 1 and 2 varies from 19% to 26% and 17% to 23%, respectively (considering different precipitation products). However, the bias varies from 3% to 7% only when we considered sub-basin 3. Similarly, the spearman's ranked coefficient for sub-basins 1 and 2 varies from -0.36 to 0.05 and -0.35 to 0.05 respectively, whereas for sub-basin 3 the coefficient varies from 0.51 to 0.54. The RMSE over sub-basins 1 and 2 varies from 12.7 cm to 14.7 cm (~ 58 km^3 to 67 km^3) and 12.5 cm to 14.5 cm (~ 57 km^3 to 66 km^3) respectively, whereas over sub-basin 3 it varies from 10.2 cm to 11.1 cm (~ 46 to 50 km^3) only. As all the indices started to show better relationship between GRACE TWS and Water budget derived TWS on sub-basin 3, we decided to select the corresponding scale of 600 km X 600 km as the optimum scale to integrate GRACE TWS data with Landsat TIR data.

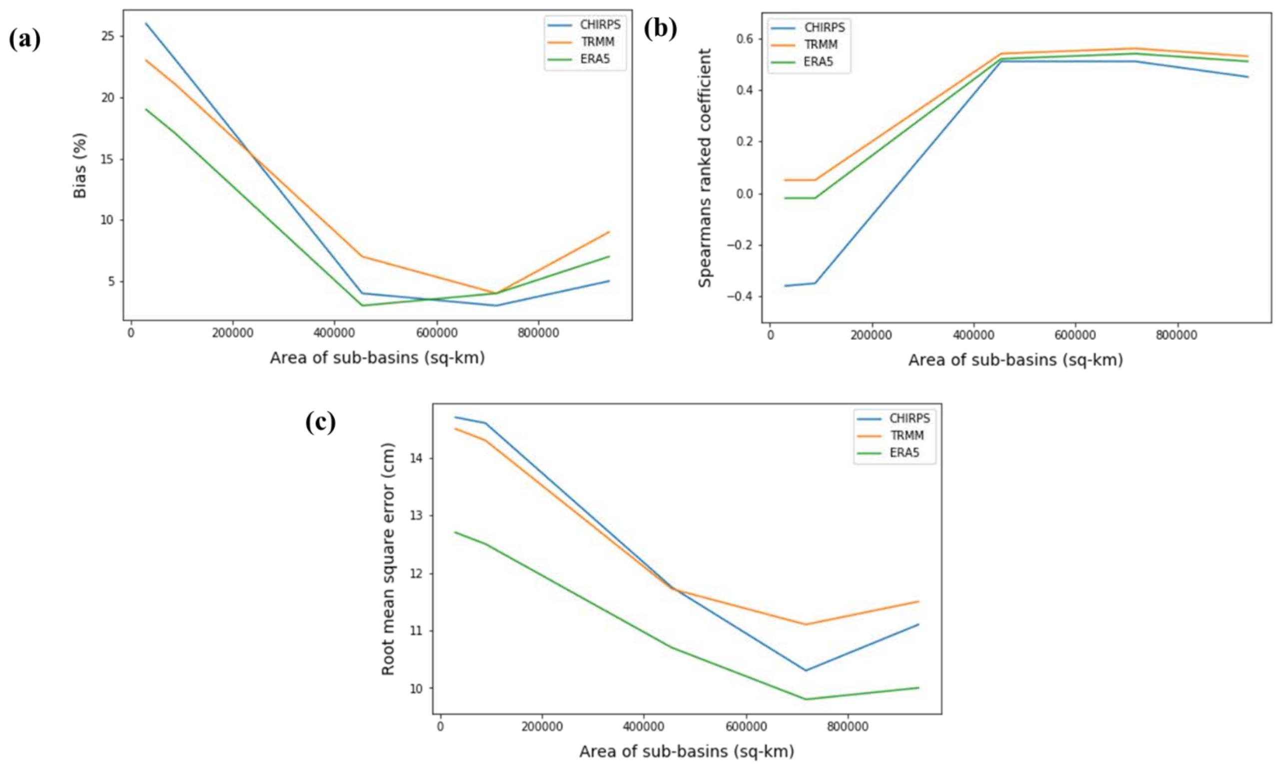


Figure 7: (a) Bias, (b) Spearman's rank coefficient, and (c) RMSE between GRACE TWS and water budget TWS anomalies from 2002 to 2014. Different colors represent results for different precipitation products (blue: CHIRPS, orange: TRMM and green: ERA5)

5.3 GRACE TWS Validation Using Water Budget Approach

We further verified GRACE-identified regions where groundwater is potentially declining due to excessive dry season irrigation at the selected scale of 600 km X 600 km (sub-basin 3 of Ganges basin). We compared the dry (winter) season averaged GRACE TWS and water budget TWS anomalies from 2002 to 2014. The results showed a similar decreasing pattern of GRACE TWS and water budget derived TWS anomalies, particularly from 2005 onwards (Figure 8). This similarity in trends between TWS derived from two sets of independent datasets support our hypothesis that GRACE TWS is a strong proxy for groundwater storage change during the dry season. The delta between two sets of TWS anomalies is expected considering the uncertainties involved in the water budget model. The blue curve in Figure 8 represents the water budget TWS anomaly using SEBAL ET. It essentially represents the actual ground condition of what was happening from 2002 to 2014. As SEBAL ET is the actual water consumption by plants, the storage change observed using SEBAL ET is a representation of actual storage change over the irrigated lands. As the decreasing storage pattern is clearly related to increasing SEBAL ET during dry season, we can postulate that the total storage or groundwater storage is going down due to increasing groundwater irrigation. A similar decreasing pattern indicates that dry season GRACE TWS is able to capture the signal of groundwater storage decline due to excessive dry season irrigation. We further verified using GLDAS-NOAH based TWS anomaly by comparing with SEBAL based and GRACE TWS anomaly (red curve). The dry season GLDAS based TWS anomaly resulted in a declining trend as well and the pattern of the curve agreed with other two TWS anomaly curves (Figure 8).

