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Key Points:

- Comprehensive comparison of satellite- and modeling-based irrigation water use rates
- Where discrepancies between satellites and models are higher, the added value of remote sensing in reproducing ground truth emerges
- The integration of satellite-based irrigation water use estimates into modeling platforms is encouraged

Supporting Information:

Supporting Information may be found in the online version of this article.

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Satellite-Based Estimates of Irrigation Water Use Versus Modeling Reconstructions: How Much do They Differ?

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Abstract Knowing water amounts destined for agricultural practices, essentially consisting of irrigation water use (IWU), is essential for water resources management. Although explicit and consistent information on IWU is generally lacking worldwide, remote sensing and modeling platforms offer valuable solutions for estimating it. The objective of this work is to perform an intercomparison between satellite-based IWU products and modeling reconstructions over four main irrigation hotspots worldwide: the Contiguous United States (CONUS), the Ebro basin (Spain), India, and the Murray-Darling basin (Australia). Remote-sensing-based IWU estimated through Soil-Moisture-Inversion (SM-Inversion) and SM-Delta approaches are considered. As modeled data, five Global Hydrological Models are evaluated: H08, PCR-GLOBWB, WaterGAP, LPJmL, and QUAAlloc. Reference irrigation volumes are exploited to assess which source is more reliable. Over CONUS and Murray-Darling basin, lower discrepancies between data sources (satellite or modeling) are detected. Referring to spatially-averaged IWU magnitudes, the comparison over CONUS provides RMSE ranging from 9.52 to 12.21 mm/month, BIAS between 3.24 and 7.06 mm/month, and Pearson correlation (r) from 0.77 to 0.90. The same intervals for the Murray-Darling basin are 8.04–17.70 mm/month for RMSE, 4.81–12.63 mm/month for BIAS, and 0.42–0.85 for r . Consequently, over such areas, similar performances in reproducing actual irrigation amounts by satellite estimates and modeling reconstructions, when available, are found. Over the Ebro basin, where the strongest discrepancies are found, satellite-based data sets outperform model outputs in reproducing reference data. The lack of in situ observations for India prevents a clear assessment of the results, but insights on differences introduced by parametrizations are established.

Plain Language Summary Understanding how much water is used for irrigation is crucial for a rational management of water resources, but this information is often unavailable worldwide. Satellite observations and model simulations can be used to estimate the amounts of water used for irrigation. Both approaches carry intrinsic strengths and limitations. For this reason, this work is aimed at comparing state-of-the-art satellite- and model-based irrigation water use (IWU) estimates over four case studies: the Contiguous United States (CONUS), the Ebro basin (Spain), India, and the Murray-Darling basin (Australia). Results highlight that the two data sources provide comparable estimates over CONUS and the Murray-Darling basin. Where discrepancies between satellites and models are higher (i.e., the Ebro basin), satellite-based estimates reproduce ground truth better than model-based ones. Overall, results (especially over India) highlight the need for more integration of remotely sensed irrigation dynamics into models.

1. Introduction

The exploitation of water resources by humans for various purposes has always been a sign of progress, accompanying and often promoting the evolution of several civilizations (Hosseiny et al., 2021; Pietz and Zeisler-Vralsted, 2021). Humans use water for agricultural, industrial, and civil purposes. Such uses contribute to maintaining high levels of well-being, but in quantitative terms, the volumes of water used for the agricultural sector, primarily consisting of irrigation water use (IWU), far exceed (i.e., around 80% of the total abstractions) those used for industrial and civil purposes (Abbot et al., 2019). Detailed knowledge of irrigation volumes is strategic for socio-economic reasons (Fischer et al., 2022; van Maanen et al., 2022) as well as for properly characterizing water and energy balances (Dari, Quintana-Seguí, et al., 2024; Lachenmeier et al., 2024; Maina et al., 2024; Udina et al., 2024). However, explicit data on IWU is rarely available, if not generally absent worldwide (Dorigo et al., 2021). Currently, the main sources of spatio-temporal distributed regional or global

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estimates of IWU are remote sensing observations and modeling data sets; census-derived statistics are a supplementary source of information, but often not dynamic in time and with limitation due to coarse spatial aggregation (Dorigo et al., 2021; McDermid et al., 2023).

The use of satellite-retrieved hydrological variables and/or vegetation indices as proxies for monitoring irrigation dynamics has recently spread, resulting in several studies focused on irrigation detection in space and time (Dari, Morbidelli, et al., 2024; Deines et al., 2019; Elwan et al., 2022; Gao et al., 2018; Le Page et al., 2020), and, more challenging, on irrigation quantification (Brocca et al., 2018; Brombacher et al., 2022; Dari et al., 2025; Jalilvand et al., 2019; Kragh et al., 2024, 2025; Zappa et al., 2024). Leveraging satellite data for irrigation detection and quantification brings the benefit of relying on observations, underlying the capability of detecting changes in features of the land surface regardless of their nature (i.e., natural or anthropogenic). On the other hand, remote sensing retrievals of irrigation detection and quantification suffer from limitations due to their intrinsic spatial and temporal resolutions. Previous studies highlighted the importance of disposing of remotely sensed observations whose spatio-temporal resolution matches with irrigation dynamics (i.e., extension and timing) to properly reproduce them (Lalluet et al., 2024; Zappa et al., 2022, 2024).

Global Hydrological Models (GHMs) are increasingly equipped with specific modules for reproducing anthropogenic activities, representing a valid alternative to reconstruct IWU (to cite a few, de Graaf et al., 2014; Hanasaki et al., 2018; Pokhrel et al., 2015; Rost et al., 2008; Wada et al., 2013; Zhou et al., 2020). Their main advantage consists of providing continuous simulations in space and time, but they are sensitive to underlying assumptions that can fail in reliably reproducing human dynamics. For instance, irrigation can be triggered by soil-moisture-deficit thresholds or by missing amounts of rainfall needed to equal crop evaporation (Haddeland et al., 2006). Even though the same assumptions are often at the basis of guidelines commonly applied in agriculture, real dynamics can diverge due to farmers behavior or automated procedures. In addition, as highlighted by Zhou et al. (2020), GHMs are subject to uncertainties linked to the allocation of irrigation water sources or rely on simplifications, such as the neglect of actual water availability for satisfying a certain irrigation demand. The meteorological forcing used can be another source of potential uncertainties (Huang et al., 2018a).

This study aims at comparing satellite- and modeling-based IWU estimates over four case studies: the Contiguous United States (CONUS), India, and the Ebro and Murray-Darling basins in Spain and Australia, respectively. All the considered data sets are open-access. The satellite-based IWU products were recently released by Lalluet et al. (2025) and rely on the Soil-Moisture-Inversion (SM-Inversion; Dari et al., 2023) and on the SM-Delta (Zappa et al., 2024) methods. IWU from four GHMs, available through Huang et al. (2018b) plus outputs from QUAAlloc (Cárdenas Belleza et al., 2024), have been considered. The rationale of this work is to assess discrepancies between IWU estimates from remote sensing and modeling platforms over areas where the knowledge of irrigation amounts is crucial. Furthermore, where possible in light of the availability of in situ data, an assessment is carried out to determine which data source aligns closer to the real-world dynamics.

2. Case Study Regions

Four main irrigation hotspots worldwide have been selected as case studies. They are CONUS, the Ebro basin (Spain), India, and the Murray-Darling basin (Australia). The central role of irrigation with respect to water budget dynamics and to land-atmosphere interactions over all these areas is widely documented in literature (Dari, Quintana-Seguí, et al., 2024; Dangar et al., 2021; Ketchum et al., 2023; Kirby et al., 2014; Lachenmeier et al., 2024; Lunel et al., 2024, to cite a few). The Köppen–Geiger classification (Beck et al., 2018) for the pilot areas is shown in Figure 1. By cross-referencing this information with the distribution of areas equipped for irrigation provided in Supporting Information S1 (see Figure S1 in Supporting Information S1), it results that over CONUS, irrigation is mainly practiced in the West, characterized by cold semiarid climate (BSk) switching to hot and cold desert climates (BWh and BWk, respectively). To a minor extent, irrigation is practiced in the Eastern portion of CONUS as well, under humid subtropical conditions (Cfa). Well-known irrigation hotspots are located, among the others, in California Central Valley, Nebraska High Plains, portions of Idaho, the Mississippi Floodplain, and the Saint Luis Valley (Zaussinger et al., 2019). In the Ebro basin, irrigation is mainly practiced over hot and cold semiarid climatic zones (BSH and BSk, respectively). The central valley of the Ebro basin is crossed by a dense network of irrigation canals fed by a system of reservoirs on the slopes of the Pyrenees (Dari et al., 2020). A high heterogeneity in terms of applied irrigation techniques can be found (Paolini et al., 2023). Irrigated areas in India cover most of the country and are still expanding (Mehta et al., 2024); they are mainly

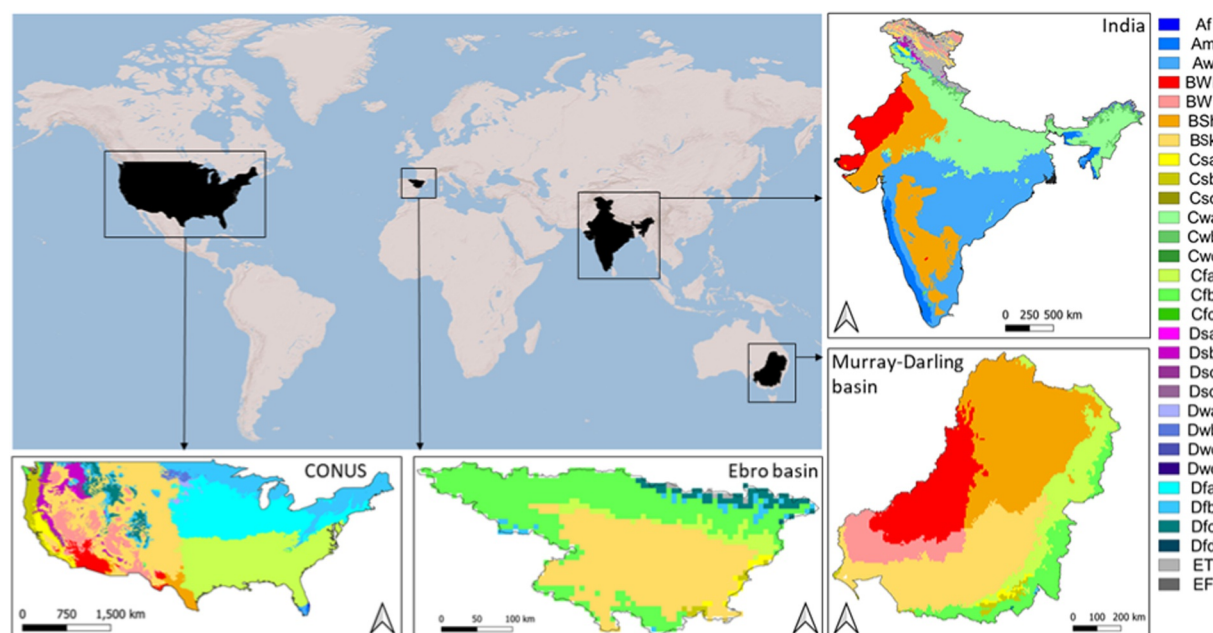


Figure 1. Case studies and their climatic features according to the Köppen–Geiger classification. The Miller Cylindrical projection (ESRI: 53003) is adopted for the world map in the upper left.

concentrated in the Northern part of the country, interested by a humid subtropical climate (Cwa), and in hot semiarid and desert (BSh and BWh, respectively) zones in the Western side. More than 85% of groundwater withdrawals in India are destined to irrigation, thus making the country the world's major user of sub-surface water resources (Giroto et al., 2017). Previous studies highlighted decreasing trends of groundwater storage in Northeastern India attributable to the pumping for irrigation (Asoka et al., 2017; Rodell et al., 2009). Finally, in the Murray-Darling basin, irrigation mainly occurs over hot and cold semiarid areas (BSh and BSk, respectively). The Murray-Darling basin is often considered as the food bowl of Australia and it accounts for over two-thirds of all the IWU at the country level (Bretreger et al., 2020). Both surface water and groundwater are used for irrigation, with groundwater exploitation found mainly in alluvial formations.

