



Article

NASA's MODIS/VIIRS Global Water Reservoir Product Suite from Moderate Resolution Remote Sensing Data

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Abstract: Global reservoir information can not only benefit local water management but can also improve our understanding of the hydrological cycle. This information includes water area, elevation, and storage; evaporation rate and volume values; and other characteristics. However, operational wall-to-wall reservoir storage and evaporation monitoring information is lacking on a global scale. Here we introduce NASA's new MODIS/VIIRS Global Water Reservoir product suite based on moderate resolution remote sensing data—the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Visible Infrared Imaging Radiometer Suite (VIIRS). This product consists of 8-day (MxD28C2 and VNP28C2) and monthly (MxD28C3 and VNP28C3) measurements for 164 large reservoirs (MxD stands for the product from both Terra (MOD) or Aqua (MYD) satellites). The 8-day product provides area, elevation, and storage values, which were generated by first extracting water areas from surface reflectance data and then applying the area estimations to the pre-established Area–Elevation (A–E) relationships. These values were then further aggregated to monthly, with the evaporation rate and volume information added. The evaporation rate and volume values were calculated after the Lake Temperature and Evaporation Model (LTEM) using MODIS/VIIRS land surface temperature product and meteorological data from the Global Land Data Assimilation System (GLDAS). Validation results show that the 250 m area classifications from MODIS agree well with the high-resolution classifications from Landsat ($R^2 = 0.99$). Validation of elevation and storage products for twelve Indian reservoirs show good agreement in terms of R^2 values (0.71–0.96 for elevation, and 0.79–0.96 for storage) and normalized root-mean-square error (NRMSE) values (5.08–19.34% for elevation, and 6.39–18.77% for storage). The evaporation rate results for two reservoirs (Lake Nasser and Lake Mead) agree well with in situ measurements (R^2 values of 0.61 and 0.66, and NRMSE values of 16.25% and 21.76%). Furthermore, preliminary results from the VIIRS reservoir product have shown good consistency with the MODIS based product, confirming the continuity of this 20-year product suite. This new global water reservoir product suite can provide valuable information with regard to water-sources-related studies, applications, management, and hydrological modeling and change analysis such as drought monitoring.



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1. Introduction

Reservoirs serve as a lifeline in water management (e.g., irrigation, hydropower generation, water supply, and flood control), especially under the ongoing fast population growth and changing climate [1–5]. Globally, reservoirs supply about 40% of the total irrigation water demand [1] and contribute to more than 60% of renewable energy via hydroelectricity [6]. Reservoir storage varies according to natural climate variability as well as the human water use/demand for different sectors (i.e., domestic, agricultural, and industrial). On one hand, near-real-time reservoir storage monitoring is essential for mitigating the negative effects of hydro-climatic extremes (droughts and floods) [7,8]. On the other hand, long-term records of water retained by global reservoirs can help to evaluate the human impacts on global and regional water cycles [9,10]. However, because gauge observations for reservoir storage (and/or elevation) are typically not shared, both of the aforementioned data needs are difficult to satisfy at regional and global scales.

Among the reservoir water budget terms, reservoir evaporation accounts for a substantial amount of the loss of available water—particularly for reservoirs in arid/semi-arid regions [11]. For example, the evaporation volume of Lake Tahoe (located in the western U.S.) represents 40–60% of the total reservoir output [11]. The annual evaporation rate of Lake Mead is ~1800 mm/year [12], which greatly exceeds the surrounding evapotranspiration rate (~50 mm/year) [13]. At a regional scale, the water losses due to evaporation for 200 reservoirs in Texas are equivalent to 20% of their active storage value [14]. Thus, it is crucial to incorporate information about reservoir evaporation losses into existing water management practices. Nonetheless, because reservoir evaporation information obtained through reliable in situ measurements (e.g., eddy covariance, energy balance) is hard to acquire, pan evaporation data (which is less accurate due to the lack of consideration of heat storage and fetch effects) have been commonly used as an approximation [11]. For most developing countries, even data about pan evaporation (or its equivalent) are not available.

Satellite remote sensing provides an alternative for filling in such reservoir data gaps. Since the 1990s, satellite radar altimeters have been utilized to measure the water levels of large lakes and reservoirs [15]. To date, several databases have been developed to monitor the water levels of inland water bodies at a global scale—including the Global Reservoir and Lake Monitor (G-REALM) [16], the Hydroweb database [17], and the Database for Hydrological Time Series of Inland Waters (DAHITI) [18]. Meanwhile, the global surface area variations of lakes and reservoirs have been assessed from various satellite instruments, such as the Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) [19–24]. Pekel et al. [19] developed a Global Surface Water (GSW) dataset using expert system classifiers based on Landsat observations obtained over the last three decades. The more recently published Global Reservoir Surface Area Dataset (GRSAD) provides monthly water area values for over 7000 reservoirs [20], which were generated by correcting the underestimations due to cloud contamination in the GSW dataset. Khandelwal et al. [21] generated an 8-day composite water area time series dataset for 94 reservoirs using MODIS multispectral data at 500 m resolution. In the meantime, many studies have focused on generating satellite-based reservoir storage estimations by combining elevation and area observations collected from multiple missions [17,25–27]. For example, Gao et al. [25] monitored storage values for 34 global reservoirs (which represented 15% of the total global reservoir capacity during that period) from 1992 to 2010 by combining water surface areas from MODIS with water elevations from satellite radar altimetry. The Hydroweb database (<http://hydroweb.theia-land.fr/>, accessed on 30 December 2020) estimates the storage changes for about 60 large lakes and reservoirs beginning in 1992, using multi-source satellite imagery (e.g., MODIS and Landsat) and radar altimetry data [17]. More recently, Busker et al. [27] analyzed the monthly volume variations between 1984 and 2015 for 137 lakes and reservoirs at a global scale by combining water area values from the GSW dataset [19] and elevation values from DAHITI [18].

Meanwhile, some new approaches have been recently developed to estimate evaporation rates and losses from space. For instance, Zhang et al. [14] estimated the monthly

evaporation volumes based on pan-derived evaporative rates and Landsat surface areas for more than 200 reservoirs in Texas. Zhao and Gao [28] used the Penman Equation (with the heat storage and fetch effects addressed), and generated a first long-term evaporation data record for over 700 reservoirs in the contiguous United States. Zhao et al. [29] further improved the calculation of the heat storage change term by leveraging MODIS water surface temperature data. Many other approaches have been developed and tested at individual locations [30–32].

Despite the development of remotely sensed reservoir datasets, consistent, comprehensive, long-term, and operationally monitored reservoir products are still lacking at the global scale. Therefore, we present here a newly developed NASA global water reservoir product suite (MxD28 and VNP28) from moderate resolution remote sensing data. The suite provides 8-day and monthly measurements of area, elevation, and storage, along with monthly evaporation rates and evaporative volumetric losses for 164 global reservoirs. This paper is organized as follows. Section 2 describes the overview of the reservoir product. Section 3 explains the materials and methods that were used to generate the MODIS products. Section 4 shows the MODIS product validation results and evaluates the consistency between the MODIS and VIIRS results. Section 5 discusses the limitations and potential applications of this reservoir product.

2. Overview of the Global Water Reservoir Product Suite

2.1. Brief Description of the Selected Reservoirs

This product suite provides data for 164 reservoirs (locations are shown in Figure 1) with areas larger than 25 km², which were selected from the Global Reservoir Bathymetry Dataset (GRBD) [33]. It includes 151 man-made reservoirs (2672 km³) and 13 regulated natural lakes (23,811 km³). The total storage capacity of the 151 man-made reservoirs represents 45.82% of the global capacity (in its category) according to the Global Reservoir and Dam Database (GRanD) [34]. Table 1 summarizes the attributes of these 151 reservoirs at the global and continental scales. More details about the individual reservoirs (both man-made reservoirs and regulated natural lakes) and their attributes are provided in Table A1. At the continental scale, it has the largest coverage in Africa (76.61%) and the lowest in Europe (20.59%) in terms of storage capacity.

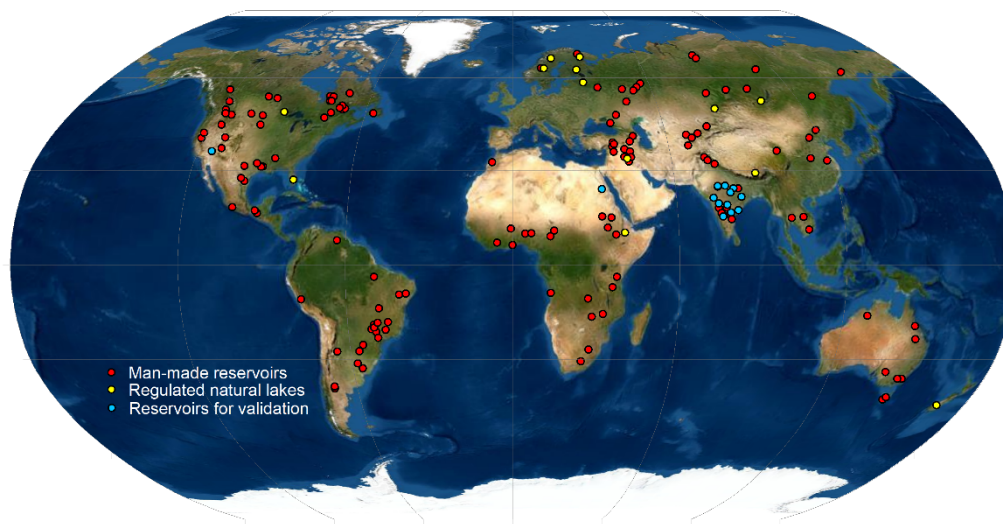


Figure 1. Locations of the 151 man-made reservoirs (in red and blue) and 13 regulated natural lakes (in yellow) are contained in this product. The reservoirs labeled in blue are used for validation purposes.