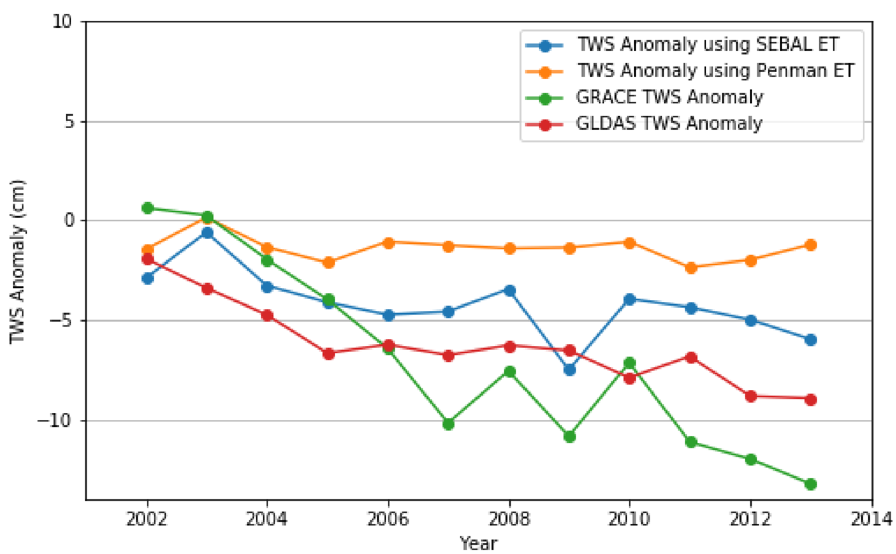


Figure 8: Verification of GRACE-identified region over sub-basin 3 of Ganges basin (Figure 3) where groundwater is potentially declining due to excessive dry season irrigation using water budget derived TWS. Green line represents dry season GRACE TWS, Red line represents dry season GLDAS TWS, blue line represents dry season water budget derived TWS using SEBAL ET, and orange line represents water budget derived TWS using Penman-Monteith ET.

The orange curve in Figure 8 shows another set of water budget derived TWS obtained using Penman-Monteith ET instead of SEBAL ET. As discussed before, the Penman-Monteith ET is the crop water demand, hence the TWS we are getting using Penman-Monteith ET is representing the scenario if need based irrigation (i.e. irrigating according to crop water demand) had been undertaken hypothetically from 2002-2014. We observed that switching to need based irrigation over the selected scale can potentially arrest the current depletion trends of groundwater (net change becomes negligible; Figure 8). We found that there is no declining trend of TWS when Penman-Monteith ET (need-based irrigation) is used in lieu of actual (SEBAL) ET that represents today's rampant waste of groundwater. Thus, we can postulate that it is theoretically possible to save extensive amounts of irrigation water during dry season by prioritizing the critical zones based on an IAS that can facilitate crop water need-based irrigation. We should note that, before using SEBAL ET and Penman-Monteith ET for our study, we had carried out an evaluation of SEBAL (observed) ET and Penman-Monteith ET using ground truth data over a location in Bangladesh called Gazipur where we had access to in-situ and quality controlled lysimeter data. This location is home to Bangladesh Agricultural Research Institute (BARI- Coordinates: 90.415024, 23.987559) in Bangladesh. Details on this evaluation are described in the supplementary section.

5.4 Verification of SEBAL ET over cropped regions

Our proposed integration of GRACE TWS and LANDSAT TIR data in an operational IAS is valid when we compare the relationship between SEBAL ET and groundwater table data. Before quantifying the impact of improved IAS, we verified the actual water consumption (ET) according to SEBAL method using DTW data (mentioned in section 3.4) to prove that the actual water consumption (SEBAL ET) is a proxy to groundwater table decline over dry season irrigated regions.

The correlation coefficients of SEBAL ET and DTW over the cropped regions of Kanpur Nagar, Kanpur Dehat, Agra, and Lucknow of Northern India are 0.76, 0.71, 0.79 and 0.75, respectively (Figure 9). Similarly, the correlation coefficients over the cropped regions of Sargodha, Layyah, Muzaffargarh, and Sheikhupura in Eastern Pakistan are 0.87, 0.79, 0.75 and 0.85, respectively (figure 10). These positive correlations indicate that with increasing ET (crop water consumption), the DTW increases consistently (water table lowers). Such consistent correlation provides strong evidence that actual water consumption (SEBAL ET) is a strong proxy for groundwater table decline during dry season over irrigated landscapes of South Asia.

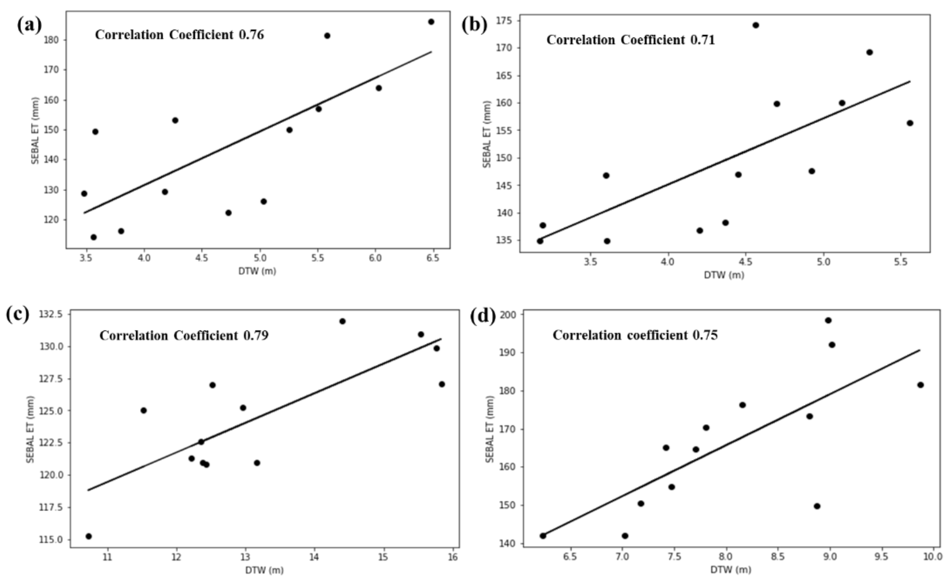


Figure 9: Correlation between SEBAL ET and depth to water table (DTW) during dry season (2002 to 2014) over cropped regions of (a) Kanpur Nagar, (b) Kanpur Dehat, (c) Agra, and (d) Lucknow. Each circle represents a dry season.