3. Materials and Methods

3.1. Satellite-Based IWU Data Sets

In this study, remote-sensing-derived IWU products developed within the Climate Change Initiative—Anthropogenic Water Use (CCI-AWU; <https://climate.esa.int/en/projects/anthropogenic-water-use/>) project, funded by the European Space Agency (ESA), have been assessed (Laluet et al., 2025). They rely on two different methodologies driven by satellite soil moisture as the main input, namely the SM-Inversion (Brocca et al., 2018; Dari et al., 2023, 2025) and the SM-Delta (Zappa et al., 2024; Zaussinger et al., 2019) approaches. From the full set of IWU products developed by Laluet et al. (2025) relying on the methodologies described above, each differing by the input soil moisture data set employed, only the best performing ones resulting from the comprehensive validation study by Laluet et al. (2026b) have been selected. For the CONUS and the Ebro basin, the considered IWU products are those obtained by forcing both methodologies with CCI passive soil moisture data (a product obtained by merging several passive microwave data sets; Dorigo et al., 2017). For India and the Murray-Darling basin, SM-Inversion and SM-Delta-derived IWU data sets using as input CCI combined soil moisture data (obtained by merging passive and active SM data sets; Dorigo et al., 2017) outperform the others. Both the SM-Inversion and the SM-Delta approaches also require evaporation data as an input. All the SM-Inversion-based products use potential evaporation (Miralles et al., 2020) estimates from the Global Land Evaporation Amsterdam Model (GLEAM) v3.7b (Martens et al., 2017). Concerning SM-Delta, the selected products over CONUS, Ebro basin, and India rely on FLUXCOM (Jung et al., 2019) actual evaporation while the data set over the Murray-Darling basin is obtained by leveraging SSEBop (Simplified Surface Energy Balance

operational) data (Senay, 2018). A thorough description of the SM-Inversion and SM-Delta methodologies, together with details on the experiments carried out to develop the products used in this study, can be found in Laluet et al. (2026b). Nevertheless, for the sake of comprehensiveness, a brief overview of the two algorithms is provided in the next Section. Henceforth, we refer to the selected satellite-derived IWU estimates simply as “SM-Inversion” and “SM-Delta”, omitting the input data sets adopted in each specific case. The SM-Inversion and SM-Delta products are delivered on a 0.25° resolution grid and monthly-aggregated. The SM-inversion data set covers the period from 2003 to 2022; the SM-Delta one spans from 2003 to 2020. Both satellite-based products have been developed by considering, for each domain, only pixels with percentage of area equipped for irrigation higher than 5%. Such information has been derived by Mehta et al. (2022), relying on the previous work by Siebert et al. (2013, 2015) (see Supporting Information S1 for further details).

3.1.1. SM-Inversion

The method relies on the inversion of the soil water balance for backwards estimating the total amount of water entering the soil, which determines the soil moisture dynamics tracked by satellites. Irrigation is then obtained as a residual after removing known precipitation rates. The following formulation for the soil water balance is adopted:

$$Z^* \frac{dSM(t)}{dt} = I(t) + P(t) - G(t) - SR(t) - E(t) \quad (1)$$

Z^* [mm] is the soil water capacity, $SM(t)$ [–] is the soil moisture expressed as saturation degree, $I(t)$, $P(t)$, $G(t)$, $SR(t)$, and $E(t)$, all expressed in [mm/day], indicate the irrigation, precipitation, drainage, surface runoff, and actual evaporation rates.

Equation 1 can be rewritten as:

$$Win(t) = nZ \frac{dSM(t)}{dt} + G(t) + SR(t) + E(t) \quad (2)$$

with $Win(t)$ representing the total amount of input water, that is, rainfall plus irrigation ($Win(t) = R(t) + I(t)$). In line with previous implementations of the SM-Inversion approach, the drainage term can be expressed as $G(t) = aSM(t)^b$, with a and b representing soil hydraulic parameters, the $SR(t)$ term is assumed to be negligible, and the $E(t)$ term is written as $F \cdot SM(t) PE(t)$, which corresponds to compute the actual evaporation as the potential one, $PE(t)$ [mm/day], limited by the soil water content (Dari et al., 2023; Matendo et al., 2026). F is a modulating factor that is calibrated together with a , b , and Z^* . To do this, the parameters are optimized to properly reproduce known precipitation rates during non-irrigation periods (i.e., whole non-irrigation season plus days with no rainfall during the potential irrigation season). After parameters calibration, Equation 2 is implemented to estimate $Win(t)$ and $I(t)$ is then obtained as $I(t) = Win(t) - P(t)$. Further details on the methodology can be found in Dari et al. (2022, 2023, 2025).

3.1.2. SM-Delta

The method exploits discrepancies between satellite-derived and modeled irrigation proxies, namely soil moisture and evaporation, to derive irrigation estimates. The underlying assumption is that remote sensing retrievals embed irrigation dynamics, while model outputs do not (Zaussinger et al., 2019). The soil water balance equation, written in the form:

$$Z \frac{dSM(t)}{dt} = P(t) + I(t) - E(t) - R(t) - \Delta S_{rest} \quad (3)$$

where $SM(t)$, $P(t)$, $I(t)$ and $E(t)$ have the same meaning as defined in the previous section, $R(t)$ [mm] and ΔS_{rest} [m³/m³] indicate runoff and other storage changes below the surface layer (e.g., drainage), respectively. Equation 3 is valid both in the case of soil moisture and actual evaporation retrieved from satellite, $SM_{SAT}(t)$ and $E_{SAT}(t)$, or modeled, $SM_{MOD}(t)$ and $E_{MOD}(t)$. Z [mm] indicates the soil depth used to convert volumetric soil

Table 1
Features of the Satellite-Based and Modeling IWU Data Sets Compared in This Study

Data set	Data source	Type	Spatial resolution	Temporal resolution	Temporal coverage
SM-Inversion	Laluet et al. (2025)	Satellite-based	0.25°	Monthly	2003–2022
SM-Delta		Satellite-based	0.25°	Monthly	2003–2020
H08	Huang et al. (2018b)	Modeling	0.5°	Monthly	1971–2010
PCR-GLOBWB		Modeling	0.5°	Monthly	1971–2010
WaterGAP		Modeling	0.5°	Monthly	1971–2010
LPJmL		Modeling	0.5°	Monthly	1971–2010
QUAAlloc	Cárdenas Belleza et al. (2024)	Modeling	10 km	Monthly	1980–2019

moisture into water storage; the value is fixed at 50 mm (Laluet et al., 2026b). After writing Equation 3 for satellite retrievals and for modeling outputs, the two formulations can be subtracted to derive irrigation:

$$I(t) = \left(Z \frac{dSM_{SAT}(t)}{dt} - Z \frac{dSM_{MOD}(t)}{dt} \right) + \max[0; E_{SAT}(t) - E_{MOD}(t)] \quad (4)$$

Further details, including the considered sources for modeling outputs to be used as a baseline, can be found in Laluet et al. (2026b).

3.2. Modeling Reconstructions of IWU

Two data sources for IWU reconstructions through modeling simulations that are available in scientific literature have been considered. The first one is the data set described in Huang et al. (2018a), providing a historical time series of water uses for several sectors (i.e., irrigation, domestic, electricity generation, livestock, mining, and manufacturing) on a global scale. For the irrigation sector, they used IWU withdrawal estimates available from four different GHMs, namely H08 (Hanasaki et al., 2008), PCR-GLOBWB (van Beek et al., 2011), WaterGAP (Müller Schmied et al., 2014), and LPJmL (Rost et al., 2008). These estimates were adjusted through proper factors accounting for the discrepancies emerging from the comparison against country- or state-aggregated volumes reported in Food and Agriculture Organization (FAO) AQUASTAT and United States Geological Survey (USGS) statistics (Taranu et al., 2025). Monthly IWU reconstructions by Huang et al. (2018b) for the period 1971–2010 are delivered on a 0.5° resolution grid. In addition to these four data sets, water volumes allocated for irrigation purposes estimated with the QUAAlloc model (Cárdenas Belleza et al., 2024) have been considered. QUAAlloc distributes water amounts required for four main water uses (i.e., irrigation, domestic, livestock, and manufacturing and thermoelectric) to different sources of freshwater availability (i.e., surface water, renewable groundwater, and non-renewable groundwater). These requirements are then limited by the available water resources. To do so, the model relies on input data on water availability and water quality obtained from PCR-GLOBWB2 (Sutanudjaja et al., 2018) and DynQual (Jones et al., 2023) simulations, respectively. The resulting IWU reconstructions are provided on a global scale at 10 km spatial resolution, monthly aggregated, and for the time span 1980–2019. In this study, the total IWU has been considered, that is, the sum of water volumes allocated for irrigation coming from the different water sources considered in the QUAAlloc modeling framework. An overview on the satellite-based and modeling data sets compared in this study is provided in Table 1.

3.3. Reference IWU Data

Reference IWU records have been collected for all the case studies except for India, for which no explicit data could be obtained. Over CONUS, information on amounts of water applied for irrigation purposes have been derived by the 2013 and 2018 Farm and Ranch Irrigation Survey (FRIS), produced and delivered by the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA). The database, consisting of country-aggregated volumes of irrigation water abstractions, relies on surveys covering approximately 35,000 irrigated farms.

Benchmark irrigation rates for the Ebro basin have been derived from records of water volumes feeding three agricultural districts located in the basin's central valley, namely Urgell (887.6 km²), Algerri-Balaguer (70.8 km²),

and Catalan and Aragonese (1,161.5 km²). Losses due to the efficiency of the irrigation systems installed provided by Dari et al. (2020) have been adopted. Details on the location of the pilot agricultural districts are available in Supporting Information S1. The records are available through the SAIH (Sistema Automático de Información Hidrológica) platform (<http://www.saihebro.com/saihebro/index.php>). These data have been comprehensively used in the recent studies targeting the Ebro basin (see, e.g., Dari et al., 2020, 2022, 2023; Lluet et al., 2024, 2026b; Paolini et al., 2023; Zappa et al., 2024). IWU rates in mm have been obtained by dividing water volumes by the districts' areas. Because of the coarse spatial resolution of the products considered in this study, the time series of the different districts have been merged into a single time series by adopting weights based on the districts' areas, thus creating a unique IWU time series representing the whole validation domain to be compared against satellite- and modeling-based estimates. Reference IWU data for the Ebro basin is available from 2007 onwards.

Finally, for the Murray-Darling basin, reference irrigation amounts over four districts located in New South Wales have been collected, namely Murray-Wakool (1,455.2 km²), Murray-Mulwala (3,092.6 km²), Coleambally (997.0 km²), and Murrumbidgee (2,789.3 km²). Also in this case, water volumes have been converted to mm by dividing by the area of interest. Details on location and extension of the pilot districts can be found in Supporting Information S1. The reference data is provided by irrigation infrastructure operators (IIOs) managing the districts. Records are available for the period 2011–2019 for Murray-Wakool and Murray-Mulwala, 2010–2019 for Coleambally, and 2014–2019 for Murrumbidgee. For further details on the data, the reader is referred to Bretreger et al. (2020), Dari et al. (2023), Lluet et al. (2026a, 2026b), and Zaussinger et al. (2019).