Table 1. Distribution and attributes of the 151 man-made reservoirs in this product.

	Number of Reservoirs	Area ¹ (km ²)	Storage ¹ (km ³)	Storage pct. (%)
Global	151	134,137	2672	45.82
Africa (AF)	21	30,043	636	76.61
Asia (AS)	53	36,036	782	35.87
Europe (EU)	10	10,191	102	20.59
North America (NA)	38	31,360	619	47.37
Oceania (OC)	8	2166	38	45.77
South America (SA)	21	24,340	495	52.92

¹ The area and storage columns correspond to the values at capacity. “Storage pct.” represents the percentage of storage included in our product with respect to the total storage capacity (referring to Global Reservoir and Dam Database (GRanD)) of the corresponding geographical domain.

2.2. Reservoir Product Components

The reservoir product suite is organized based on different temporal resolutions: 8-day (MxD28C2 and VNP28C2) and monthly (MxD28C3 and VNP28C3) (Table 2). The 8-day product includes reservoir area, elevation, and storage values. The monthly product adds reservoir evaporation rate and volume values (in addition to the above-mentioned measurements) for each reservoir.

Table 2. Overview of the reservoir product suite.

Sensor	Product	Measured Parameters	Temporal Resolution	Time Span
MODIS	MxD28C2	Area, elevation, storage	8-day	2000 to present
MODIS	MxD28C3	Area, elevation, storage, evaporation rate and volume	Monthly	2000 to present
VIIRS	VNP28C2	Area, elevation, storage	8-day	2012 to present
VIIRS	VNP28C3	Area, elevation, storage, evaporation rate and volume	Monthly	2012 to present

3. Data and Methods

3.1. Input Datasets

The input datasets used for the development of the reservoir product are summarized in Table 3. For MxD28C2, the 8-day Terra/Aqua surface reflectance (MxD09Q1) [35] data were collected for water area extraction. For VNP28C2, we used the 8-day VIIRS/NPP surface reflectance (VNP09H1) [36]. In particular, only the near-infrared (NIR) band was used due to its high spatial resolution (i.e., 250 m for MODIS and 500 m for VIIRS). The NIR band has been commonly utilized for the extraction of water bodies because it is strongly absorbed by water but scarcely absorbed by terrestrial dry soil and vegetation [37]. The Area–Elevation (A–E) relationships were adopted from the GRBD [33], which have proven to be of high quality through validation against in situ data. Then, the 8-day water area estimations were applied to the A–E relationships to derive elevation and storage values (see Section 3.2.1 for more details). Moreover, we used the 8-day day/night land surface temperature (LST) products (MxD21A2 [38] and VNP21A2 [39]) and Global Land Data Assimilation System (GLDAS) [40] meteorological forcing data to estimate the evaporation rates and volumes (see Section 3.2.2 for a more detailed approach).

Table 3. Summary of the input data names, sources, and purposes used in this product.

Input Data Name	Source	Purpose
8-day MODIS (Terra/Aqua) surface reflectance	MxD09Q1	Area
8-day VIIRS (NPP) surface reflectance	VNP09H1	Area
Area–Elevation (A–E) relationship	GRBD	Elevation and storage
8-day MODIS (Terra/Aqua) land surface temperature ¹	MxD21A2	Evaporation rate
8-day VIIRS (NPP) land surface temperature ¹	VNP21A2	Evaporation rate
Meteorological data	GLDAS	Evaporation rate

¹ The land surface temperature contains day/night surface temperature for inland water areas.

3.2. Methodology

In this section, we use MODIS products to demonstrate the algorithms, and the same algorithms were adopted to generate VIIRS-based products. Detailed descriptions of all of the algorithms involved in the product’s development (e.g., the enhancement water classification algorithm and evaporation rate estimation algorithm) are provided in the Algorithm Theoretical Basis Documentation (ATBD) [41], which is available through the product website (<https://modis-land.gsfc.nasa.gov/modgwr.html>, accessed on 30 December 2020). Since the product suite has yet to be formally released by NASA, the MODIS results presented in this paper were generated by executing the algorithms on the Google Earth Engine (GEE) [42], while the VIIRS results were generated on our local computer cluster (due to lack of VIIRS data on GEE).

3.2.1. Algorithm for the 8-Day Products

Figure 2 shows the algorithm for generating the MxD28C2 8-day product. First, the 8-day reservoir area values were extracted from the 250-m Near Infrared (NIR) band, along with the quality assurance (QA) band, of MODIS Terra/Aqua surface reflectance (MxD09Q1) data. During the classification process, an area enhancement algorithm (Zhang et al. [26]) was adopted to minimize the effects of various sources of contamination (e.g., cloud and snow/ice). Then, the area values were applied to the A–E relationship for the given reservoir provided by the GRBD [33] to calculate the corresponding elevation values. Lastly, the reservoir storage was estimated using Equation (1) (Gao et al. [25]):

$$V_{MODIS} = V_c - (A_c + A_{MODIS})(h_c - h_{MODIS})/2 \quad (1)$$

where V_c , A_c , and h_c represent storage, area, and water elevation values at capacity; and V_{MODIS} , A_{MODIS} , and h_{MODIS} are the estimated storage, area, and water elevation values from MODIS, respectively.

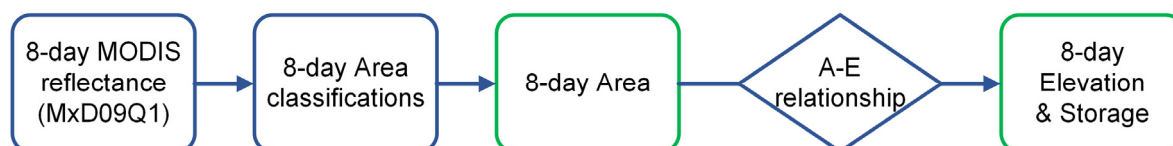


Figure 2. Flow chart of the algorithm for deriving the MxD28C2 product, which contains 8-day area, elevation, and storage results for the 164 reservoirs. The green boxes represent the product components.

The water area extraction values from MODIS serve as a foundation for elevation and storage estimations. Here we use our experience with the Cahora Bassa reservoir (Mozambique, Africa) as an example to explain the classification and enhancement processes. When classifying this reservoir, we initially buffered the shapefile (provided by HydroLAKES database [43]) outward by 1 km and then further used it to extract the NIR band images. The buffered area covers the maximum water extent, and the following classification and enhancement operations were implemented inside of this area to reduce the computational cost. For each 8-day period, the MxD09Q1 NIR images that overlap with the reservoir were

first selected (Figure 3a). The pixels contaminated by clouds, cloud shadow, and snow/ice (identified using the QA band of MxD09Q1) were labeled as ‘NoData’ (the blank areas in Figure 3b represent the contaminated pixels). Then, the Otsu thresholding method [44] was used to extract the water area from the NIR image (Figure 3c). It is obvious that the water area was underestimated due to contaminations (as shown in Figure 3c). Lastly, in combination with the water occurrence (percentile) image provided by the GSW (Figure 3d), we applied the enhancement algorithm developed by Zhang et al. [26] (Figure 3e) to correct the underestimations. The enhanced water areas show clear boundaries (Figure 3f). More details about the framework of MODIS water classification and enhancement can be found in Zhang et al. [26]. Note that it may happen that some extreme area values still exist even after the enhancement process. To eliminate the effects of these outliers, we used three standard deviations to remove them and used an interpolation method to fill in the data gap. This issue will be addressed in a future release of the enhancement algorithm [29].

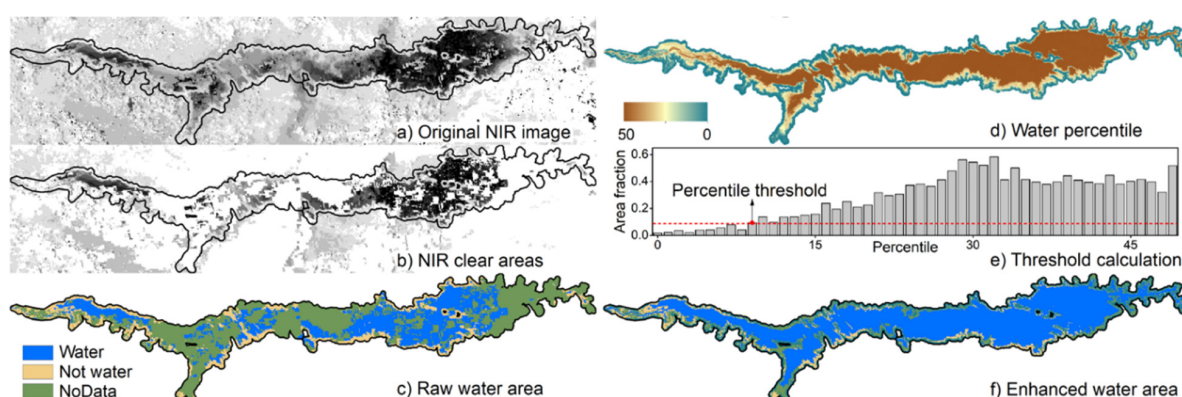


Figure 3. A demonstration of the water enhancement algorithm using the Cahora Bassa reservoir (Mozambique, Africa) on 1 January 2007, as an example: (a) original Near Infrared (NIR) image, (b) clear areas in NIR extruding the cloud contaminations, (c) water areas extracted from image (b), (d) water occurrence (percentile) image, (e) percentile threshold used for enhancement, and (f) water areas after enhancement.