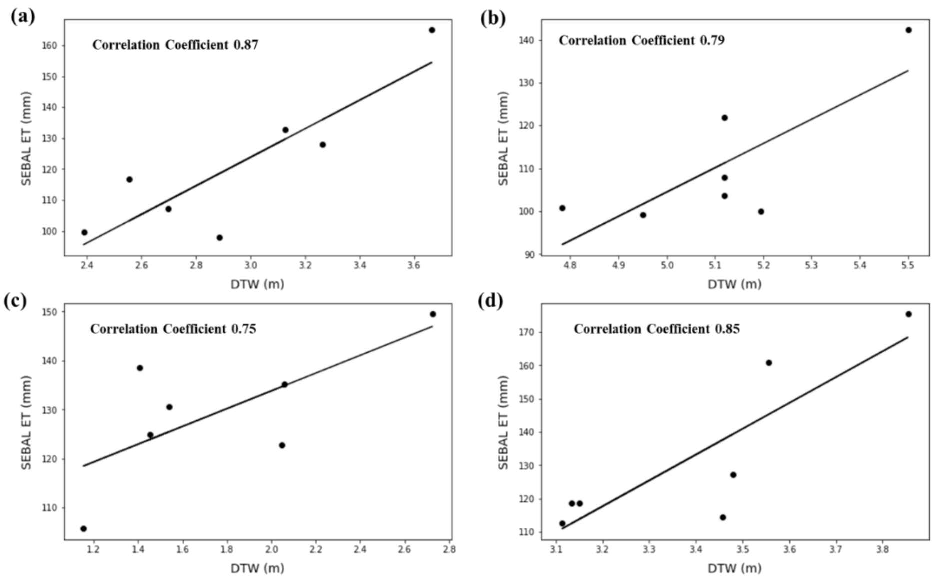


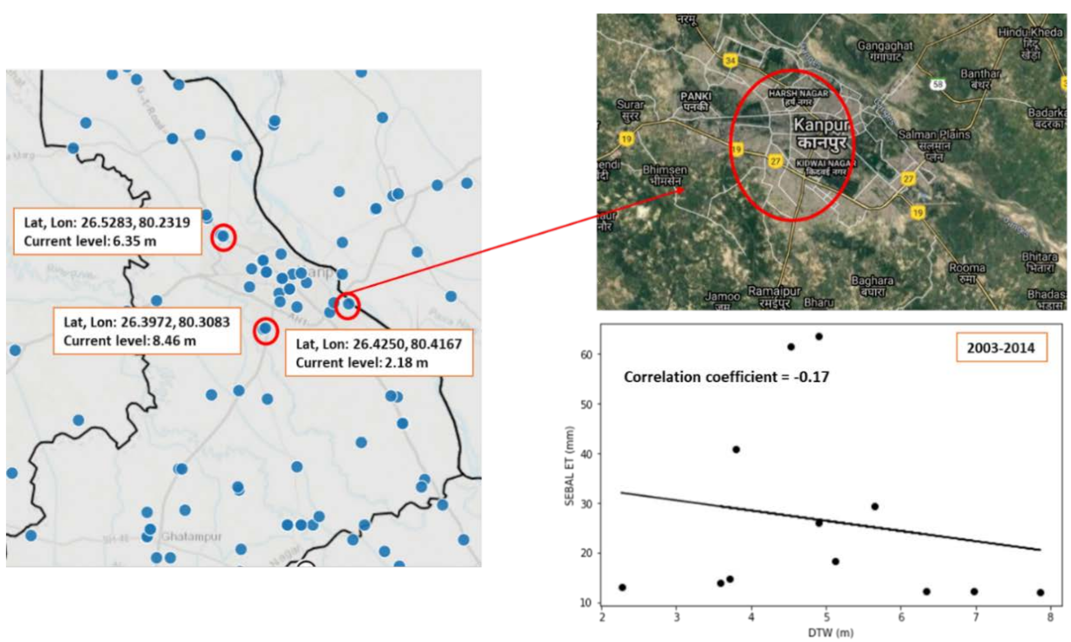
Figure 10: Correlation between SEBAL ET and depth to water table (DTW) during dry season (2005 to 2013) over cropped regions of (a) Sargodha, (b) Layyah, (c) Muzaffargarh, and (d) Sheikhupura. Each circle represents a dry season.

To further prove the role of SEBAL ET as a proxy for groundwater table change, we compared the DTW data over non-cropped regions (i.e. “control” or “placebo” regions where no crops are grown) of selected districts (Kanpur Nagar, Agra, and Lucknow) with SEBAL ET. We reported a low negative and near-zero correlation (Figure 11). For Kanpur Nagar, Agra, and Lucknow, the correlation coefficients of SEBAL ET and DTW are -0.17, -0.31, -0.03, respectively over non-cropped regions (figure 11). These correlations indicate that with increasing DTW (decreasing groundwater table), actual ET is not increasing over non-cropped (i.e., non-irrigated) regions. As the control points are over urbanized areas, we can speculate that the groundwater table is getting extracted to lesser amounts for non-agricultural purposes.

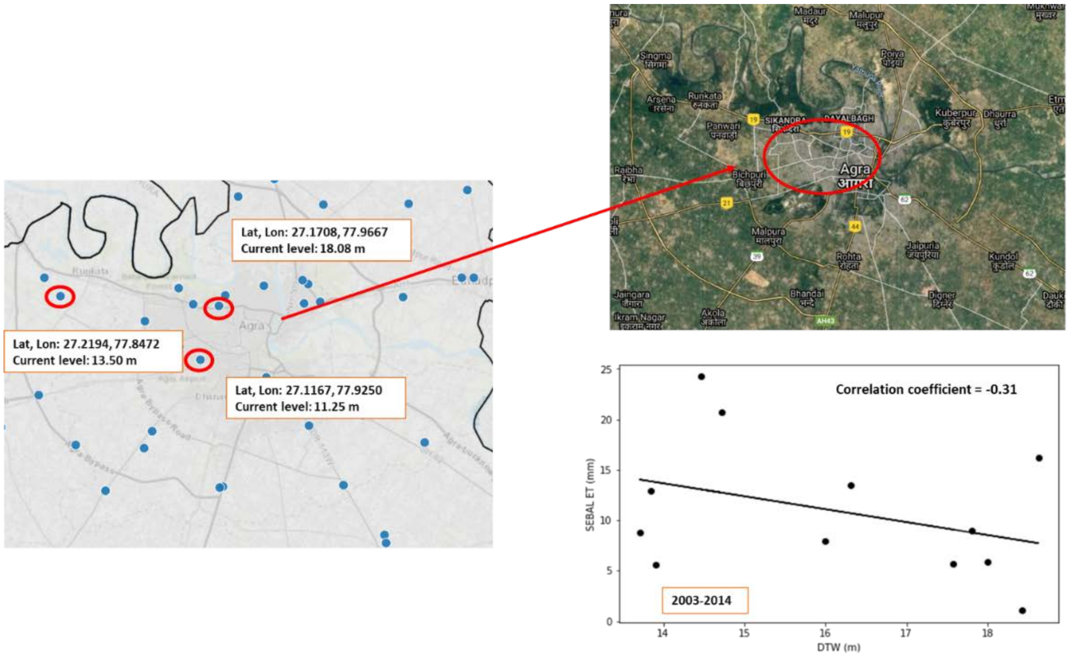
5.5 Potential irrigation water savings during dry season with IAS

The ultimate goal of this study was to validate if significant amount of water can be saved during dry season using need-based irrigation advisory for the targeted zones identified by GRACE and Landsat TIR data. Hence, we compared the actual water consumption by plants and water required for crop growth and calculated the percentages of over/under irrigation over the selected irrigation districts. The percentages of over-irrigation demonstrated by our results represent the potential savings of groundwater if there was an IAS service in place during dry seasons from 2002 to 2014 in the irrigation districts. The spatial variation of percentages over/under irrigations over those 8 irrigation districts are shown in figures 12 and 13. Different colors in the map, represent different range of percentages. Red represents the areas with over-irrigation greater than 100% (severe over-irrigation). The orange, yellow, and green colors indicate the areas with over-irrigation varying between 50-100% (moderate over-irrigation), 0-50% (mild over-irrigation) and less than 0% (under irrigation), respectively. We observed that there are extensive areas within each irrigation district that are suffering from severe or moderate over-irrigation.