3.4. Methods of Assessment

In order to have spatial consistency, all the modeled IWU data sets have been resampled to the 0.25° satellite-based products spatial grid. To do this, the nearest-neighbor method has been applied for the resampling of coarser resolution data from Huang et al. (2018b). Concerning QUALoc outputs, being available at the higher 10 km resolution, the linear interpolation has been applied after downgrading the original resolution to 20 km (i.e., by averaging the 10 km pixels falling within 20 km cells). Moreover, since IWU estimates from QUALoc are provided in m³/month instead of mm/month, they have been converted to mm by dividing by the pixel area. Finally, the spatial mask defined by pixels having a percentage of area equipped for irrigation higher than 5% used for developing the satellite-based products (see Supporting Information S1), has been applied to the modeled IWU data sets.

As a first comparison, discrepancies between area-averaged IWU estimates from satellite and modeling over each pilot area have been quantified. The adopted metrics are Root Mean Square Error (RMSE), BIAS, and Pearson correlation (r). As a second step, a pixel-wise analysis has been carried out to investigate the spatial patterns of the metrics above. All the analyses have been carried on a monthly temporal scale. In light of the temporal coverage of the different data sets considered in this study (see Table 1), the comparison between satellite-based IWU estimates and reconstructions from Huang et al. (2018a) has been carried out targeting the overlapping period from 2003 to 2010, while the longer period 2003–2019 has been adopted for the assessment against QUALoc outputs. Finally, in the third analysis, satellite- and model-derived IWU estimates have been compared with the available in situ observations to assess their accordance from ground truth. The same metrics defined above have been adopted.

4. Results

4.1. Large-Scale Average Magnitudes

In this Section, monthly IWU rates from satellite- and modeling-based data sets spatially averaged over the case studies are compared. Results are summarized in Table 2, in which performance metrics, that is, RMSE, BIAS, and r are reported. Note that they have been calculated by considering the full length of the data availability period, that is, involving both irrigation and non-irrigation seasons. Scatter plots referring to each comparison are provided in Supporting Information S1.

Concerning CONUS, it can be immediately seen that spatially-averaged satellite-based IWU is generally higher than modeling reconstructions, as highlighted by the positive BIAS values ranging from 3.24 mm/month (SM-Inversion against H08) to 7.06 mm/month (SM-Delta against QUALoc). The RMSE varies between 9.52 mm/

Table 2

Metrics Computed Between Monthly Satellite- and Modeling-Based IWU Rates Spatially-Averaged Over Each Case Study

	SM-inversion			SM-delta		
	RMSE [mm/month]	BIAS [mm/month]	r [–]	RMSE [mm/month]	BIAS [mm/month]	r [–]
CONUS						
H08	10.68	3.24	0.79	12.20	4.55	0.83
PCR-GLOBWB	10.77	3.84	0.77	12.17	5.15	0.81
WaterGAP	9.52	3.97	0.81	10.01	5.28	0.88
LPJmL	10.18	3.54	0.80	11.49	4.85	0.84
QUAAlloc	10.59	5.73	0.82	12.21	7.06	0.90
Ebro basin						
H08	30.65	14.70	−0.36	25.39	15.30	−0.03
PCR-GLOBWB	25.14	16.24	0.50	22.82	16.84	0.47
WaterGAP	22.19	14.99	0.68	21.56	15.59	0.54
LPJmL	23.44	16.05	0.84	21.22	16.65	0.80
QUAAlloc	22.38	15.74	0.68	19.76	14.58	0.59
India						
H08	20.80	−1.57	0.12	17.62	−7.17	0.13
PCR-GLOBWB	17.67	0.73	0.35	11.94	−4.87	0.58
WaterGAP	28.90	1.31	−0.36	25.97	−4.29	−0.53
LPJmL	22.21	−1.18	−0.05	17.02	−6.78	0.16
QUAAlloc	20.45	1.77	0.35	13.67	−3.42	0.70
Murray-Darling basin						
H08	17.70	12.51	0.59	11.72	8.20	0.45
PCR-GLOBWB	17.38	12.51	0.63	11.62	8.20	0.42
WaterGAP	17.25	12.55	0.70	11.11	8.25	0.72
LPJmL	17.43	12.63	0.85	11.38	8.32	0.77
QUAAlloc	14.07	9.38	0.58	8.04	4.81	0.63

Note. Note that the considered period is 2003–2010 for all the comparisons except for those involving QUAAlloc, for which the longer time span 2003–2019 is considered.

month (SM-inversion vs. WaterGAP) to 12.21 mm/month (SM-Delta vs. QUAAlloc). Temporal dynamics of remotely sensed and modeled IWU reveal an overall good agreement, with r varying from 0.77 (SM-Inversion against PCR-GLOBWB) to 0.90 (SM-Delta vs. QUAAlloc). Results over the Ebro basin reveal a higher disagreement between satellite- and model-based estimates with respect to the CONUS. RMSE ranges between 19.76 mm/month (SM-Delta vs. QUAAlloc) and 30.65 mm/month (SM-Inversion vs. H08). Temporal dynamics vary widely, from a negative r value of −0.36 found in the comparison between SM-Inversion and H08 to a strongly positive correlation of 0.84 obtained from the same remotely sensed product evaluated against LPJmL. BIAS ranges between 14.58 mm/month (SM-Delta against QUAAlloc) to 16.84 mm/month (SM-Delta against PCR-GLOBWB), highlighting larger irrigation volumes estimated by the satellite-based approaches with respect to models. Over India, BIAS ranges between −7.17 mm/month (SM-Delta vs. H08) to 1.77 mm/month (SM-based against QUAAlloc), with negative values that are more frequent than positive ones, implying that IWU rates from modeling tend to be higher than those retrieved through remote-sensing-based approaches. Highly variable discrepancies in terms of temporal dynamics are found, with r ranging between −0.53 and 0.70, obtained comparing SM-Delta against WaterGAP and QUAAlloc, respectively. RMSE values span from 11.94 mm/month (SM-Delta against PCR-GLOBWB) to 28.90 mm/month (SM-Inversion vs. WaterGAP). The comparison performed over the Murray-Darling basin reveals that, in line with outcomes for CONUS and the Ebro basin, IWU retrieved from satellite observations is higher than the modeled ones, with positive BIAS values ranging from 4.81 mm/month (SM-Delta against QUAAlloc) to 12.63 mm/month (SM-Inversion vs. LPJmL). RMSE ranges

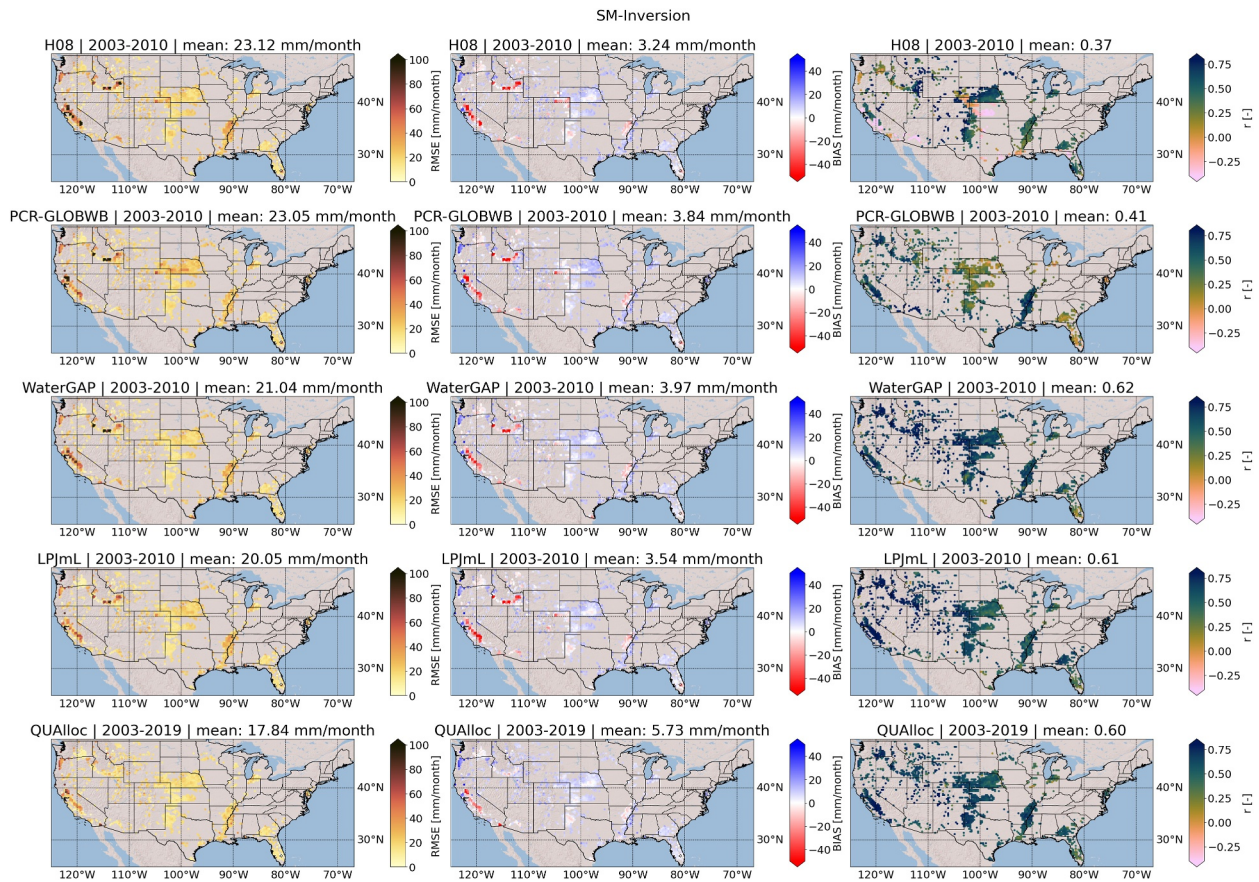


Figure 2. Maps of RMSE, BIAS, and r obtained by comparing monthly IWU estimates from the SM-Inversion data set with modeling reconstructions over CONUS. Each row refers to a different model.

between 8.04 mm/month (SM-Delta vs. QUAalloc) and 17.70 mm/month (referring to the comparison between SM-Inversion and H08), while r spans from 0.42 (SM-Delta vs. PCR-GLOBWB) to 0.85 (SM-Inversion against LPJmL), indicating an overall good agreement in terms of temporal dynamics.

Altogether, the assessment in terms of large-scale average magnitudes reveals that satellite-based approaches tend to estimate higher IWU rates than modeling over all the case studies except for India. Over CONUS and Murray-Darling basin, homogeneous insights are derived from the different comparisons that indicate a higher agreement (i.e., lower discrepancies and higher correlations) with respect to outcomes over the Ebro basin and India. Over such areas, the disagreement between satellite- and modeling-based IWU rates is generally higher and metrics vary widely across different data sets, as evidenced, for instance, by negative to positive r values found. Notably, this large variability does not concern the BIAS observed over India, for which modest values are detected.