3.2.2. Algorithm for the Monthly Products

The MxD28C3 product includes the evaporation rate and volumetric evaporation loss in addition to the area, elevation, and storage results at monthly temporal resolution. Figure 4 shows the algorithm for generating the MxD28C3 monthly product. The monthly area values were first estimated based on the composite of the 8-day area classifications and then converted into monthly elevation and storage results using the A–E relationship (Figure 4). In addition, monthly evaporation rates were estimated after the Lake Temperature and Evaporation Model (LTEM) [29] using MODIS LST product (MxD21A2) and meteorological data from GLDAS [40]. Lastly, the monthly evaporative volumetric losses were calculated as the product of evaporation rate and reservoir area values.

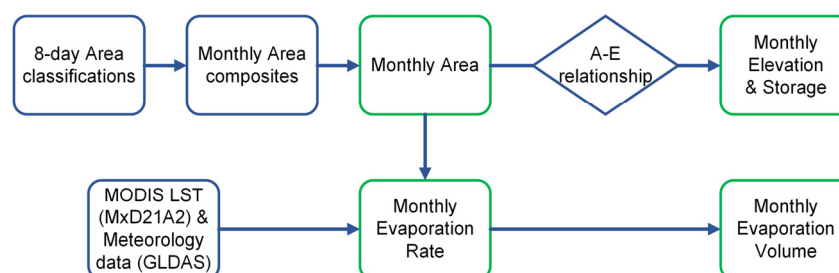


Figure 4. Flow chart of the algorithm for deriving the MxD28C3 product, which contains monthly area, elevation, storage, evaporation rate, and volumetric evaporation loss results for the 164 reservoirs. The green boxes represent the product components.

4. Results

This paper primarily focuses on validating the MODIS-based products (Sections 4.1–4.3) and evaluating the consistencies between VIIRS and MODIS products (Section 4.4). With regard to MODIS, when both 8-day MOD (Terra) and MYD (Aqua) area results are available on the same date, we selected the one with less cloud contamination. Similarly, the validations of the MODIS elevation and storage products also adopted those values associated with the less contaminated areas.

4.1. Comparing Water Surface Areas with Landsat-Based Results

At the global scale, long-term in situ reservoir area records are still lacking. Therefore, we compared the MODIS area values with Landsat-based results (at a finer spatial resolution of 30 m) for purposes of area validation. The Landsat monthly reservoir area values for all of the 164 reservoirs were collected from GRSAD between 2000 and 2018 [20]. GRSAD corrected the water area underestimation of the GSW dataset caused by both cloud/shadow/ice contamination and the Landsat-7 scan line corrector failure [20]. Note that the Landsat-based area estimation for a given month was based on the one or two images obtained during that month, while the monthly MODIS area value was derived from the composite of the 8-day classification. However, due to the deficiency of the in situ area values, we used this Landsat-based dataset to validate the overall consistency of the MODIS area products.

According to Figure 5, the MODIS-based area values agree well with the Landsat-based results (with an R^2 value over 0.99). Additionally, the data points are mainly centered on the 1:1 line (slope = 0.99). The disagreements that do exist can be attributed to two sources. The first is because Landsat and MODIS collected data at different dates. If a reservoir experienced a large change within a month, it may have caused a large area discrepancy. The second is related to the low spatial resolution of MODIS, which makes it more susceptible to mixed pixels. This can explain the area underestimations for relatively small reservoirs.

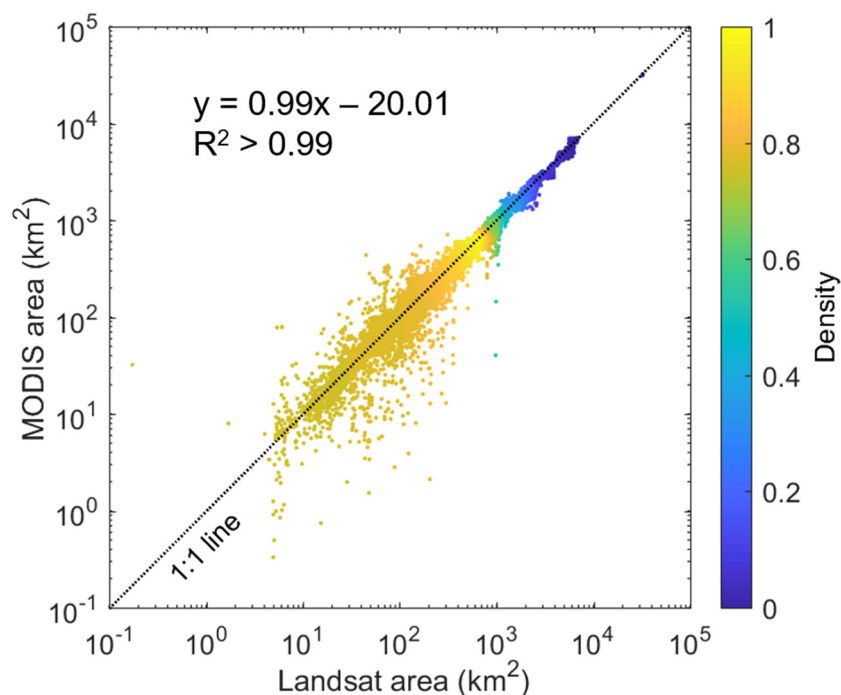


Figure 5. The density plot of monthly area estimations between Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) from February 2000 to December 2018 for the 164 reservoirs. Note that the x-axis and y-axis use a logarithmic scale, and there are a total of 37,228 (227×164) pairs.

4.2. Validating the MODIS Elevation and Storage Products against In Situ Observations

For the elevation and storage validations, we collected in situ daily observations for twelve Indian reservoirs (Ukai, Matatila, Ranapratap Sagar, Gandhi Sagar, Bargi, Hirakud, Jayakwadi, Sriram Sagar, Nagarjuna Sagar, Yeleru, and Tungabhadra) from the Indian Central Water Commission (<http://cwc.gov.in/>, accessed on 30 December 2020) between 2000 and 2019. We used the Indian reservoirs for validation purposes because they experience large dynamics that can better evaluate the efficiency of our algorithm.

The validation results of the 8-day MODIS elevation and storage products are shown in Figures 6 and 7, respectively. Overall, the elevation estimations from MODIS agree well with the in situ data (Figure 6), with an average R^2 value of 0.87, an average RMSE value of 2.22 m, and an average NRMSE value of 12.28%. The biases (e.g., overestimation for Tungabhadra and underestimation for Yeleru) are caused by a combination of mixed pixels of reservoir edge, parameterization of the enhancement algorithm, and the mismatch of MODIS water areas with Landsat water areas, which were used to derive A–E relationships for GRBD. With regard to the storage validations (Figure 7), they have similar patterns with those of the elevation results because they were both derived from area time series. Validations against in situ data show an average R^2 value of 0.88, an average RMSE value of 0.47 km^3 , and an average NRMSE value of 13.20%.

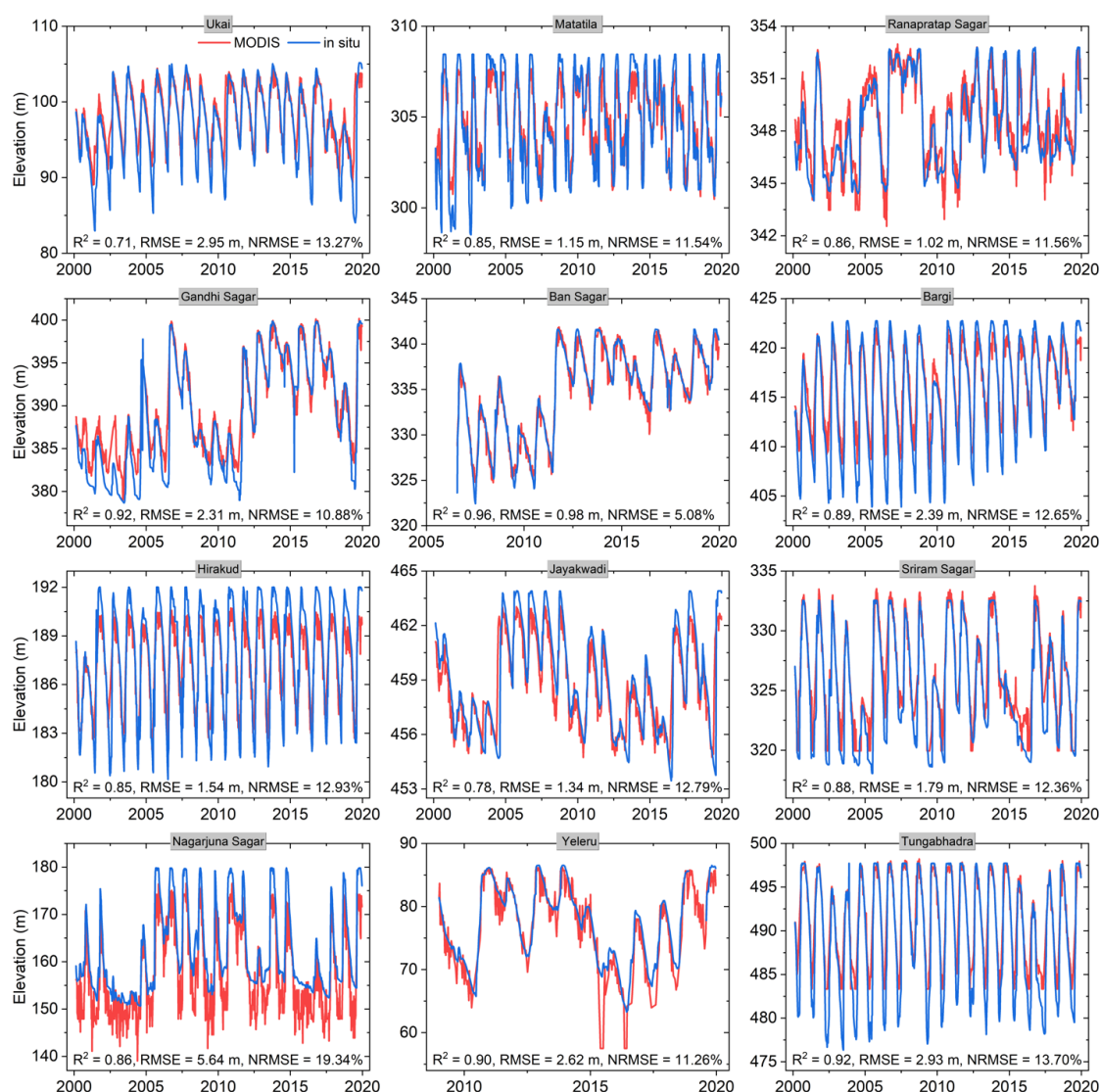


Figure 6. Validation of MODIS 8-day elevation products for twelve Indian reservoirs from 2000 to 2019.