(a)



(b)



(c)

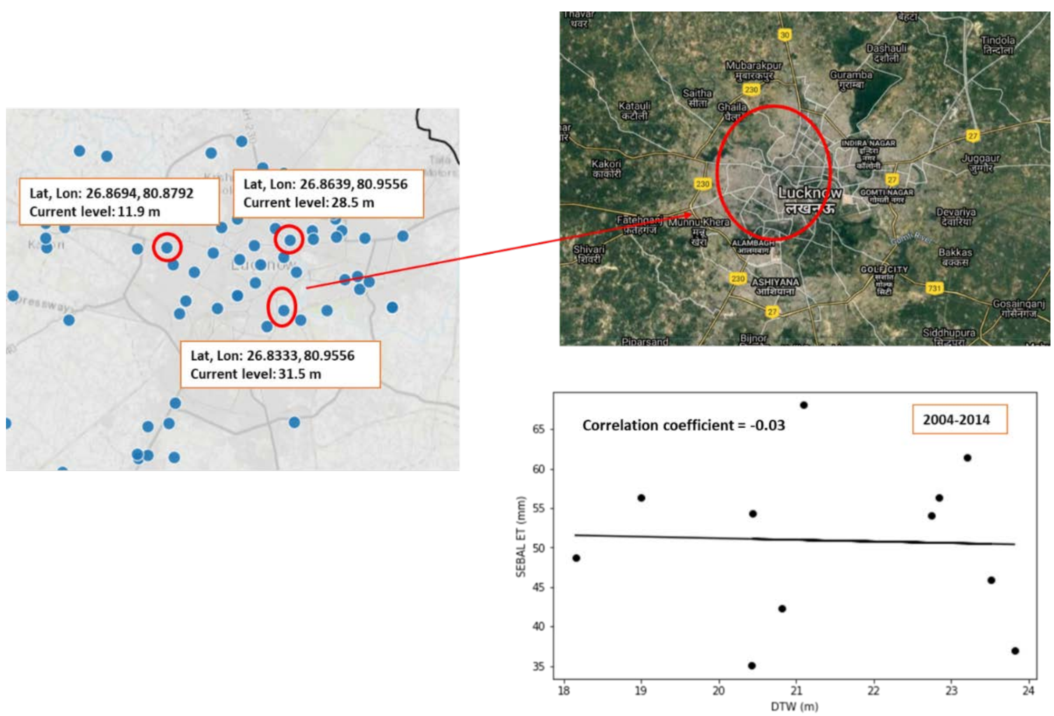


Figure 11: Correlation between SEBAL ET and DTW during dry season over control regions (non-cropped) of (a) Kanpur Nagar, (b) Agra, and (c) Lucknow.

Next, we summarized our multi-year analysis of ET data to understand the pattern of average irrigation scenario for each month of the growing season during the dry season (Figures 14 and 15). The results suggested a similar pattern of over-irrigation over the selected districts. The higher percentages of over-irrigation (median and 75th percentile greater than 100) associated with wheat were observed at the beginning of dry season (November, December and, January) with maximum variability and then again in April. For instance, in Figure 14 (a), for Indian irrigation districts, the median value during November is approximately 150% and the variability of 25th and 75th percentiles are around 130% and 170%, respectively. The medians and variabilities are much lower during February and March (below 100%). The median value (~80%) and variabilities of 25th and 75th percentiles (~30% to 150%) again increased during April. All other districts showed similar patterns, with expected variabilities due to variation in soil type, soil moisture condition, weather conditions and farmers' irrigation practice.