4.2. Spatial Patterns

In this section, results of the pixel-wise comparison between monthly IWU rates from remote sensing and modeling are presented. Figures 2 and 3 provide the maps of RMSE, BIAS, and r over CONUS obtained by comparing the considered modeled data sets against SM-Inversion and SM-Delta, respectively. The spatial mean of the values shown in the maps is indicated above each panel. Note that, because of its intrinsic definition, average BIAS values do not differ from those reported in the previous Section. The same hierarchy of agreement arises from the comparison against the two satellite-based products. In fact, for both SM-Inversion and SM-Delta the lowest average RMSE and BIAS are obtained in the comparison against QUAalloc (17.84 mm/month for SM-Inversion and 18.23 mm/month for SM-Delta) and H08 (3.24 mm/month from SM-Inversion and 4.55 mm/month for SM-Delta), respectively. IWU reconstructions from WaterGAP provide the highest r values against satellite estimates (average r equal to 0.62 and 0.64 for SM-Inversion and SM-Delta, respectively). Both

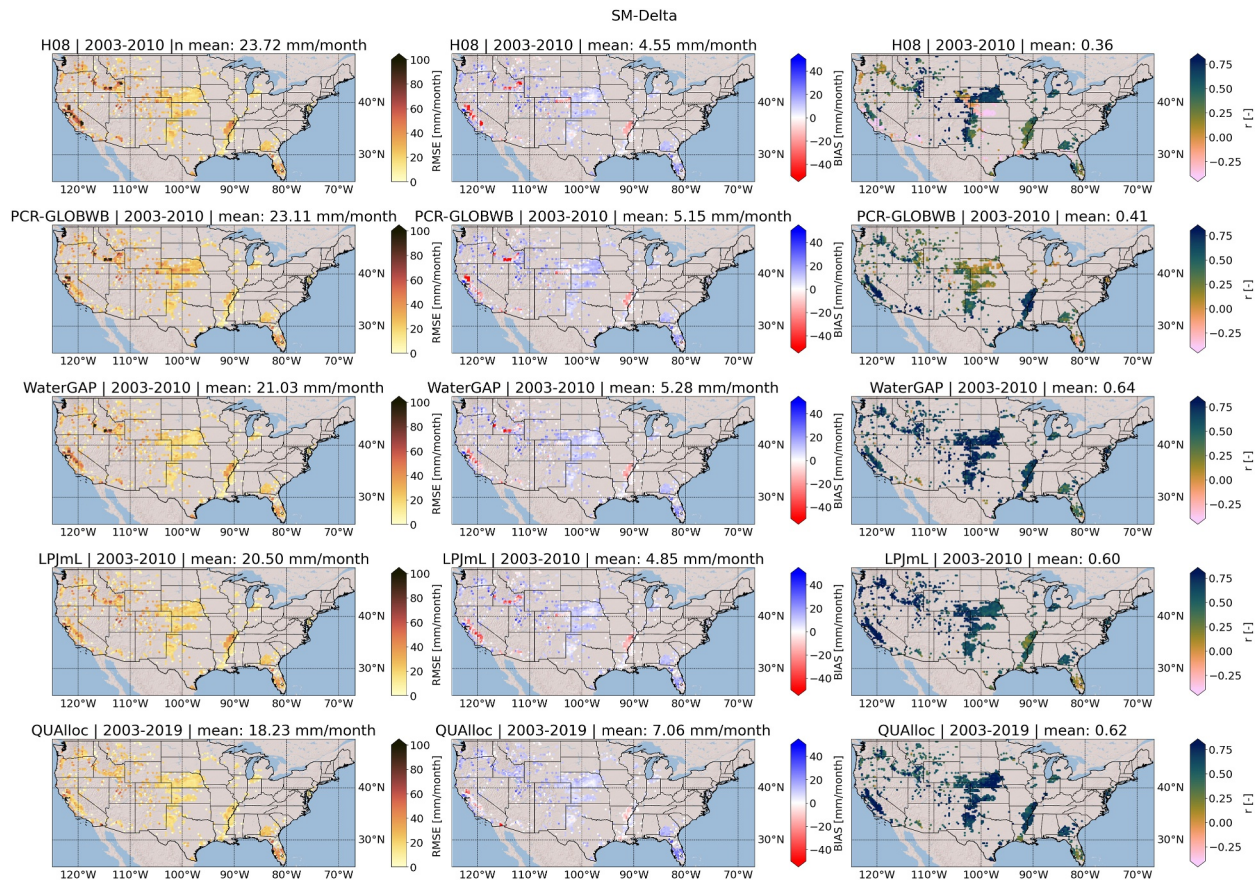


Figure 3. Maps of RMSE, BIAS, and r obtained by comparing monthly IWU estimates from the SM-Delta data set with modeling reconstructions over CONUS. Each row refers to a different model.

satellite-derived data sets show recurring patterns of high RMSE associated to sensibly negative BIAS values over two well-known irrigation hotspots over CONUS, namely California valley and Snake River Plain (Lawston et al., 2017; Martin et al., 2025; Zaussinger et al., 2019). Discrepancies over such areas are larger than elsewhere, with SM-Inversion and SM-Delta (the latter to a minor extent) reproducing less irrigation than most of the considered models.

Figures 4 and 5 summarize the outcomes over the Ebro basin. SM-Inversion and SM-Delta products show consistent behaviors, with lowest RMSE found against QUALoc (average value equal to 25.43 mm/month for SM-Inversion and to 23.01 mm/month for SM-Delta) and highest r against LPJmL (average value of 0.73 and 0.65). Because of the limited extension of this case study with respect to the coarse resolution adopted in the analysis, it is difficult to clearly assess the spatial heterogeneity of the metrics. Nevertheless, a tendency to higher RMSE and BIAS values in the upper central portion of the domain can be observed for SM-Inversion; for SM-Delta, the same metrics slightly degrade toward the East.

Outcomes referring to India are shown in Figures 6 and 7. Metrics for SM-Inversion- and SM-Delta-derived data sets provide consistent spatial patterns, with IWU rates lower than modeled ones over the Northern and, to a minor extent, Western portions, as highlighted by negative BIAS values. BIAS maps also reveal that the low average values found are actually due to spatial heterogeneity of portions where satellite-derived IWU exceeds modeling reconstructions (positive BIAS) and vice versa. Another interesting result is the large portion of the Indian territory showing negative r values in the comparison between the two satellite-based products and WaterGAP. SM-Inversion generally provides lower BIAS but higher RMSE values with respect to SM-Delta. In this pixel-wise analysis, both satellite-derived products show the best agreement in terms of RMSE (average value of 34.54 mm/month and of 25.41 mm/month for SM-Inversion and SM-Delta, respectively) and r (on average equal to 0.24 and 0.44, values revealing an overall limited correlation) against IWU modeled by QUALoc.

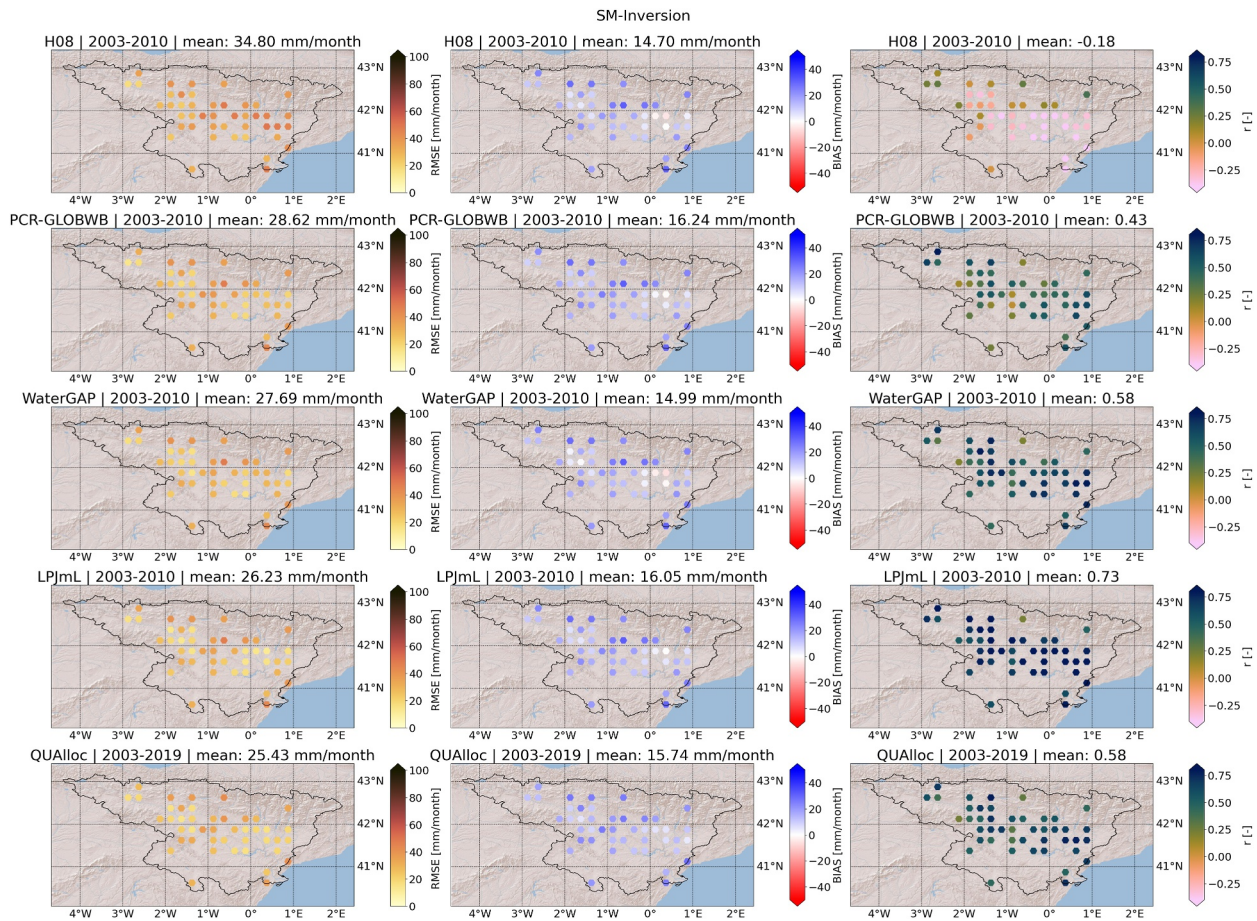


Figure 4. Same as Figure 2 but referring to the Ebro basin.

Over the Murray-Darling basin, for both SM-Inversion and SM-Delta, RMSE and BIAS remain stable in terms of magnitude and spatial distribution across all the comparative modeled data sets (Figures 8 and 9). For both sources of satellite-derived IWU, r is sensibly higher when compared with LPJmL outputs (average value of 0.64 and 0.51 against SM-Inversion and SM-Delta, respectively). SM-Delta systematically provides lower RMSE, BIAS, and r against modeled IWU reconstructions than SM-Inversion, whose outputs are therefore further from modeled IWU rates, even though better correlated.

4.3. Comparison Against In Situ Observations

Results shown in the previous Sections detail the discrepancies in space and time between the considered satellite- and modeling-based IWU products. However, they do not allow to clarify which differences are due to a better representation of reality. Hence, IWU from remote sensing and modeling have been compared with available reference data to understand which data source most closely approximates ground truth.

The comparison over CONUS is shown in Figure 10. Country-scale aggregated volumes of IWU from the FRIS database for 2013 and 2018 have been considered. For these years, model reconstructions are only available from QUALoc, which is the unique modeling approach considered (in red), in addition to SM-Inversion (in black) and to SM-Delta (in light blue). States with reported volumes lower than 0.1 km^3 have not been involved in the comparison. IWU from QUALoc tends to underestimate benchmark volumes (BIAS equal to -1.43 km^3 and to -1.29 km^3 for 2013 and 2018, respectively), in contrast to overestimates detected for the satellite-based products (only one negative but close-to-zero BIAS value found for SM-Inversion in 2018). QUALoc systematically provides the lowest RMSE for the reference years (2.44 and 2.62 km^3) while SM-Inversion shows the lowest BIAS (0.87 km^3 and -0.22 km^3).