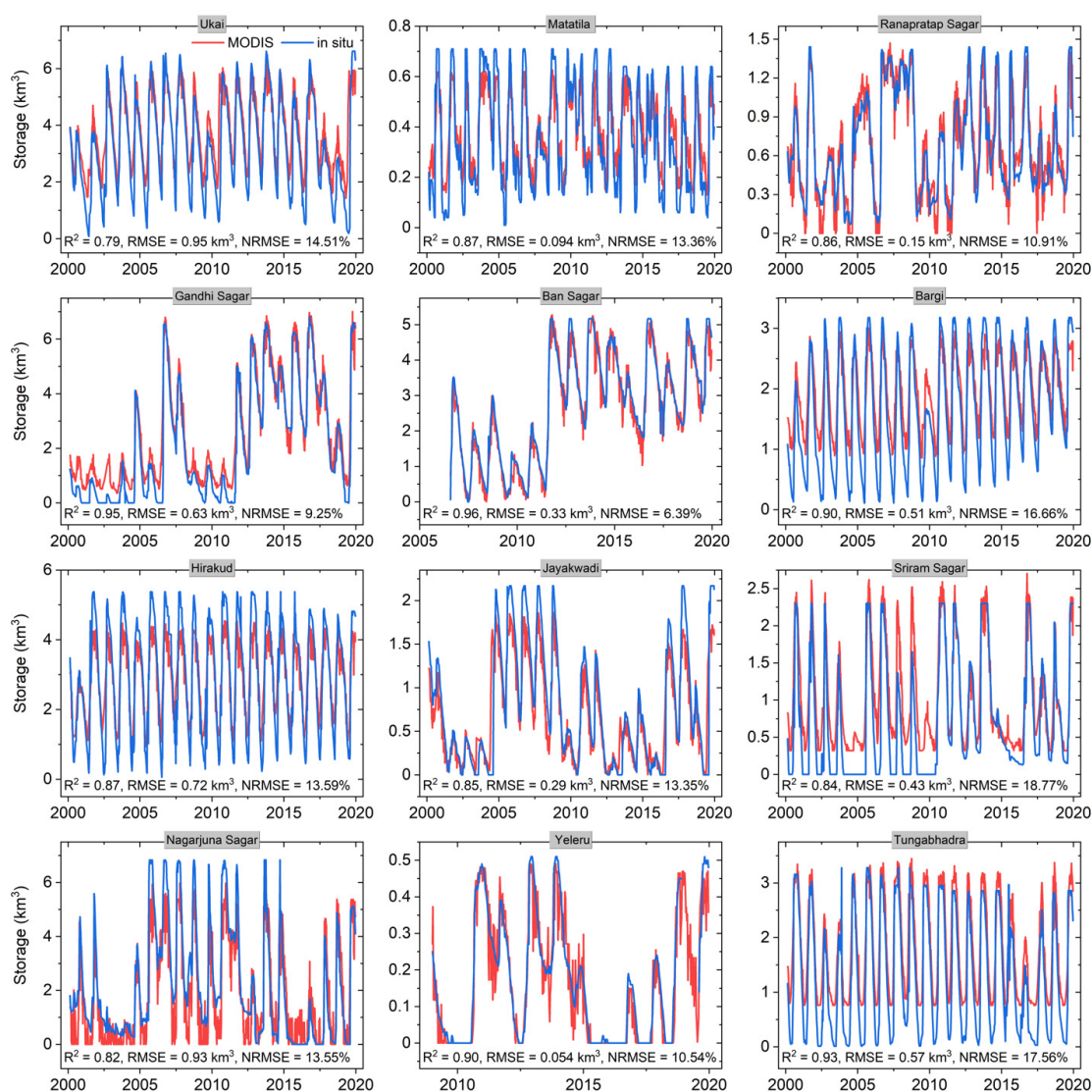


Figure 7. Validation of MODIS 8-day storage products for twelve Indian reservoirs from 2000 to 2019.

Next, we validated the monthly elevation and storage products over these twelve Indian reservoirs. The daily in situ elevation and storage values were averaged at a monthly step and were then compared to the monthly MODIS products (Figures A1 and A2). The validation results show similar patterns as those of the 8-day products but higher accuracies. This is because the monthly reservoir area values were generated from the composited results of three or four 8-day reservoir areas from MxD28C2, and the composition process further reduced the adverse effects of cloud contamination at the 8-day time step. As shown in Figure A1, the MODIS-based elevations show good consistency with the in situ measured data, with an average R^2 value of 0.90, an average RMSE value of 1.99 m, and an average NRMSE value of 11.33%. Regarding the storage validations (Figure A2), the results are consistent with those of the elevations, with an average R^2 value of 0.91, an average RMSE value of 0.43 km³, and an average NRMSE value of 11.91%.

4.3. Validating the Evaporation Rate Product against In Situ Observations

The evaporation rate results were validated over two locations—Lake Nasser in Africa and Lake Mead in North America—where high-quality in situ observations are available. The eddy covariance (EC) evaporation rate measurements for Lake Mead between 2010 and 2015 were provided by the United States Geological Survey (USGS) [12]. With regard to Lake Nasser, the evaporation rate estimations were obtained using the Bowen ratio

energy budget (BREB) method [45]. Although it is not as accurate as EC observations, the BREB method has been widely utilized to estimate evaporation rates due to its operability and reliability [46]. As shown in Figure 8, the MODIS evaporation rate products have good overall agreement with values obtained via observation (with R^2 values of 0.61 and 0.66, and NRMSE values of 16.25% and 21.76%). Compared to the results that were calculated using the regular Penman equation (without heat storage), our MODIS evaporation rate estimates have shown great improvements in terms of both annual peak values and seasonal variations. For Lake Nasser, the R^2 value increased from 0.30 to 0.61, with the NRMSE decreasing from 26.86% to 16.25%. A greater improvement is observed for Lake Mead in terms of both R^2 (from 0.26 to 0.66) and NRMSE (from 41.06% to 21.76%). These results suggest that better evaporation rate estimates are achieved when considering heat storage within the algorithm. It should be noted that this evaporation rate algorithm was validated over more locations in Zhao et al. [29]. Comparisons of evaporation rates calculated from different datasets (GLDAS + MxD21 and TerraClimate + MxD11) indicate that the performances are similar, even though the LST and meteorological data are slightly different (Figure A3).

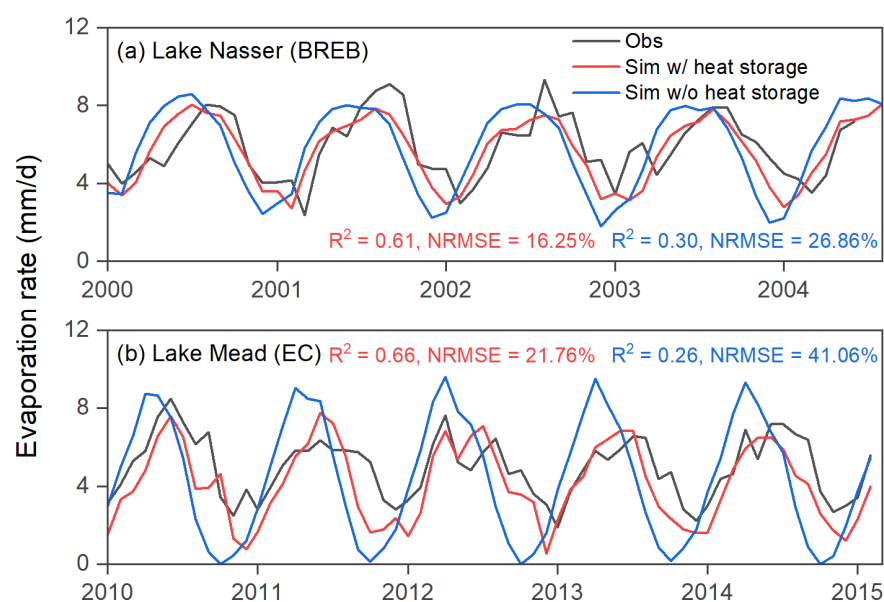


Figure 8. Validation of the evaporation rates for (a) Lake Nasser and (b) Lake Mead using Bowen ratio energy budget (BREB) estimations and eddy covariance (EC) measurements. The evaporation rate for Lake Mead (from 2010 to 2015) was calculated using MYD21A2 land surface temperature (LST) data because the current version of MOD21A2 only covers the years from 2000 to 2005 (when acquired in November 2020). The evaporation rate for Lake Nasser (from 2000 to 2004) was calculated using MOD21A2 because the MYD21A2 product started from July 2002.