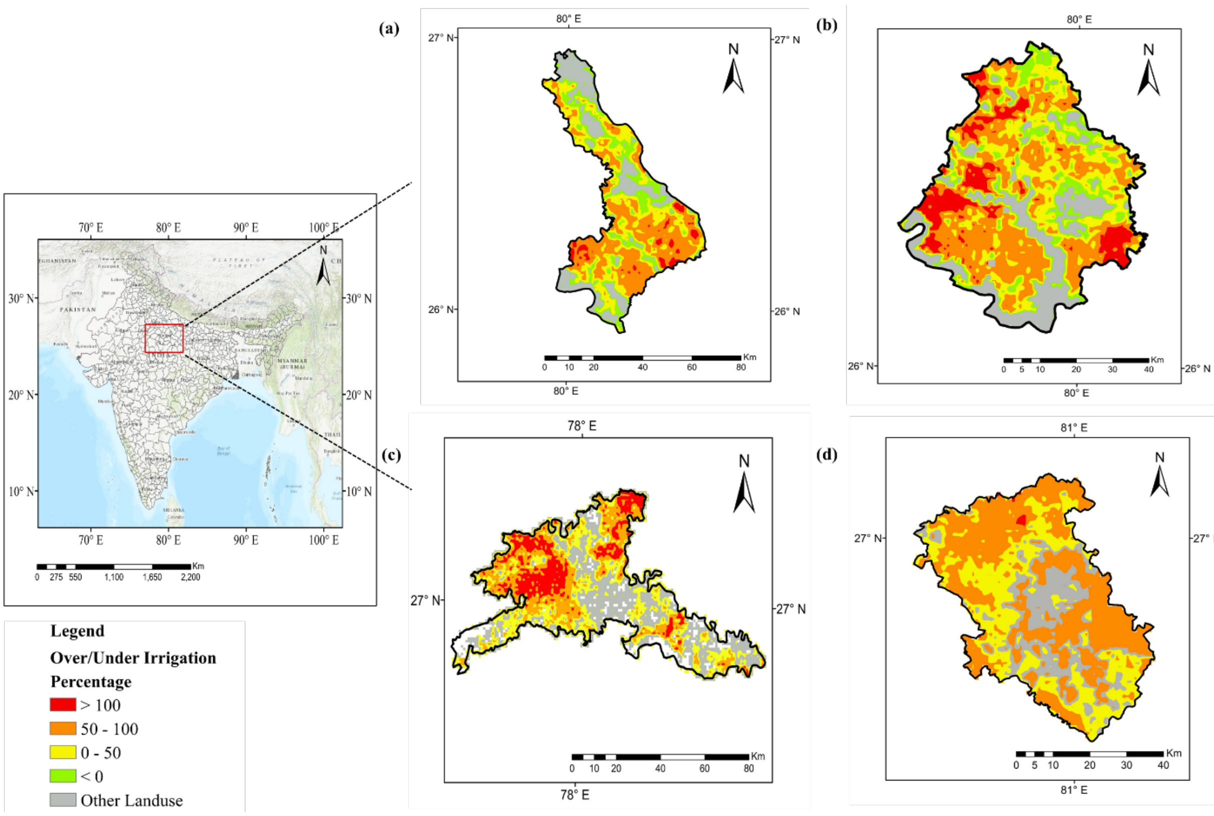


Figure 12: Spatial variation of over/under irrigation (January 2013) over (a) Kanpur Nagar, (b) Kanpur Dehat, (c) Agra, and (d) Lucknow in India. Colors showing red, orange, yellow, and green represent percentages greater than 100 (severe over-irrigation), 50-100 (moderate over-irrigation), 0-50 (mild over-irrigation), less than 0 (under irrigation), respectively. Grey color represents the uncropped areas. The scale of the data used is 60mX60m from Landsat TIR bands.

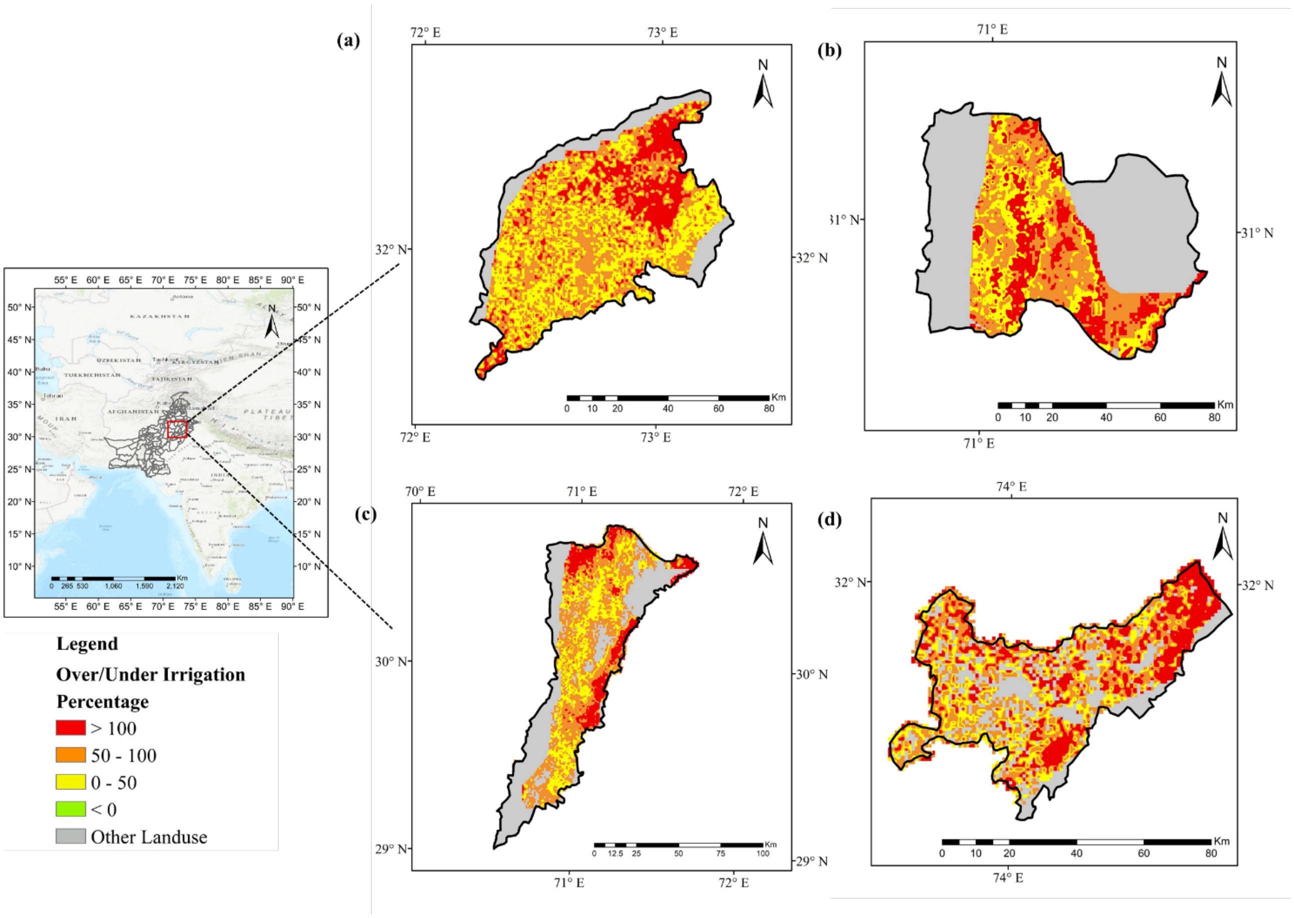


Figure 13: Spatial variation of over/under irrigation (January 2013) over (a) Sargodha, (b) Layyah, (c) Muzaffargarh, and (d) Sheikhupura in Pakistan. Colors showing red, orange, yellow, and green represent percentages greater than 100 (severe over-irrigation), 50-100 (moderate over-irrigation), 0-50 (mild over-irrigation), less than 0 (under irrigation), respectively. Grey color represents the uncropped areas. The scale of the data used is 60mX60m from Landsat TIR bands.

Given the traditional irrigation practice in South Asia, we are speculating that the higher percentages of over-irrigation at the beginning of dry (winter) season is due to over watering the seeds and young plants or watering more frequently than needed due to the initially-dry soils. Because of this excess/frequent watering, the monthly sum of SEBAL ET (actual water consumption) is higher, which in turn gives us the higher percentage of over-irrigation. In April, as the crop is ready for harvest, a high percentage of over-irrigation may be an effect of some other anticipated effects. For example, there could be an overlap of the rice-growing season that begins in April. In some districts of India there is winter rice that grows simultaneously with wheat and in some districts of Pakistan sugarcane starts growing from April (FAO, 2020). Due to unavailability of high-resolution and time-varying crop maps, we considered only wheat grown all over the cropped regions on targeted districts. Thus, Penman-Monteith ET provided much smaller values than what it should be, whereas SEBAL ET estimated the actual water consumption. This may potentially result in a high over-irrigation percentage not entirely attributable to the harvested stage of wheat in April. In addition, we assumed Ks = 0.5 for estimating the crop water demand which might be different in the actual scenario based on the soil moisture condition and the pre-monsoon thunderstorms that are common in April. We also estimated SEBAL and Penman-Monteith ETs averaged over the entire cropped regions where plot types, farmer's behavior in decision-making (to irrigate or not to irrigate) may vary and can introduce variability in the estimated percentages in each district.