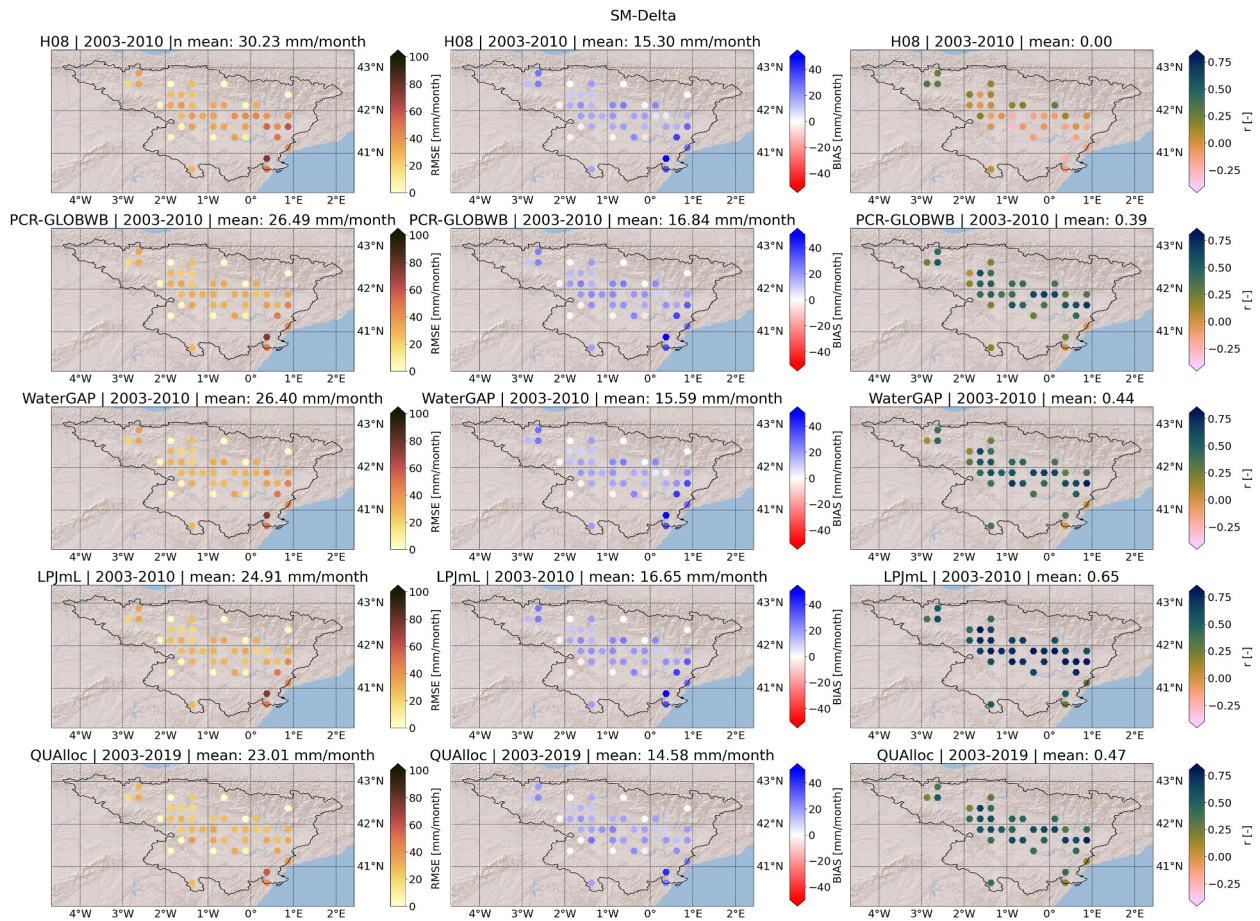


Figure 5. Same as Figure 3 but referring to the Ebro basin.

The assessment over the Ebro basin has been carried out by considering two different time spans. Reference IWU observations are available from 2007 onwards, hence the period 2007–2010 has been considered for the comparison between satellite-based products and modeling reconstructions from Huang et al. (2018a); the longer time frame of 2007–2019 has been adopted instead for the assessment against QUAAlloc. Results are shown in Figure 11; plots with a white background refer to the period 2007–2010, while outcomes for the time span 2007–2019 are provided in panels with a light gray background. Each satellite- or modeling-based data set is indicated by a different color. Satellite-derived IWU data sets systematically outperform model-based estimates from H08, PCR-GLOBWB, WaterGAP, and LPJmL (period 2007–2010). The only notable exception is the highest correlation (r equal to 0.95) found between reference irrigation amounts and IWU from LPJmL. The overall lowest RMSE (equal to 17.33 mm/month) and BIAS (3.10 mm/month) are achieved by the SM-Delta product. Concerning the comparison against QUAAlloc, SM-Inversion and SM-Delta provide better results than QUAAlloc in terms of RMSE and BIAS. Comparable r values are found. Overall best results in terms of RMSE and BIAS, equal to 20.82 mm/month and -6.56 mm/month, respectively, are obtained for SM-Delta, while the highest r (equal to 0.83) is detected for IWU estimated through SM-Inversion.

Concerning the Murray-Darling basin, reference IWU data is available for different time spans depending on the agricultural district: 2011–2019 for Murray-Wakool and Murray-Mulwala, 2010–2019 for Coleambally, and 2014–2019 for Murrumbidgee. Among the considered modeling reconstructions, such periods are covered by QUAAlloc only. Results for each agricultural district are shown in Figure 12; the same colors previously used are adopted to indicate the various products. QUAAlloc provides similar performances to satellite-derived approaches, which are, in some cases, outperformed. Over the Murray-Wakool district, the lowest RMSE is found for SM-Inversion (13.35 mm/month), highest r for SM-Delta (0.47), and lowest BIAS for QUAAlloc (-2.63 mm/month). Over Murray-Mulwala, SM-Delta provides most satisfactory RMSE (21.13 mm/month) and r (0.46)

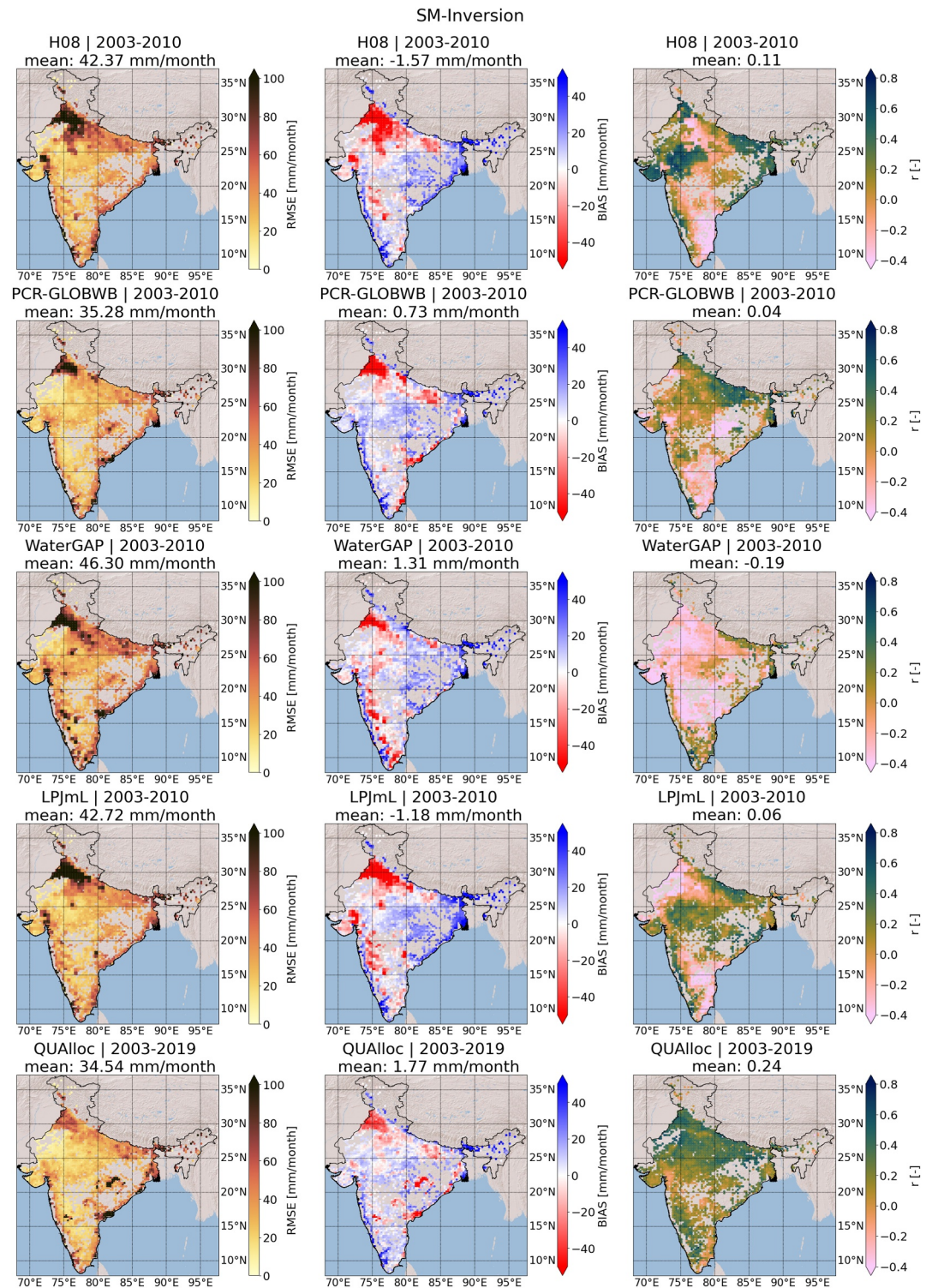


Figure 6. Same as Figure 2 but referring to India.

values, the lowest BIAS (-8.25 mm/month) is obtained in the comparison against SM-Inversion. Concerning Coleambally, SM-Delta provides the lowest RMSE (26.70 mm/month) and the highest r (0.68), with QUALoc showing the lowest BIAS (-2.40 mm/month). Finally, over Murrumbidgee, QUALoc provides the most satisfactory metrics, with RMSE and BIAS equal to 16.52 mm/month and -10.29 mm/month, respectively, and r value of 0.74.