4.4. Consistencies between VIIRS and MODIS Products

MODIS sensors have successfully operated for more than 20 years. The MODIS successor, VIIRS, was launched on 28 October 2011, onboard the Suomi National Polar-orbiting Partnership (Suomi NPP). Therefore, VIIRS plays an important role in extending the continuity of this product suite. The reliability of the water area estimation controls the quality of the other products (i.e., the elevation, storage, and evaporation results). Because the VIIRS 8-day reflectance data (VNP09) are not available on GEE and the VIIRS input data are very large and computationally intensive, we selected six Indian reservoirs from which to evaluate the consistency of VIIRS and MODIS data by comparing the 8-day area estimations from January 2012 to August 2020.

As seen in Figure 9, the VIIRS-based area values agree well with those of MODIS, with R^2 values ranging from 0.80 to 0.90. The 8-day elevation and storage values also

have good consistency, as they are based on the area estimations. In addition, high-quality monthly products can be generated from 8-day composite results (which are not shown here). Note that the VIIRS results are noisier than those from MODIS because of its coarser spatial resolution (500 m vs. 250 m). We also applied the outlier removal and gap-filling procedures to the area estimations from VIIRS, which led to smoother time series values.

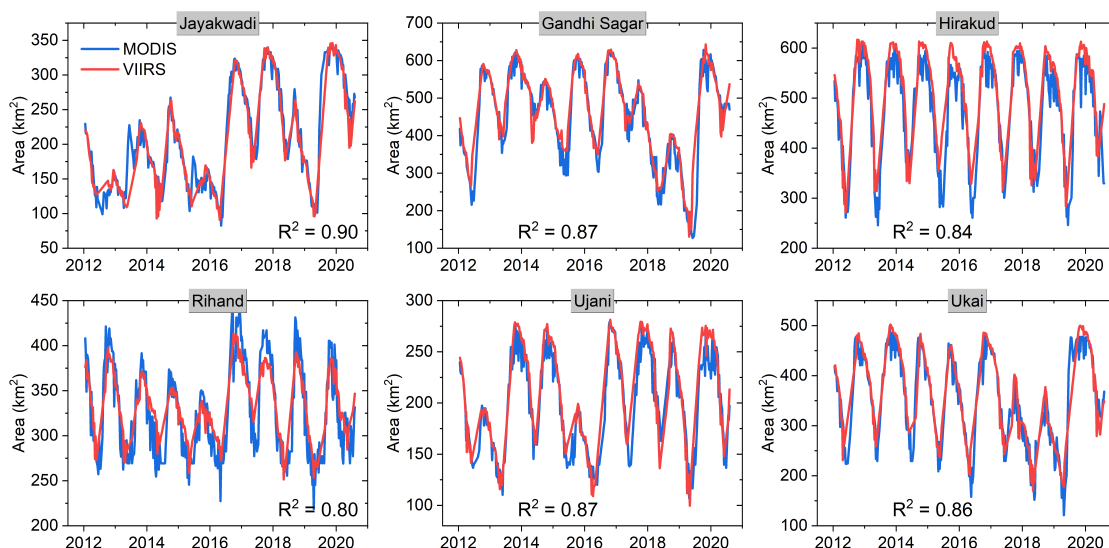


Figure 9. Comparison of 8-day area values between MODIS and Visible Infrared Imaging Radiometer Suite (VIIRS) from January 2012 to August 2020.

Additionally, we selected Lake Mead to compare the evaporation rates from January 2012 to April 2015 (Figure 10). Validation results show that the evaporation rates of VNP28C3 have a higher accuracy than those of MYD28C3 in terms of R^2 (0.76 vs. 0.66) and NRMSE (15.92% vs. 21.76%). Meanwhile, the evaporation rate results suggest a good consistency between VNP28C3 and MYD28C3 ($R^2 = 0.92$). It is noteworthy that the difference between MODIS and VIIRS evaporation rates is mainly attributed to the LST data. It has been reported that MODIS and VIIRS LST data have good agreement (>0.99) [47]. Therefore, the VIIRS-based evaporation rate values for other reservoirs should also be reliable and have good consistencies with those from MODIS.

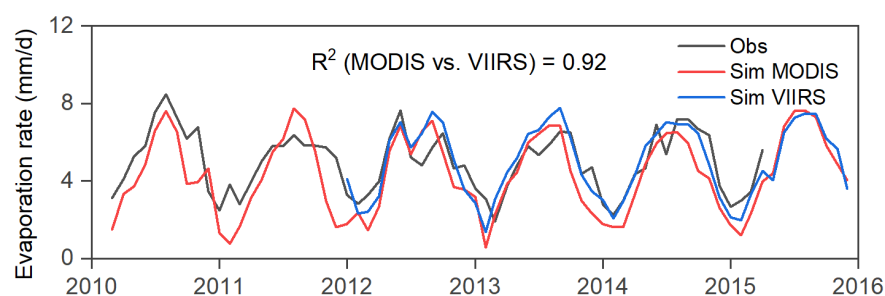


Figure 10. Comparison of monthly evaporation rates for Lake Mead between MODIS and VIIRS.

5. Discussion

5.1. Benefits of the MODIS/VIIRS Based Water Elevations as Compared to Radar Altimetry Products

Global reservoir elevation products are mainly based on measurements collected by satellite radar altimeters. We compared the MODIS 8-day elevation product with two radar altimetry products (Hydroweb and G-REALM) in terms of reservoir coverage and temporal resolution (Figure 11). Overall, the MODIS product and radar altimetry products agree well with each other (Figure 12). Given that the MODIS and VIIRS 8-day products are very

similar, Figure 11 also represents the relationship between the VIIRS product and most radar altimetry products (except that the VIIRS start date is in 2012). Despite the similarities, the MODIS/VIIRS product suite can offer new benefits over traditional radar altimetry products in two ways. First, the MODIS/VIIRS products can provide reservoir water elevations at an 8-day temporal resolution. In comparison, Hydroweb data are at the monthly temporal resolution, and G-REALM data range from 10-day, to 27-day, to 35-day (depending on the sensor). Second, this global water reservoir product suite is characterized by continuous and consistent records since 2000 for all of the 164 reservoirs (some examples are shown in Figure 12). Currently, there are 234 lakes and reservoirs included in Hydroweb, 73 of which are reservoirs (<http://hydroweb.theia-land.fr/>, accessed on 10 October 2020). G-REALM provides elevation values for a total of 241 reservoirs (out of 340 water bodies <https://ipad.fas.usda.gov/lakes/images/LakesReservoirs.pdf>, accessed on 10 October 2020). Only five reservoirs are monitored at an interval of 27 days in the period from February 2016 to the present. The 35-day products are from May 2002 to October 2010 and cover 33 reservoirs. The majority of reservoirs (203) are routinely measured at a 10-day time scale. However, 58 of them are lacking observations from August 2002 to July 2008 (examples include Qapshaghay Bogeni, Mosul, and Powell, which are shown in Figure 12). From 2000 to 2020, only 145 reservoirs from G-REALM have continuous records. By contrast, the MODIS/VIIRS products do not have this data gap issue.

5.2. Limitations and Sources of Uncertainties

There are still some limitations that need to be addressed. First, only the relatively large reservoirs are included due to the moderate resolutions of MODIS/VIIRS. For smaller reservoirs, it is more appropriate to take advantage of missions with high spatial resolutions (e.g., Landsat and Sentinel-2). Second, some reservoirs are susceptible to mountain shadows (but this has only small effects on large reservoirs). This overestimation can be eliminated using topography information. For example, Li et al. [48] overlapped water classification maps with Shuttle Radar Topography Mission (SRTM) DEM data to exclude the mountain pixels.

The sources of uncertainties with regard to the reservoir surface area are associated with both the raw image classification using the reflectance product, and the classification enhancement algorithm. The accuracy of the Ostu classification of the NIR images is affected by the mixed pixels (i.e., partially covered by water and partially covered by land) at the reservoir boundaries, as well as by ice over the reservoirs. The reliability of the enhancement algorithm depends on the data quality of both the water occurrence image and the raw water classification. In high-latitude regions, the water occurrence image generally shows small surface area dynamics (i.e., the distribution of occurrence values highly skewed to the left). Thus, the pixels with low occurrence values have relatively large uncertainties. Under such conditions, the enhancement algorithm might generate an incorrect threshold value—typically leading to an overestimation of the surface area.

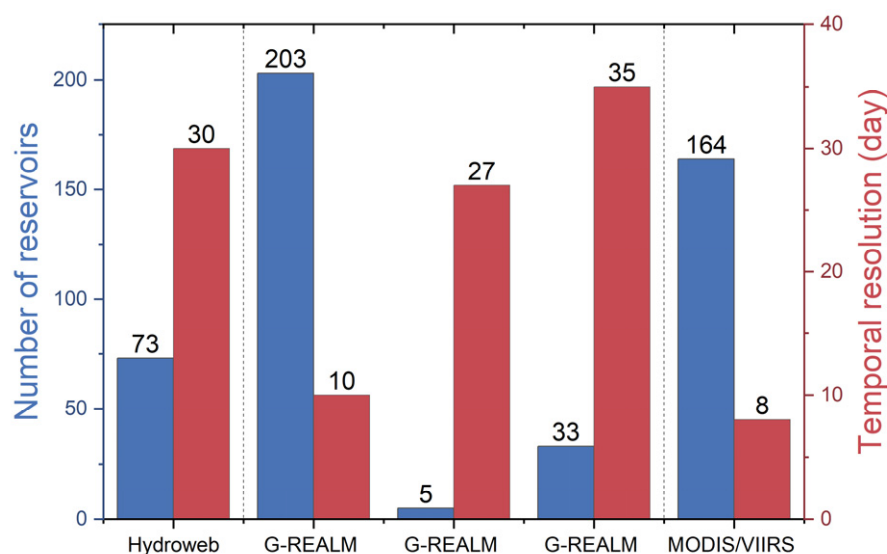


Figure 11. Comparison of reservoir coverage and temporal resolution of elevation measurements between satellite radar altimetry products (i.e., Hydroweb and G-REALM) and MODIS/VIIRS based products.