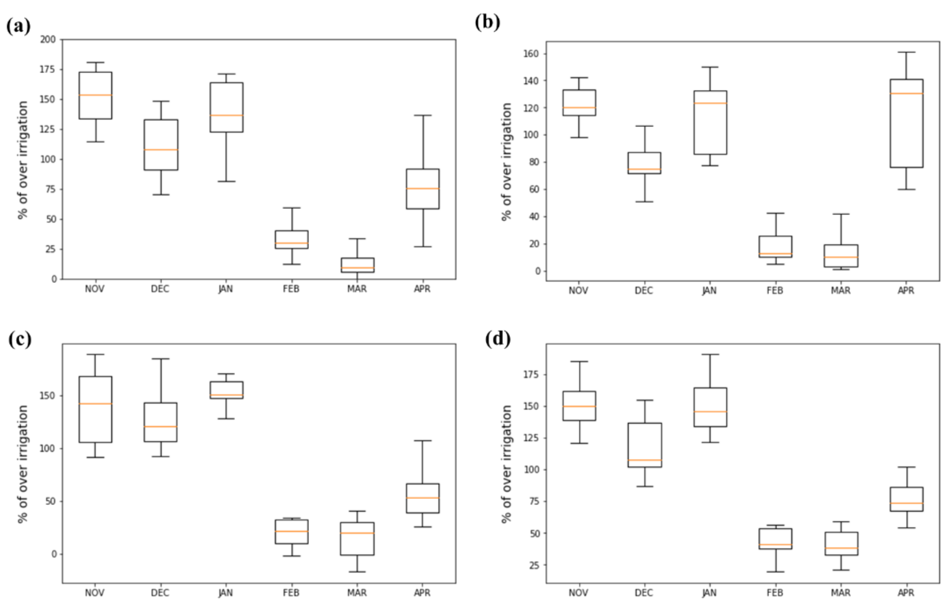


Figure 14: Percentages of over-irrigation (considering wheat) during dry season over (a) Kanpur Nagar, (b) Kanpur Dehat, (c) Agra, and (d) Lucknow. The orange lines of the boxplots correspond to the median values of percentages of over-irrigation.

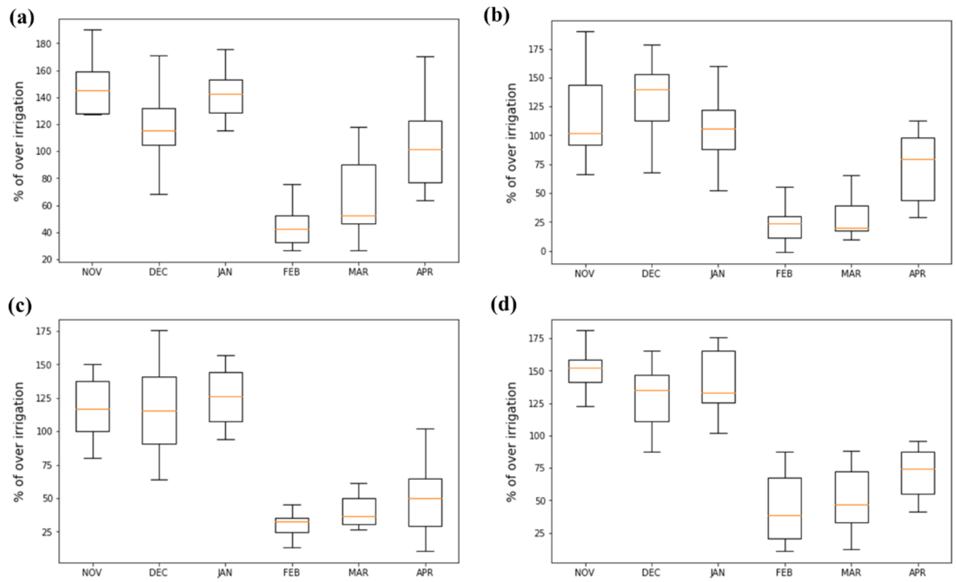


Figure 15: Percentages of over-irrigation (considering wheat) during dry season over (a) Sargodha, (b) Layyah, (c) Muzaffargarh, and (d) Sheikhupura. The orange lines of the boxplots correspond to the median values of percentages of over-irrigation.

We evaluated that the multi-year assessment of irrigation corresponded to an average amount of up to 85% (~80 million m^3), 80% (~90 million m^3), 85% (~ 95 million m^3), and 87% (~ 65 million m^3) groundwater that could be potentially saved during dry season over Kanpur Nagar, Kanpur Dehat, Agra, and Lucknow, respectively if farmers followed the IAS advisory. Similarly, an average amount of up to 97% (~160 million m^3), 77% (~140 million m^3), 78% (~ 155 million m^3), and 95% (~ 150 million m^3) groundwater could be potentially saved during dry season over Sargodha, Layyah, Muzaffargarh, and Sheikhupura, respectively. Hence, with an improved IAS, an average amount of 85% (80 million m^3) and 87% (150 million m^3) of groundwater could be saved during a dry season in districts of Northern India and Eastern Pakistan, respectively. It should be noted that this potential saving (> 80%) is much larger than the earlier surveyed savings of 40% of groundwater with the current IAS that does not precision-target regions based on groundwater waste footprint.

6. Conclusions

According to our study, the improvement of an existing operational IAS may help reduce the excessive pumping (during dry season) of groundwater in South Asia where agricultural expansion remains a critical threat to groundwater sustainability. Proper use of an improved IAS service that can target in a precise manner the most over-irrigating regions, given the limited bandwidth for outreach, can reduce even further the cost of both fuel for pumping and irrigation advisory texts. In this study, we have argued that an operational IAS can even be more effective if we integrate the GRACE TWS and Landsat TIR data to strategically target regions with more alarming rates of depletion, followed by advising specific farmers and their plots (at scale of 60 m X 60 m) on how much to reduce pumping.