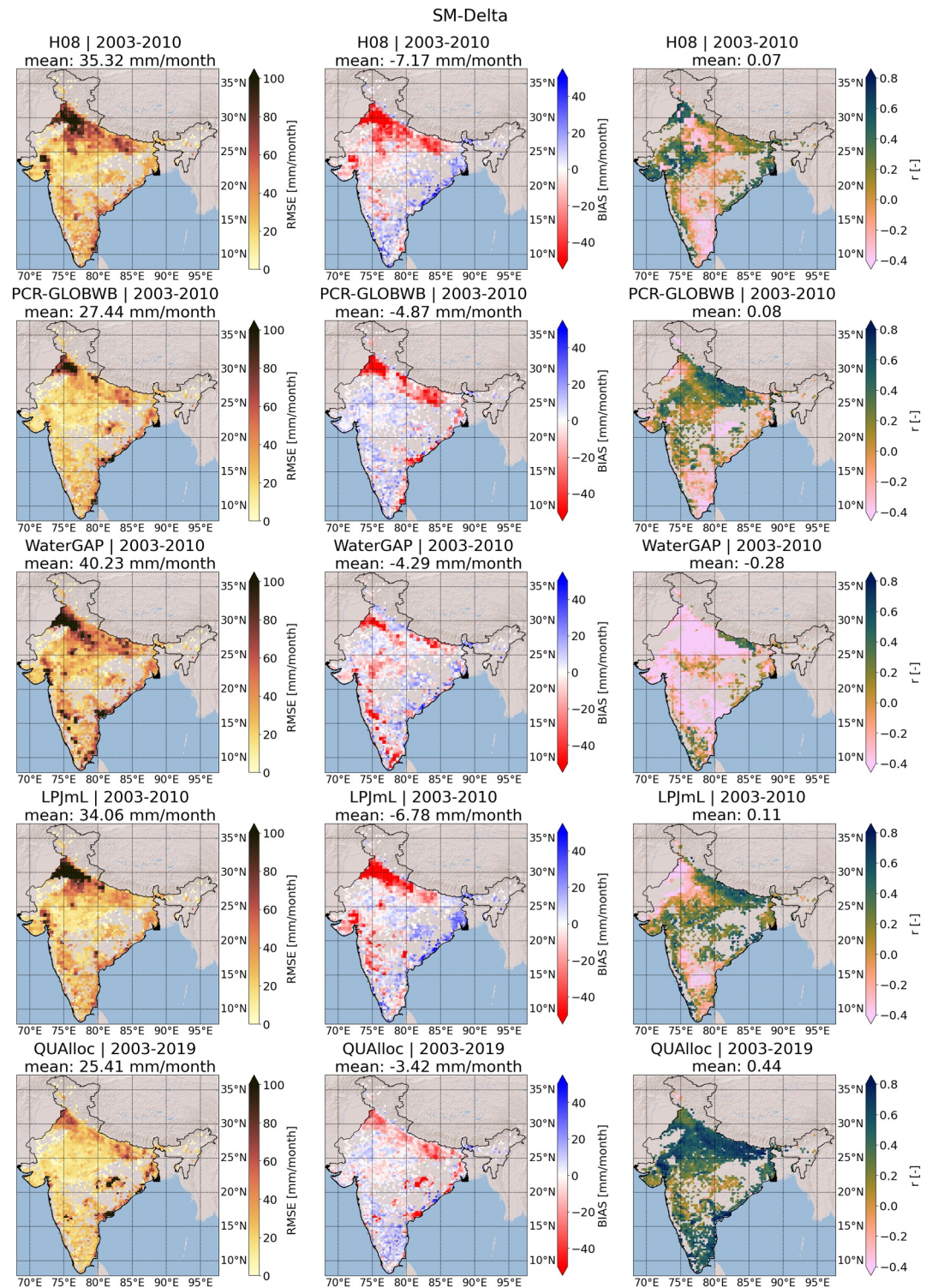


Figure 7. Same as Figure 3 but referring to India.

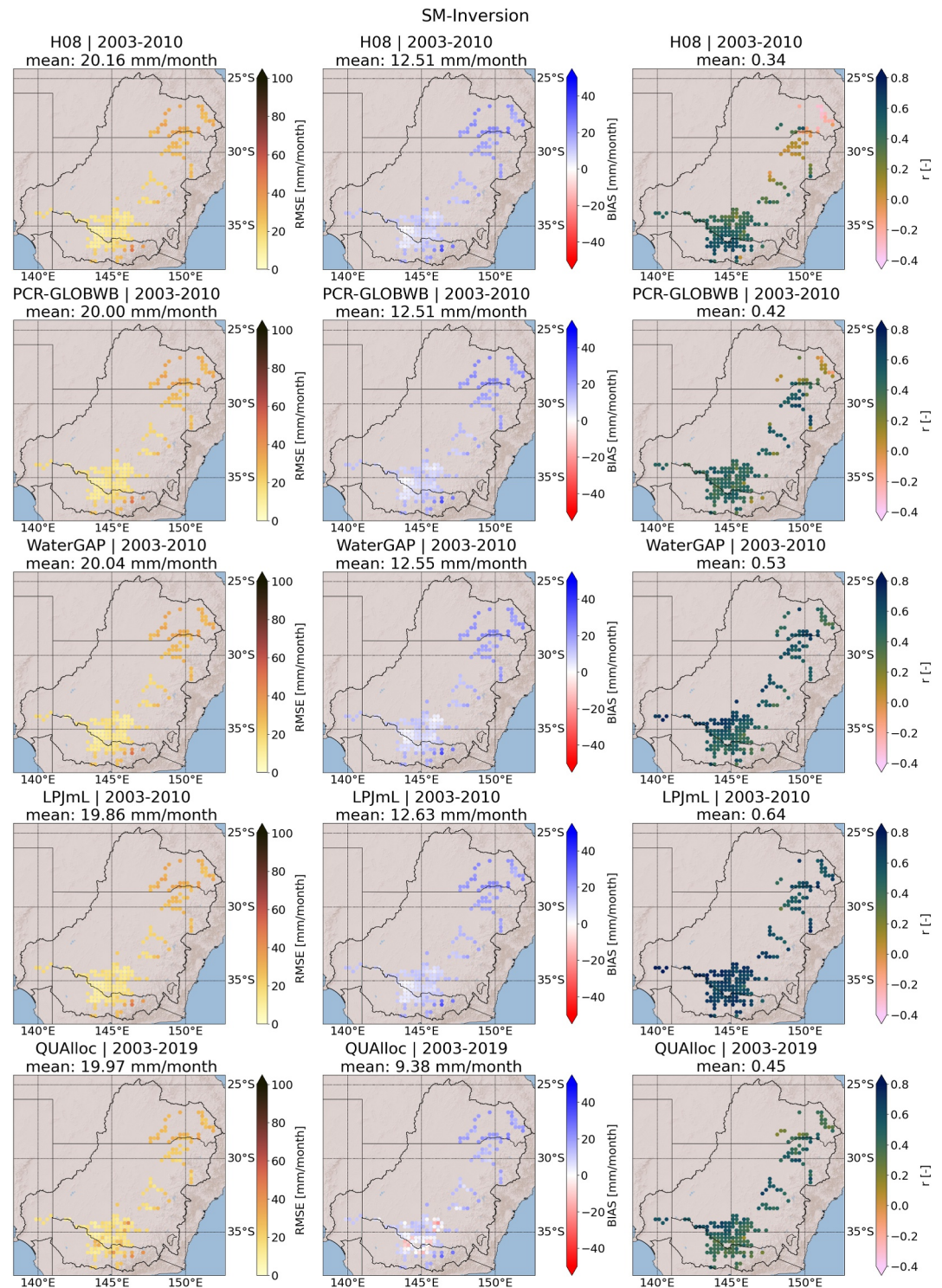


Figure 8. Same as Figure 2 but referring to Murray-Darling basin.

5. Discussion

In this study, two recently developed IWU products based on satellite-based proxies of irrigation, being soil moisture and evaporation, have been compared against modeling reconstructions from global hydrological models (Cárdenas Belleza et al., 2024; Huang et al., 2018b). Four main irrigation hotspots worldwide have been

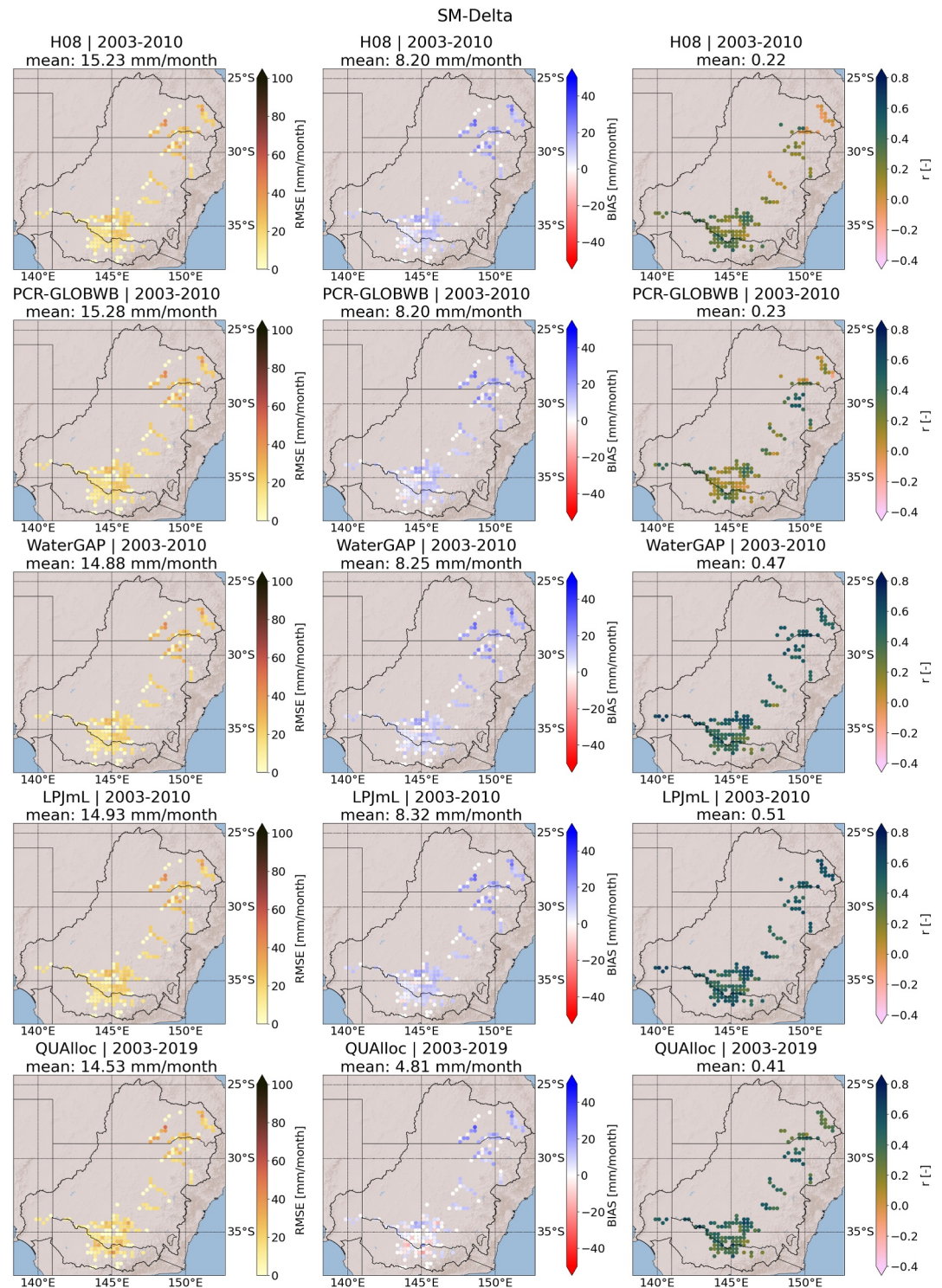


Figure 9. Same as Figure 3 but referring to Murray-Darling basin.

considered. As expected, discrepancies attributable to the different satellite- or model-based approaches to reproduce IWU have emerged, which contribute to highlight the uncertainties existing around anthropogenic activities in the water resources management realm (McDermid et al., 2023). Concerning the assessment of spatial patterns presented in Section 4.2, it is important to clarify that the resampling needed to ensure consistency across the different data sets analyzed may introduce a source of uncertainty affecting the reported metrics. Such an