The reservoir elevation and storage estimation uncertainties include reservoir surface area uncertainties (see above), A–E relationship uncertainties, and reservoir configuration uncertainties. According to Equation (1), the estimated storage will be biased if the characteristics at capacity (storage, area, and elevation) are not accurate. Even when these factors have been correctly documented, the storage capacity may have changed due to sedimentation over time. Since the reservoir elevations are inferred only from areas and A–E relationships, they are not affected by reservoir configuration uncertainties. Moreover, while a non-linear relationship may perform better for some reservoirs, linear relationships were found to perform quite well for most of the reservoirs [33]. The linear A–E relationship represents a second-order polynomial reservoir cross-section, which is more realistic than other cross-section shapes [49].

Sources of evaporation rate uncertainty mainly include forcing data uncertainty and model structure/parameter uncertainty. Specifically, the forcing data used in this study (i.e., GLADS-2.1) are a land-based meteorological record. Although the increased humidity on the reservoir surface is represented by the wind function [28,50], differences in the wind speeds between reservoir and land regions are ignored, which might introduce some uncertainties [51]. In addition, the LTEM and its parameters can also produce uncertainties. For example, the formulation of the light attenuation coefficient (λ_{PAR}) is simplified. However, λ_{PAR} is affected by suspended solids, phytoplankton concentration level, and spectral distribution of solar radiation, and thus is constantly changing [52,53].

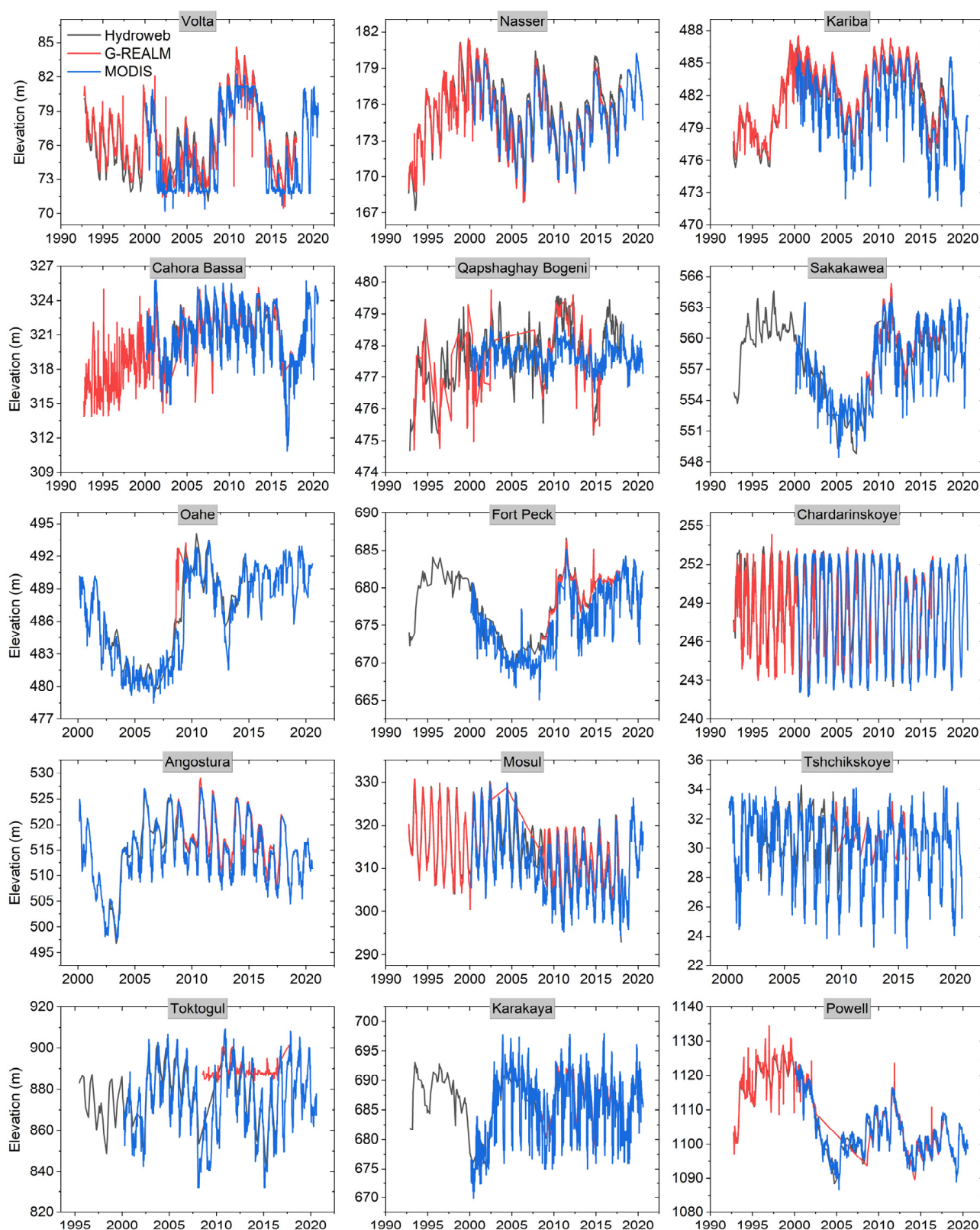


Figure 12. Comparison of elevation time series values between radar altimetry products (Hydroweb and G-REALM) and the MODIS-based product. Note that the elevation measurements provided by G-REALM are not available between 2002 and 2008 for the Qapshaghay Bogeni, Mosul, and Powell reservoirs due to a data gap. These are filled in by linear interpolation.

The reservoir volumetric evaporation uncertainty can be attributed to evaporation rate and surface area uncertainties, which have been discussed above.

5.3. Future Directions and Potential Applications

Several efforts are planned in the future to improve the current MODIS/VIIRS product suite. To reduce area estimation errors, the edge detection algorithm developed in Zhao et al. [29] will be employed to overcome the limitations of the current image enhancement approach. Furthermore, the design of the Terra (MOD) and Aqua (MYD) combined product components (MCD28C2 and MCD28C3) will allow it to automatically select less contaminated images for the users (thus leading to more accurate area estimates). It is also essential to conduct a comprehensive comparison between the MODIS and VIIRS products, especially given that the MODIS-era is close to an end. This analysis will be carried out after these products are made available through NASA. Additionally, a greater number of large reservoirs can be monitored by developing A–E relationships over locations where radar altimetry and ICESat data are unavailable. For instance, both Zhang and Gao [54] and Li et al. [55] have demonstrated the potential of using DEM data for generating A–E relationships for global reservoirs. Moreover, ICESat-2 (launched in September 2018) [48] and the Surface Water and Ocean Topography (SWOT) mission (planned for launch in 2022) [56] will provide more accurate elevation observations (as compared to radar altimetry and DEM). This should lead to the generation of A–E relationships over many more reservoirs.

The reservoir product can have multiple potential applications. First, it provides critical information for water resources management—especially for reservoirs in trans-boundary river basins where gauge observations are not shared. Moreover, it can help to calibrate and validate the operation rules incorporated into the global hydrological models that have a reservoir module. This can improve our understanding of the reservoirs' role in the hydrological cycle and water budgets [10,57]. For instance, Shah et al. [58] examined the role of reservoirs in water and energy budgets using the Variable Infiltration Capacity (VIC) model in the Indian sub-continent.

Additionally, time series values of reservoir storage variations at the basin scale can be used to evaluate hydrological droughts. Figure 13 shows the total reservoir storage variations in the Colorado and Murray–Darling river basins. The Colorado River basin has experienced a prolonged hydrological drought since the year 2000, even though the underlying meteorological drought only lasted for the first few years. This hydrological drought has been exacerbated by increased water use [59]. Moreover, the Murray–Darling river basin experienced the longest four-year reservoir-based hydrological drought on record from 2006 to 2010. However, the majority of the prior studies of droughts across the globe [60–66] considered only streamflow variations in their assessments of hydrological drought. This is because continuous long-term reservoir data with a high temporal resolution are lacking at a global scale (either for use in analysis or for the calibration of global hydrological models). Neglecting the reservoir storage component in hydrological drought assessment can lead to biases and uncertainties, as water is increasingly consumed, stored, and diverted through water management activities (i.e., reservoir operations) [66,67]. Therefore, this product can fill in this crucial research gap and can help stakeholders, water managers, and policymakers to improve existing hydrological drought management practices.