Our results demonstrated the importance of GRACE TWS data to cost-effectively and rapidly identify the most critical regions of unsustainable groundwater decline due to excessive dry season irrigation. The rate of groundwater decline during the dry season may vary from year to year and is difficult to monitor due to lack of in-situ monitoring in South Asia. To maximize the impact of IAS, we focused on a local/district scale and selected eight irrigation districts from Ganges and Indus basins based on the DTW analysis. We compared the relationship of actual water consumption of crops based on SEBAL method with groundwater table data to verify the idea of using GRACE TWS and LANDSAT TIR data in an operational IAS. Strong correlation ranging from 0.71 to 0.79 and 0.75 to 0.87 were found over the Ganges and Indus Basins' districts, respectively. Such consistent correlations provide strong evidence on integration of LANDSAT TIR data to monitor the extent of over-irrigation in an IAS to advise farmers where and when to reduce pumping and stabilize groundwater tables in future. However, a quick identification of over irrigation over a large spatial scale is the first step to taking corrective measures. Once it is established that significant over-irrigation is taking place over a large region (as might be potentially indicated by GRACE data), water managers can then zoom in and apply more localized diagnostics (such as Landsat based ET water tracking for over-irrigation or other alternatives). For example, in those large regions, once the hot spots are further verified with Landsat and other location information, one can then take very localized corrective measures such as growing rice over raised beds. Studies indicate that such technique result in significant water savings (Soomro et. al 2015).

Advantage of using freely available global satellite observations at high spatial and temporal resolutions makes our proposed improved IAS conceptually transferable to any region in the world where unsustainable dry season irrigation is suspected. Farmers can benefit from such satellite based precision-targeting IAS by observing how extensive the groundwater waste is when compared to crop water need. The IAS advisory may then encourage farmers to pump less based on crop water needs. Monitoring of SEBAL ET can also help detect behavioral change of farmers in reducing over-irrigation during dry season. Finally, follow up evaluation of GRACE TWS over a larger spatial scale and longer follow-up time period can be explored to understand the effectiveness of an improved IAS that has been in continuous service and whether there is merit in continuing the IAS if there is no tangible impact for national water agencies.

We believe that with such an improved IAS operationalized, the net savings in groundwater can allow the aquifers the necessary breathing space to recharge a little more with each year's monsoon rainfall in South Asia. As our first practical trial, we are planning to improve the existing IAS in Pakistan with our proposed methodology to save groundwater resources cost effectively and track the long-term impact of this improved IAS. We plan to develop a cloud computing-based tool where GRACE TWS data will be integrated with Landsat TIR in the existing IAS used by

PCRWR of Pakistan. This tool will empower PCRWR to find the vulnerable groundwater zones much more rapidly at a scale of 600 km X 600 km (or smaller if necessary). The tool will then help PCRWR zoom in those zones to identify a much higher resolution map on the extent of over-irrigation at the farmer or plot scale using Landsat TIR at 60m X 60m. Such a tool will then make it easier for PCRWR to prioritize zones, farmers and plots that need to be sent irrigation advisory given that only a finite and small fraction of the 4 million farmers of Pakistan can receive such a service today. We hope to report the experience of developing and implementing such a tool for prime time use by a stakeholder in a forthcoming publication.

Data Availability Statement:

All remote sensing data used in this study are publicly available at GEE data catalogue: https://developers.google.com/earth-engine/datasets/catalog (see section 3 for finding the links to each dataset). In-situ well data are available from https://indiawris.gov.in/wris/.

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Author Role: Indira Bose conceptualized the study, analyzed data, wrote the manuscript. Faisal Hossain conceptualized the study, edited the manuscript and coordinated with other co-authors who have been involved in irrigation advisory in South Asia. Hisham Eldardiry, Shahryar Ahmad and Nishan K. Biswas edited the manuscript and provided the necessary tools, codes and training on the use of cloud computing and remote sensing data. Zeeshan Ahmad was involved in developing the irrigation advisory system for Pakistan and provided input for correctly describing how it was set up. Hyongki Lee edited the manuscript and helped analyze GRACE data. Authors Mazharul Aziz and Md Shah Kamal Khan of Bangladesh Department of Agricultural Extension provided input on editing and understanding implications of the findings for launching the improved irrigation advisory system for People's Republic of Bangladesh. All co-authors edited the manuscript, provided input in the design of the study, and helped analyze data.

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[Journal of Water Resources Research]

Supporting Information for

[Integrating Gravimetry Data with Thermal Infra-red Data from Satellites to Improve Efficiency of Operational Irrigation Advisory in South Asia]

[Indira Bose[1], Faisal Hossain[1], Hisham Eldardiry[1], Shahryar Ahmad[1], Nishan K. Biswas[1], Ahmad Zeeshan Bhatti[2], Hyongki Lee[3], Mazharul Aziz[4] and Md. Shah Kamal Khan[4]]

[[1]Department of Civil and Environmental Engineering, University of Washington, Seattle, USA, [2]University of Prince Edward Island, Charlottetown, Prince Edward Island, Canada, [3]Department of Civil and Environmental Engineering, University of Houston, Houston, USA, [4]Department of Agricultural Extension, Khamarbari, Farmgate, Dhaka, Bangladesh]

Contents of this file

Text S1
Figures S1 to S3
Tables S1

Introduction

This supporting information provides detail on evaluation of the SEBAL ET and Penman-Monteith ET results using ground truth data that has been referred in subsection 5.3 of the main article.

Text S1.

We have carried out an evaluation of SEBAL (observed) ET and Penman-Monteith ET using ground truth data over a location in Bangladesh called Gazipur where we had access to in-situ and quality controlled lysimeter data. This location is home to Bangladesh Agricultural Research Institute (BARI- Coordinates: 90.415024, 23.987559) in Bangladesh. We were provided lysimeter data for 2017 and 2018 for a number of crops.

First, we collected length of crop growth period, crop coefficients, and total water use based on lysimeter data from BARI. We considered wheat, maize and sunflower with an average 120 days (December to March) growing period for these three crops. Then we calculated Penman ET (cropwater demand) and SEBAL ET (observed ET) for the time periods of 2017 and 2018. Figure S1 below shows the comparison between SEBAL ET and in-situ lysimeter based total water use from BARI data. Figure S2 shows comparison between Penman-Monteith ET and in-situ lysimeter based total water use from BARI data. For 2017 and 2018, the % errors between SEBAL ET and lysimeter based total water use, and Penman-Monteith ET and lysimeter based total water use are provided in table S1. We see that for wheat and maize, Penman-Monteith ET matches well with total water use. This indicates that our Penman ET estimation method is robust based on the input data that is used. The % errors in case of SEBAL (actual ET) are understandably larger but the trend is similar. SEBAL ET is an areal average over 100 X 100 m pixel and it is quite likely that other land use and crops are within that pixel centered around the BARI coordinates. The correlation between Penman-Monteith ET and lysimeter based total water use was found to be very strong. For 2017 and 2018, the correlation between Penman-Monteith ET for three crops and lysimeter based water use are 0.88 and 0.87, respectively.

In another study reported in Hossain et. al. (2020), we demonstrate robust validation of ET estimation techniques for Kanpur city in the Gangetic plains of India. In Kanpur, we had automatic weather stations (AWS) and carried out an ET-based irrigation advisory scheme during 2018-2019 for 150 winter wheat farmers. There, we evaluated weekly crop water demand calculated using Penman-Monteith ET based on meteorological variables from Global Forecasts System (GFS) and those obtained from in-situ measurements from AWS (figure S3 below). We see clearly that the GFS-based Penman estimation technique matches closely with that based on weather and radiation data from an AWS. The results suggested that there is a good agreement between these two datasets with 6.96 mm RMSE and 0.98 mm bias per week.