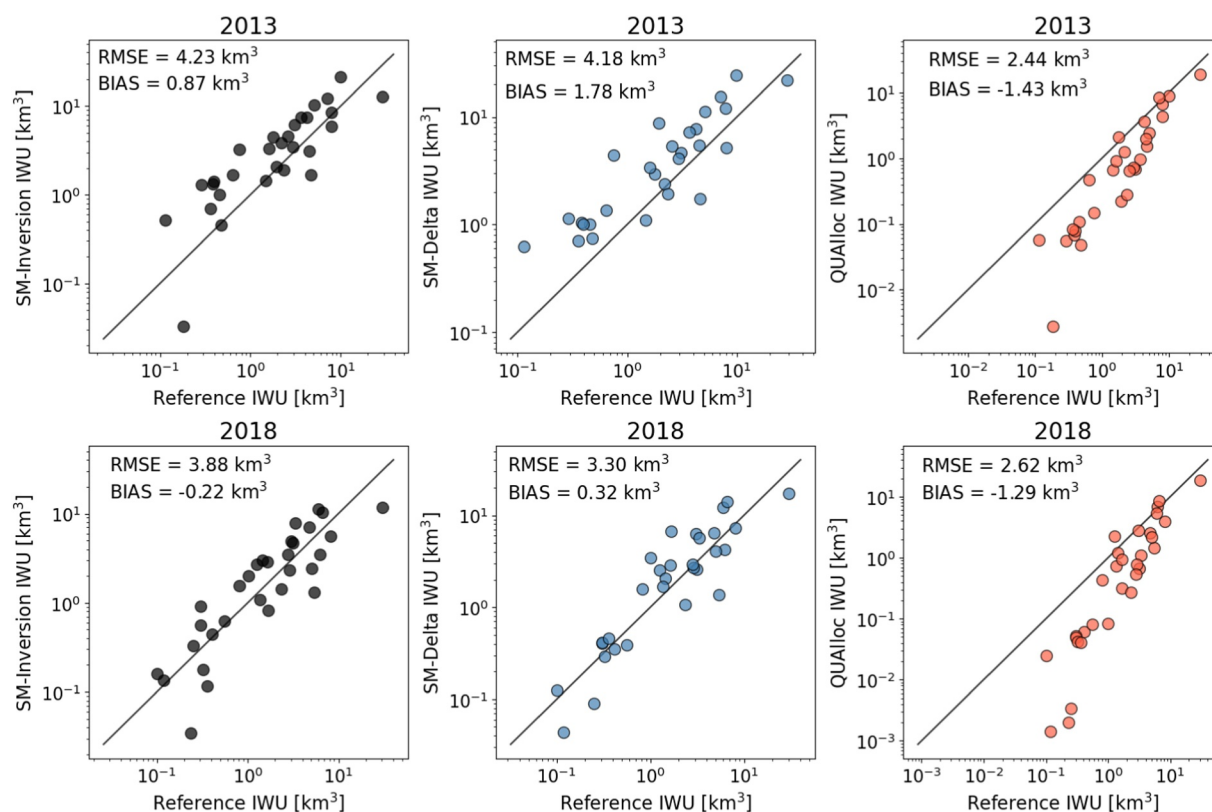


Figure 10. Comparison of seasonal reference IWU volumes against those reproduced by SM-Inversion (black), SM-Delta (light blue), and QUAAlloc (red) for CONUS. The upper panels refer to 2013, the lower ones to 2018. Note that the logarithmic scale is adopted to properly visualize results.

effect increases with the increase in resolution mismatch, but several studies (e.g., Bailey et al., 2023; Rajulapati et al., 2021) highlight that it is often secondary in large-scale analyses.

Over CONUS, satellite-derived IWU estimates tend to exceed modeling reconstructions (positive BIAS), although they are often well correlated. This means that they agree on the temporal dynamics of reproduced irrigation. Such a result is surely affected by a matching between irrigation seasons assumed by the selected modeling frameworks and the SM-Inversion and SM-Delta approaches (Laluet et al., 2026b). For the satellite-based methods, irrigation seasons are derived by the crop calendars from Portmann et al. (2008), not much different from the data source (Portmann et al., 2010) used in PCR-GOBWB and thus in QUAAlloc. H08, WaterGAP, and LPJmL rely on climate conditions instead (Huang et al., 2018a). The comparison against country-aggregated reference volumes, possible only for the QUAAlloc modeled data set, reveals that model outputs outperform remote-sensing-based retrievals in terms of RMSE, but not in terms of BIAS (especially for SM-Inversion). QUAAlloc IWU is almost systematically lower than reference values, while satellite-based estimates alternatively reproduce overestimates over some countries and underestimates in others.

The Ebro basin is the case study showing the largest discrepancies between satellite- and model-derived IWU, despite correlations being still acceptable (0.4–0.6) or even good (0.6–0.8) considering outputs from all the considered models except for H08 (see Table 2). The evaluation against in situ data, here possible for all the modeled data sets considered (even though for uneven time spans), reveals that the differences above support the reliability of satellite-derived products, as they almost systematically outperform model-based IWU. Hence, it can be asserted that the discrepancies between satellite and model IWU rates are due to the irrigation signal being better represented by the former. Recently, the SM-Inversion and SM-Delta approaches already proved their suitability for quantifying irrigation volumes over the Ebro basin through high-resolution satellite soil moisture retrievals as an input, such as Sentinel-1 (Dari et al., 2023; Zappa et al., 2024) or downscaled SMOS (Soil Moisture and Ocean Salinity) and SMAP (Soil Moisture Active Passive) data (Dari et al., 2020). It is noteworthy

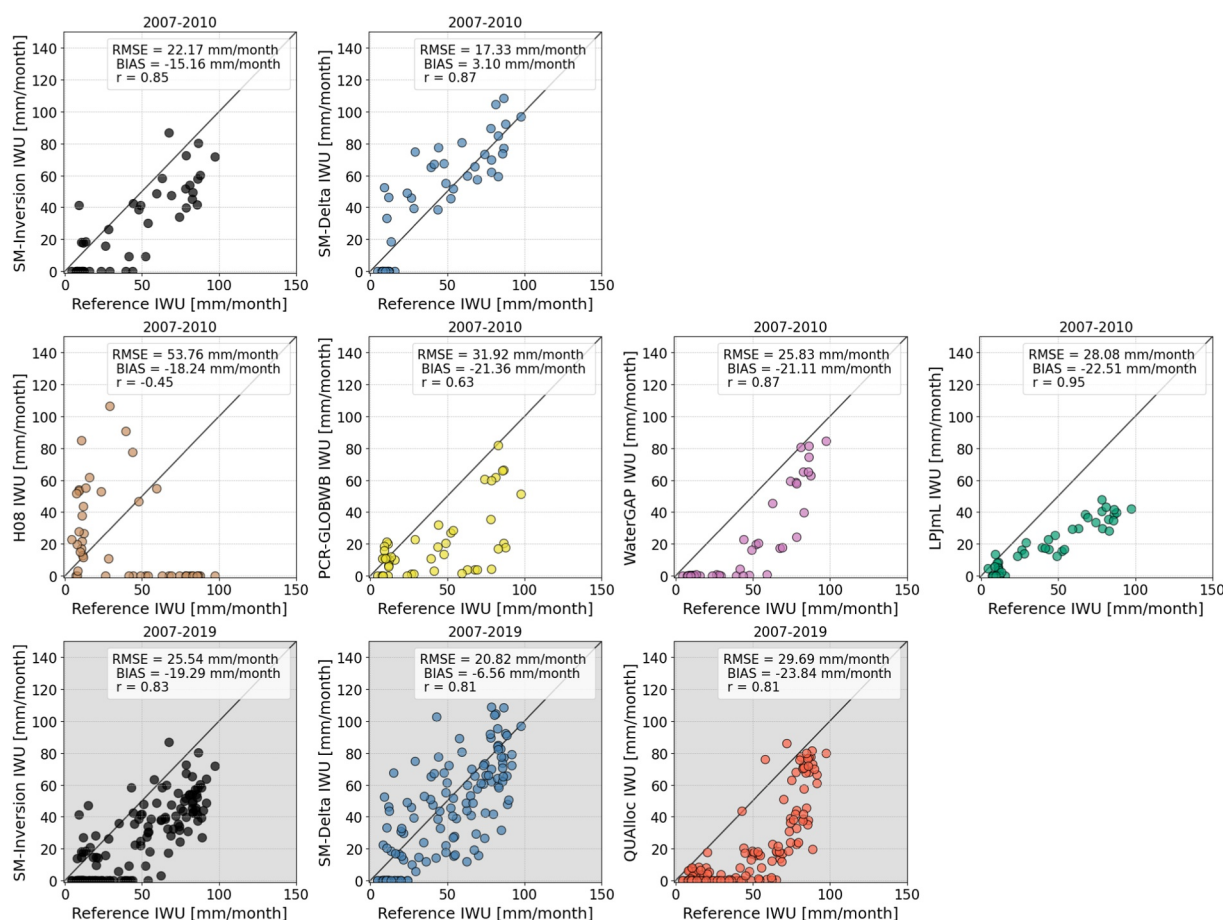


Figure 11. Comparison of monthly reference IWU against estimates from SM-Inversion (black), SM-Delta (light blue), H08 (light brown), PCR-GLOBWB (yellow), WaterGAP (purple), LPJmL (green), and QUALoc (red) for the Ebro basin. White and light gray backgrounds are adopted for analyses targeting the 2007–2010 and the 2007–2019 periods, respectively.

that the Ebro basin is, among the pilot sites, the one where the nominal size of agricultural areas may determine higher impacts of the resampling procedure on the computation of pixel-wise metrics.

Over India, substantial discrepancies between satellite- and model-derived IWU emerge. The lack of reference data does not allow to clarify uncertainties and to state which data source (satellite or modeling) better reproduces ground truth; however, when compared with various model-based reconstructions, the two remote sensing-based approaches provide results that are consistent with one another. The analysis of country-scale average magnitudes highlights low BIAS values across all the comparisons (maximum value of -7.17 mm/month between SM-Delta and H08), but it is important to recall that the pixel-wise comparison reveals that the country-scale behavior is determined by alternation of portions with negative and positive values. To assess the extent to which this circumstance affects the results, further analysis carried out by computing the absolute BIAS (i.e., obtained by averaging absolute values of discrepancies) is provided in Supporting Information S1. As shown in Figures S7 and S8 in Supporting Information S1, spatially-averaged values of absolute BIAS span from 17.19 mm/month (SM-Delta vs. QUALoc) to 34.14 mm/month (SM-Inversion vs. WaterGAP). All the comparisons highlight the Northeastern portion of the country as the region where higher discrepancies are found; noticeably, it is one of the most intensively irrigated areas of India (Ambika et al., 2016). An interesting aspect concerns the poor correlation between approaches based on satellite data and, in particular, IWUs by Huang et al. (2018a) as depicted from the analysis of large-scale averaged magnitudes (see Table 2). Over India, irrigation practices are concentrated in two main seasons, namely Rabi (November–March) and Zaid (April–June), the latter being the driest one (Sen Roy et al., 2011). In the period from July to September, the Kharif season, crops mainly rely on rainfall. Time series of monthly IWU from satellite- and model-based approaches shown in Figure S11 in Supporting Information S1 are