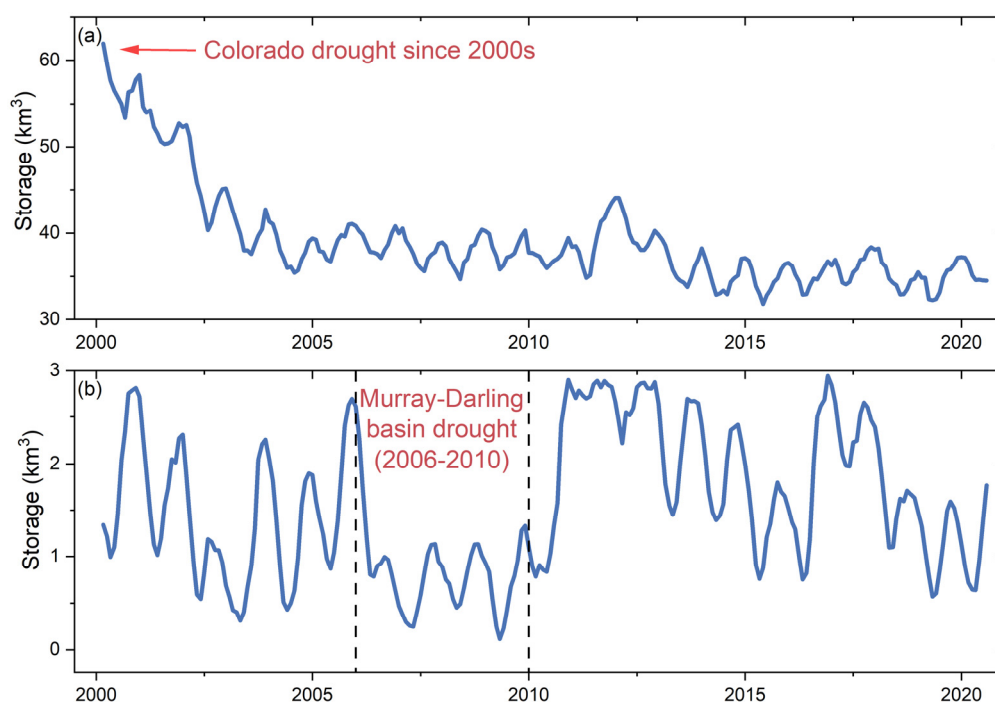


Figure 13. Total reservoir storage variations in the (a) Colorado and (b) Murray-Darling river basins.

6. Conclusions

This paper presents the development and validation results of NASA’s global water reservoir product suite (MxD28 and VNP28), which includes 8-day and monthly water area, elevation, and storage values and monthly evaporation rate and volume values. This product consists of 164 reservoirs that represent nearly half of the total global capacity (Figure 1 and Table 1). The water area values show good consistency with those from high-resolution Landsat measurements (Figure 5). Validations against in situ observations over twelve reservoirs suggest a high level of accuracy for the elevation and storage products (Figures 6 and 7). Validations over Lake Nasser and Lake Mead indicate that the evaporation rate product also has a high quality (Figure 8). Moreover, a comparison of 8-day reservoir area estimations between MODIS and VIIRS (Figure 9) again shows good consistency, which ensures the continuation of this long-term reservoir product.

Compared with other remotely sensed reservoir products, the advantages of our product can be summarized as follows. First, the product provides consistent measurements for area, elevation, and storage and for evaporation rate and volume values. For most of the current products, the measurements provided are generally for a specific aspect. For example, the radar altimetry products tend to combine observations from multiple satellite missions, which may have data gaps and large uncertainties (Figure 12). Second, the higher temporal resolution (8-day) can provide timely information useful for water management (e.g., water supply and flood mapping). Although Landsat can provide more accurate area estimations due to its higher spatial resolution, its longer revisit time (16 days) makes it not suitable for timely monitoring purpose. Furthermore, we have demonstrated that reservoir storage variations can be a good indicator of hydrological drought. This reservoir product can help to better understand the drought propagation process from the meteorological to hydrological perspectives.

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Data Availability Statement: This global water reservoir product suite will be available at <https://lpdaac.usgs.gov/> and <https://ladsweb.modaps.eosdis.nasa.gov/>, accessed on 30 December 2020.

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Appendix A

Table A1. List of the 164 reservoirs and their attributes.

Lake ID	GResD ID	Name	Ctry	CONT	A–E Coeff. ¹ <i>a, b</i>	<i>V_c</i> ² (km ³)	<i>A_c</i> ² (km ²)	<i>E_c</i> ² (m)	Lon (°)	Lat (°)
1 *	5058	Baikal	Russia	AS	0.0045, 312.77	23,615.39	32,265.61	456.88	104.322	52.235
2	3667	Volta	Ghana	AF	0.0037, 55.59	148.00	8502.00	86.65	0.059	6.304
3	4478	Nasser	Egypt	AF	0.0047, 152.82	162.00	6500.00	183.28	32.887	23.969
4	4056	Kariba	Zambia	AF	0.011, 424.98	180.00	5400.00	485.41	28.760	−16.521
5	5055	Bratsk	Russia	AS	0.0066, 367.92	169.27	5470.00	403.85	101.784	56.285
6	4787	Zaysan	Kazakhstan	AS	0.0047, 370.21	49.80	5490.00	395.74	83.346	49.657
7	2294	Guri	Venezuela	SA	0.014, 217.17	135.00	4250.00	278.38	−62.996	7.766
8	1995	Caniapiscau	Canada	NA	0.012, 489.00	53.79	4275.00	541.08	−69.783	54.850
9	1394	Robert Bourassa	Canada	NA	0.011, 143.99	61.70	2905.00	176.24	−77.451	53.785
10	2516	Sobradinho	Brazil	SA	0.0057, 375.27	34.10	3017.90	392.50	−40.825	−9.421
11	712	Cedar	Canada	NA	0.0022, 250.49	9.64	2668.46	256.29	−99.291	53.162
12	1396	La Grande–3	Canada	NA	0.025, 195.26	60.00	2451.00	257.48	−75.962	53.729
13	2365	Tucuruí	Brazil	SA	0.013, 40.96	45.50	2606.00	75.40	−49.648	−3.833
14	4375	Tsimlyanskoye	Russia	EU	0.012, 7.64	23.86	2702.00	39.44	42.109	47.612
15	5834	Zeyskoye	Russia	AS	0.021, 266.44	68.40	2420.00	316.41	127.307	53.770
16	5180	Vilyuy	Russia	AS	0.029, 182.74	35.90	2170.00	244.62	112.480	63.035

Table A1. Cont.

Lake ID	GRanD ID	Name	Ctry	CONT	A–E Coeff. ¹ <i>a, b</i>	<i>V_c</i> ² (km ³)	<i>A_c</i> ² (km ²)	<i>E_c</i> ² (m)	Lon (°)	Lat (°)
17	4783	Khantayskoye	Russia	AS	0.0044, 49.76	23.50	2221.61	59.64	87.813	68.162
18	4505	Cahora Bassa	Mozambique	AF	0.015, 286.96	55.80	2739.00	329.18	32.700	−15.584
19	6	Williston	Canada	NA	0.053, 580.99	39.47	1773.00	674.79	−122.200	56.020
20	4472	Buhayrat ath Tharthar	Iraq	AS	0.040, −19.46	85.59	2135.54	65.00	43.459	33.691
21	5056	Krasnoyarsk	Russia	AS	0.039, 162.77	73.30	2000.00	240.04	92.292	55.935
22	4623	Kama	Russia	EU	0.0074, 96.08	12.20	1915.00	110.32	56.338	58.116
23	1957	Okeechobee	United States	NA	0.0062, −5.57	5.20	1536.80	3.90	−81.101	26.941
24	5295	Hungtze	China	AS	0.0075, 1.46	13.50	2074.61	17.00	118.725	33.091
25	4474	Razazah	Iraq	AS	0.015, 11.07	25.75	1621.00	34.69	43.892	32.699
26	2023	Gouin	Canada	NA	0.00068, 402.91	8.57	1570.00	403.98	−74.104	48.358
27	4789	Qapshaghay Bogeni	Kazakhstan	AS	0.0090, 467.11	28.10	1850.00	483.71	77.104	43.923
28	753	Fort Berthold	United States	NA	0.025, 528.65	29.38	1477.40	565.10	−101.433	47.508
29	2445	Aperea	Paraguay	SA	0.022, 48.84	21.00	1600.00	84.71	−56.626	−27.392
30	870	Oahe	United States	NA	0.022, 462.73	28.35	1429.57	493.78	−100.400	44.458
31	2390	Ilha Solteira	Brazil	SA	0.032, 290.95	21.17	1200.00	329.78	−51.379	−20.371
32	4629	Saratov	Russia	EU	0.026, −0.28	12.90	1117.70	28.36	47.758	52.054
33	4350	Imandra	Russia	EU	0.19, −62.87	10.80	1062.37	136.07	32.550	67.408
34	3640	Kainji	Nigeria	AF	0.040, 94.00	15.00	1071.23	136.81	4.613	9.866
35	4785	Novosibirskoye	Russia	AS	0.014, 98.78	8.80	1070.00	113.97	83.000	54.844
36	4625	Cheboksary	Russia	EU	0.024, 39.30	13.85	1080.38	65.73	47.463	56.141
37	4359	Ilmen	Russia	EU	0.0083, 9.98	12.00	1120.00	19.28	31.280	58.457
38	4480	Jebel Aulia	Sudan	AF	0.0062, 375.01	3.50	861.19	380.39	32.484	15.240
39	1397	Opinaca	Canada	NA	0.021, 194.08	8.50	1040.00	216.10	−76.584	52.212

Table A1. Cont.