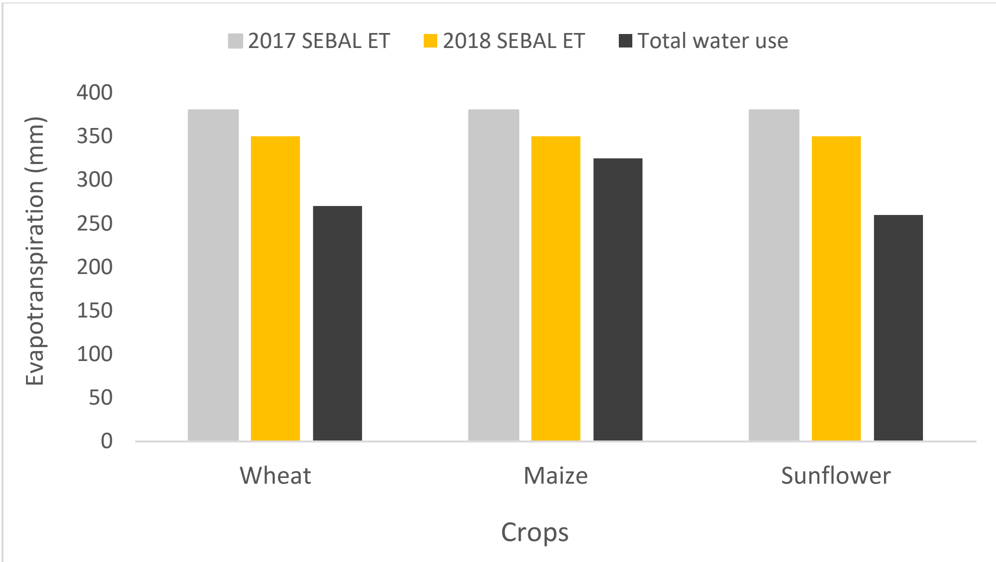

Figure S1. Comparison of SEBAL ET and lysimeter based total water use over the growing season for 2017 and 2018 at BARI field station.

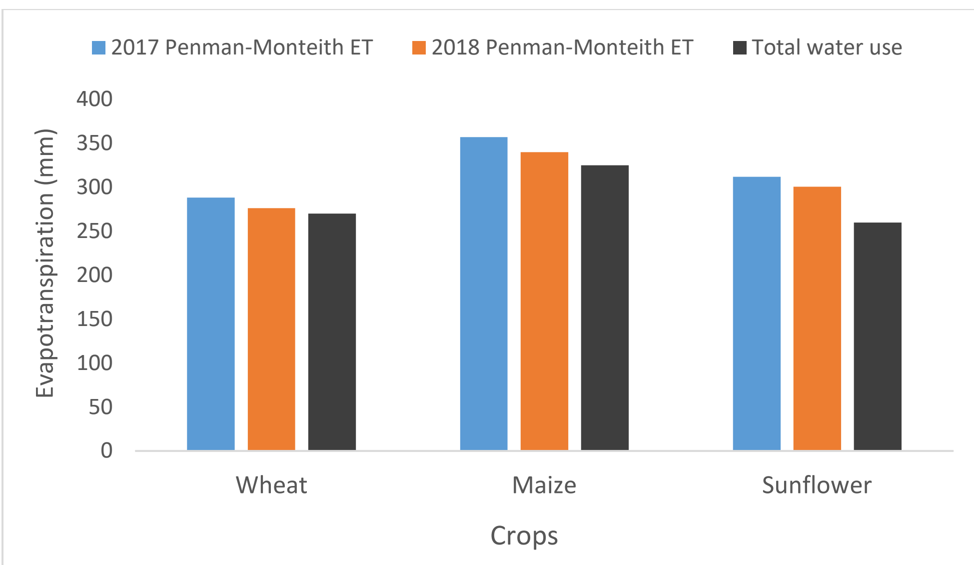

Figure S2. Comparison of Penman-Monteith ET and lysimeter based total water use over the growing season of 2017 and 2018 at BARI field station.

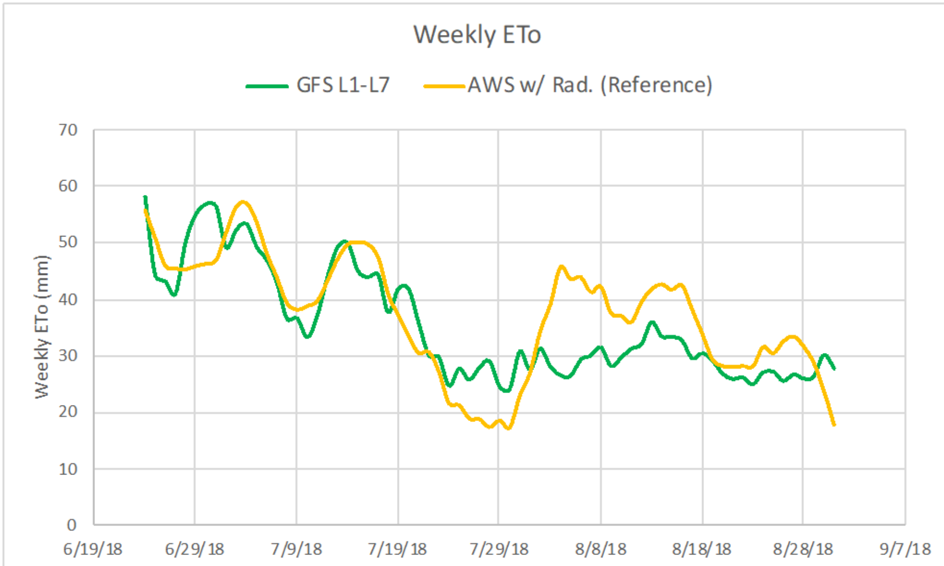

Figure S3. Comparison of weekly actual Penman-Monteith ET based on GFS and AWS data in Kanpur, India in 2018. L1-L7 represents the weekly total using GFS data.

Year	Crops	% error between Penman-Monteith ET and lysimeter based total water use	% error between SEBAL ET and lysimeter based total water use
2017	Wheat	6.80	40.74
	Maize	9.88	16.92
	Sunflower	20.01	46.15
2018	Wheat	2.28	29.63
	Maize	4.59	7.69
	Sunflower	15.65	34.62

Table S1. % errors between SEBAL ET and lysimeter based total water use, and Penman-Monteith ET and in-situ lysimeter based total water use data at the BARI field station.