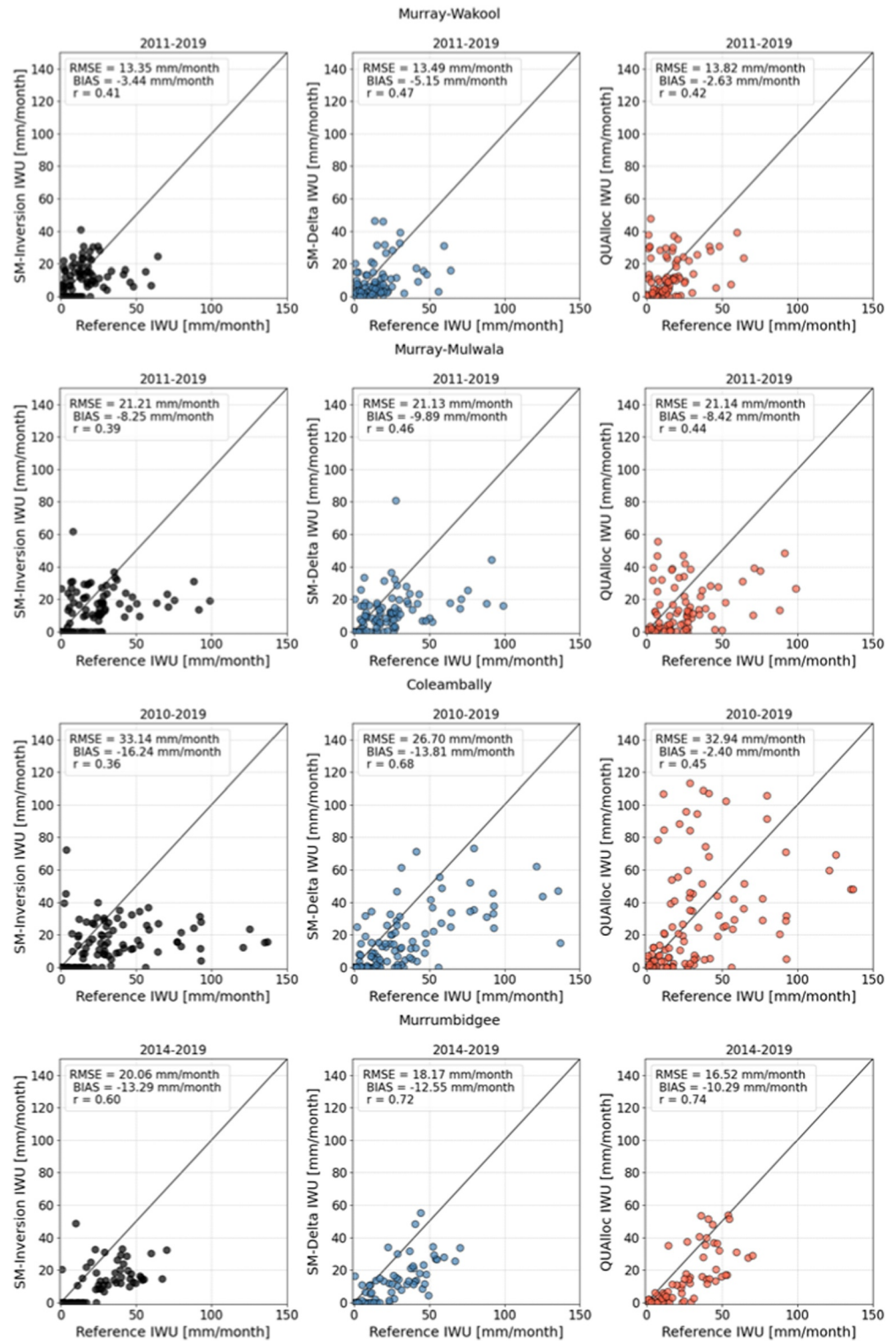


Figure 12. Comparison of monthly reference IWU against estimates from SM-Inversion (black), SM-Delta (light blue), and QUALoc (red). Each agricultural district and related analyses period are indicated as well.

informative about the low correlation found. Country-averaged magnitudes are provided. Satellite-based estimates clearly show a double peak, but a disagreement in their mutual relations can be observed, as SM-Inversion produces more irrigation during the Rabi season, while SM-Delta during Zaid. A noisier signal is reproduced by

H08 and PCR-GLOBWB. WaterGAP shows a second peak sensibly lower than the first one, while for LPJmL they often are of the same magnitude. QUALoc reproduces one peak only. In this context, some clarifications are necessary; first, the zero-irrigation shown by satellite-derived products is due to a temporal mask applied in their development chains (Laluet et al., 2026b), but, to a minor extent and for certain crops, supplementary irrigation could occur in the Kharif season as well (Chandra Panday et al., 2018; Chauhan et al., 2008). However, the absence of irrigation during Kharif in the satellite products favors the correlation analysis against WaterGAP and QUALoc, as they show similar dynamics. Even when a double peak is detected, clear indication on which season is characterized by higher consumptions does not emerge. Additionally, assigning a certain irrigation season to the whole country adds further uncertainty, as different crops located in different areas with varying extensions can be irrigated in one specific season only (Jha et al., 2022), unevenly impacting on the country-scale averages shown in Figure S11 in Supporting Information S1. India is then a critical area synthesizing both key research and monitoring gaps. In particular, the collection of reference observations is crucial to interpret differences in satellite-retrieved and modeled IWU rates, as well as for understanding which source of information best reflects the actual dynamics.

Minor discrepancies between modeling reconstructions of IWU and satellite estimates are found over the Murray-Darling basin. Due to the agreement between IWU rates retrieved by the two satellite-based approaches, consistent results emerge from the comparison against modeling reconstructions. Remotely sensed IWUs are higher than model outputs, but with similar temporal dynamics, as demonstrated by the r values obtained by the basin-scale (see Table 2) and the pixel-wise (see Figures 8 and 9) analyses. The assessment against reference irrigation amounts, only possible for QUALoc model data sets, corroborates these findings. The pilot districts are located in the Southern portion of the basin (see Figure S2 in Supporting Information S1), where discrepancies in terms of RMSE and BIAS between the satellite-based methods and QUALoc tend to be lower than elsewhere. This behavior is reflected in similar performances among the three data sets when compared to actual IWU monthly rates, which are reproduced with RMSE values higher than previous studies (see, e.g., Bretreger et al., 2020; Dari et al., 2023) but still acceptable (generally lower than 1 mm/day). The reported BIAS reveals a tendency in slightly underestimating benchmark IWU, while r values ranging from 0.4 to more than 0.6 are detected. It is noteworthy mentioning that lower RMSE values cited above refer to studies applying satellite-based methodologies with high-resolution retrievals, convenient in light of the nominal irrigation extents over the Murray-Darling basin (Zappa et al., 2022). Conversely, as explained by Laluet et al. (2026b), the satellite-based IWU products used in this study have been developed through coarser resolution data capable of ensuring long-term records, as their main aim is to foster climate studies. For this reason, satellite-based IWU products have been validated against modeling outputs, as they offer long-term and gap-free data useful for the same purpose. Nevertheless, they can suffer from uncertainties due to the irrigation schemes implemented and to the input data used (McDermid et al., 2023). Huang et al. (2018a) estimated that, concerning the four GHMs considered in their study, uncertainties due to models' structure are larger than those attributable to climate forcings; among the case studies of this work, CONUS results to be particularly affected by this issue. The authors highlighted different assumptions in irrigated areas, crop maps and calendars, as main drivers of such uncertainties. Moreover, IWU estimates from GHMs described in Huang et al. (2018a) have been rescaled in light of volumes indicated by country statistics, which can sometimes far differ from actually used amounts of water (Amali et al., 2026; Foster et al., 2020). Finally, Taranu et al. (2025) highlighted spatial and temporal inconsistencies that may affect those IWU reconstructions, proposing ad hoc harmonization procedures to reconcile them. On the satellite-based products side, one main limitation is the compromise between spatial and temporal resolution of remote sensing retrievals, which affects their possibility of matching with the spatiotemporal occurrence of irrigation practices. Several studies demonstrated that it is a crucial requirement for properly reproducing irrigation dynamics (see, e.g., Dari et al., 2022, 2025; Brombacher et al., 2022; Zappa et al., 2022; Le Page et al., 2023).

On the basis of the considerations above, an important direction for future work is the integration of satellite-based IWU products into modeling frameworks, in order to combine the strengths of observations and process-based models (De Lannoy et al., 2022). A practical pathway is the calibration of irrigation scheme parameters using satellite-based IWU data sets, which can constrain key parameters controlling irrigation magnitude and spatial distribution (Modanesi et al., 2026). By improving the realism of irrigation processes and initial conditions, calibrated models provide a more robust basis for assimilating related variables (e.g., high-resolution Synthetic Aperture Radar retrievals or satellite-based soil moisture and evapotranspiration data sets) when irrigation schemes are activated (Busschaert et al., 2024; De Lannoy et al., 2024; Modanesi et al., 2022). Within this

context, satellite-based IWU products may support data assimilation approaches indirectly, while their direct assimilation still requires further research and methodological development. In addition, satellite-based IWU products could be used as an independent benchmark to diagnose systematic biases in modeled irrigation estimates, and potentially to constrain long-term irrigation volumes through simple scaling approaches. More generally, it should be noted that most current irrigation modules rely on simplified representations, typically based on soil moisture thresholds, and only partially represent human decision-making processes, which are critical for accurately reproducing irrigation timing (Massari et al., 2021). Future developments should therefore aim to incorporate more realistic representations of irrigation practices, which is expected to enhance the effectiveness of both calibration and data assimilation experiments.

6. Conclusions

Satellite retrievals and modeling frameworks are useful tools to estimate or reproduce IWU. In this study, IWU estimated by two well-established methodologies based on remote sensing data (i.e., the SM-Inversion and the SM-Delta) have been compared against modeling reconstructions from five GHMs, namely H08, PCR-GLOBWB, WaterGAP, LPJmL, and QUAAlloc. All the data sources are freely available (Cárdenas Belleza et al., 2024; Huang et al., 2018b; Lalluet et al., 2025). The comparison has been carried out by targeting four irrigation hotspots: CONUS, Ebro basin (Spain), India, and Murray-Darling basin (Australia). Outcomes demonstrate that, over case studies where discrepancies are modest (i.e., CONUS and Murray-Darling basin), satellite- and model-based IWU rates provide comparable performances in reproducing ground truth, resulting in alternating favorable and unfavorable metrics depending on the considered data sets and areas. It is important to recall that this result is only available for the QUAAlloc modeled data set. For the case study where largest discrepancies between satellite- and model-derived estimates are detected (i.e., the Ebro basin), the added value of remote sensing observations emerges. Such a result encourages the integration of satellite-based IWU estimates into modeling frameworks, either as direct input or at least for calibration purposes. High uncertainty in the result remains considering India, due to the lack of reference IWU available for assessing the distance of the different data sources from ground truth, by making it impossible to rank satellite and modeling products. However, this result is illustrative of the discrepancies generated by the different assumptions underpinning satellite- and model-based approaches. Also in this case, further research may be oriented toward the integration of satellite-retrieved IWU into modeling platforms, for instance by adopting common assumptions or by exploiting remotely sensed observations to derive ancillary information useful in models' schemes (e.g., on the irrigation season or spatial occurrence). Finally, it would be equally valuable to quantify uncertainties in satellite-based IWU estimates propagating from each single input (Lalluet et al., 2026a), a step toward a full view of the picture that is foreseen in next studies. To this aim, comprehensive uncertainty frameworks, including ensembles or perturbation experiments that jointly account for input and structural sources of uncertainty, are under development. The broader perspective consists in disposing of robust tools for monitoring IWU and serving climate studies as well as water-energy-food nexus assessments, thus improving the understanding of human-nature interactions with respect to agricultural water management dynamics (Galli et al., 2026).

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

All the data sets used in this study are open access. The satellite-based IWU estimates are available in Lalluet et al. (2025). Modeling outputs from H08, PCR-GLOBWB, WaterGAP, and LPJmL can be found in Huang et al. (2018b), while those from QUAAlloc are available in Cárdenas Belleza et al. (2024).

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