Lake ID	GRanD ID	Name	Ctry	CONT	A–E Coeff. ¹ <i>a, b</i>	<i>V_c</i> ² (km ³)	<i>Ac</i> ² (km ²)	<i>Ec</i> ² (m)	Lon (°)	Lat (°)
40	2392	Furnas	Brazil	SA	0.044, 720.07	22.59	1127.07	769.32	−46.314	−20.667
41	2368	Serra da Mesa	Brazil	SA	0.034, 410.20	54.40	1784.00	470.07	−48.304	−13.836
42	4624	Votkinsk	Russia	EU	0.039, 53.14	9.40	850.82	86.25	54.084	56.795
43	6201	Argyle	Australia	OC	0.028, 66.44	10.76	981.21	93.97	128.741	−16.118
44	731	Rainy	Canada	NA	0.00078, 336.09	0.69	829.45	336.73	−93.358	48.620
45	307	Fort Peck	United States	NA	0.044, 643.32	22.77	969.86	685.76	−106.415	48.002
46	2375	Tres Marias	Brazil	SA	0.036, 539.11	21.00	1040.00	576.06	−45.270	−18.214
47	2012	Pipmuacan	Canada	NA	0.050, 360.46	13.90	978.00	409.16	−69.770	49.355
48	4679	Chardarinskoye	Kazakhstan	AS	0.018, 238.24	5.70	800.66	252.54	67.962	41.245
49	4626	Nizhnekamsk	Russia	EU	0.014, 50.37	13.80	1084.00	65.34	52.280	55.704
50	2456	Negro	Uruguay	SA	0.019, 62.01	8.80	1070.00	82.77	−56.420	−32.830
51	2343	Chocon	Argentina	SA	0.015, 365.75	22.00	820.00	378.20	−68.758	−39.270
52	4442	Ataturk	Turkey	AS	0.11, 454.25	48.70	817.00	541.20	38.321	37.487
53	2513	Itaparica	Brazil	SA	0.033, 279.33	10.70	781.21	305.40	−38.312	−9.138
54	4464	Assad	Syria	AS	0.059, 266.63	11.70	610.00	302.87	38.555	35.862
55	3650	Lagdo	Cameroon	AF	0.037, 190.16	7.70	691.12	216.00	13.690	9.060
56	1269	Toledo Bend	United States	NA	0.020, 39.46	5.52	636.18	52.43	−93.570	31.179
57	6922	Eastmain	Canada	NA	0.068, 245.92	6.94	602.90	286.82	−75.886	52.188
58	2009	Outardes 4	Canada	NA	0.19, 239.61	24.50	640.00	361.53	−68.908	49.708
59	4349	Kovdozero	Russia	EU	0.0019, 78.18	3.70	745.00	79.62	31.759	68.604
60	2380	Sao Simao	Brazil	SA	0.052, 369.17	12.50	703.00	405.94	−50.500	−19.017
61	610	Mead	United States	NA	0.14, 288.76	34.07	659.30	374.60	−114.734	36.020
62	5087	Yamdrok	China	AS	0.013, 4435.36	14.60	638.00	4443.49	90.377	29.095

Table A1. Cont.

Lake ID	GRanD ID	Name	Ctry	CONT	A–E Coeff. ¹ <i>a, b</i>	<i>V_c</i> ² (km ³)	<i>Ac</i> ² (km ²)	<i>Ec</i> ² (m)	Lon (°)	Lat (°)
63	1391	Angostura	Mexico	NA	0.081, 478.96	18.20	640.00	530.67	−92.779	16.401
64	4991	Srisaillam	India	AS	0.031, 253.30	8.29	534.05	269.75	78.896	16.088
65	2455	Grande	Argentina	SA	0.031, 16.89	5.00	592.83	35.08	−57.944	−31.271
66	4843	Gandhi Sagar	India	AS	0.034, 379.03	6.83	619.89	399.90	75.555	24.700
67	2397	Promissao	Brazil	SA	0.080, 342.73	7.41	513.39	384.00	−49.782	−21.296
68	282	Arrow	Canada	NA	0.17, 351.07	10.30	504.82	439.30	−117.779	49.341
69	2382	Agua Vermelha	Brazil	SA	0.056, 351.62	11.03	563.15	383.30	−50.345	−19.867
70	4898	Hirakud	India	AS	0.022, 177.26	5.38	669.62	192.02	83.855	21.520
71	3041	Kossour	Ivory Coast	AF	0.034, 169.78	27.68	1058.20	206.00	−5.474	7.033
72	4784	Kureiskaya	Russia	AS	0.050, 67.89	9.96	558.00	95.63	88.287	66.950
73	3071	Storsjon	Sweden	EU	0.0042, 291.09	8.02	484.60	293.13	14.475	63.301
74	316	Flathead Lake	United States	NA	0.13, 816.09	23.20	510.00	883.61	−114.233	47.677
75	2004	Kempt	Canada	NA	0.033, 478.60	2.22	470.44	494.18	−70.529	50.657
76	6700	Kolyma dam	Russia	AS	0.14, 390.91	15.08	454.60	453.00	150.230	62.055
77	4501	Mtera	Tanzania	AF	0.022, 688.05	3.20	478.83	698.50	35.984	−7.136
78	4686	Kayrakkumskoye	Tajikistan	AS	0.021, 335.24	4.20	513.00	346.23	69.817	40.279
79	250	Kinbasket	Canada	NA	0.32, 622.77	24.76	430.00	759.15	−118.570	52.079
80	4634	Mingechaurskoye	Azerbaijan	AS	0.072, 42.02	15.73	567.97	83.00	47.025	40.795
81	2431	Lago del Río Yguazú	Paraguay	SA	0.045, 203.13	8.47	620.00	231.14	−54.970	−25.374
82	4858	Rihand	India	AS	0.062, 241.75	5.65	426.36	268.22	83.005	24.202
83	4422	Keban Baraji	Turkey	AS	0.11, 772.51	30.60	675.00	848.79	38.759	38.808
84	2340	Los Barreales	Argentina	SA	0.31, 290.07	27.70	413.00	417.11	−68.691	−38.577
85	4859	Ban Sagar	India	AS	0.051, 317.64	5.17	471.60	341.64	81.288	24.191

Table A1. Cont.

Lake ID	GRanD ID	Name	Ctry	CONT	A–E Coeff. ¹ <i>a, b</i>	<i>V_c</i> ² (km ³)	<i>Ac</i> ² (km ²)	<i>Ec</i> ² (m)	Lon (°)	Lat (°)
86	1275	Sam Rayburn	United States	NA	0.036, 35.66	3.55	455.64	50.11	−94.108	31.066
87	2414	Barra Bonita	Brazil	SA	0.0023, 565.25	7.01	542.00	566.48	−49.229	−23.213
88	4739	Ukai	India	AS	0.042, 83.60	6.62	509.85	105.16	73.597	21.258
89	479	Utah	United States	NA	0.023, 1359.51	1.07	380.00	1368.28	−111.892	40.359
90	305	Pend Oreille	United States	NA	0.23, 541.66	54.20	381.47	628.80	−116.998	48.179
91	4994	Tungabhadra	India	AS	0.041, 483.34	3.28	349.42	497.74	76.330	15.266
92	4461	Mosul	Iraq	AS	0.16, 273.38	11.10	353.16	330.00	42.825	36.633
93	4470	Habbaniyah	Iraq	AS	0.071, 114.62	8.20	418.40	144.43	42.350	34.212
94	4946	Sriram Sagar	India	AS	0.040, 319.95	2.30	314.38	332.54	78.342	18.967
95	2376	Lago das Brisas	Brazil	SA	0.088, 471.03	17.00	559.60	520.38	−49.097	−18.408
96	2356	Meelpaeg	Canada	NA	0.0041, 269.36	2.16	314.90	270.65	−56.780	48.166
97	4260	Hendrik Verwoerd	South Africa	AF	0.069, 1236.10	5.34	374.00	1261.93	25.505	−30.621
98	1387	Malpaso	Mexico	NA	0.30, 89.06	9.17	309.45	182.00	−93.600	17.179
99	1379	Inhernillo	Mexico	NA	0.14, 116.66	12.00	400.00	173.13	−101.892	18.272
100	4184	Vaaldam	South Africa	AF	0.036, 1472.82	2.61	320.00	1484.27	28.115	−26.883
101	5062	Longyangxia	China	AS	0.18, 2518.98	24.70	383.00	2589.15	100.917	36.121
102	3727	Hoytiainen	Finland	EU	0.0064, 86.17	2.39	293.00	88.05	29.475	62.825
103	1423	Baskatong	Canada	NA	0.057, 207.29	2.63	280.00	223.14	−75.983	46.725
104	5803	Tri An Lake	Vietnam	AS	0.072, 39.48	2.76	323.00	62.79	107.035	11.108
105	2007	Peribonka	Canada	NA	0.11, 411.54	5.18	270.72	440.26	−71.255	49.904
106	4942	Jayakwadi	India	AS	0.032, 451.67	2.17	382.39	463.91	75.367	19.487
107	3638	Shiroro	Nigeria	AF	0.086, 350.90	7.00	312.00	377.73	6.837	9.972
108	4379	Tshchikskoye	Russia	EU	0.062, 16.04	3.05	286.28	33.68	39.116	44.987

Table A1. Cont.

Lake ID	GRanD ID	Name	Ctry	CONT	A–E Coeff. ¹ <i>a, b</i>	<i>V_c</i> ² (km ³)	<i>Ac</i> ² (km ²)	<i>Ec</i> ² (m)	Lon (°)	Lat (°)
109	710	Tobin	Canada	NA	0.0090, 311.23	2.20	263.86	313.59	−103.404	53.660
110	5796	Noi	Thailand	AS	0.057, 129.50	1.97	288.00	145.94	105.430	15.206
111	4483	Roseires	Sudan	AF	0.025, 475.84	7.40	450.00	487.12	34.390	11.800
112	4675	Toktogul'skoye	Kyrgyzstan	AS	0.55, 743.53	19.50	284.30	901.24	72.653	41.683
113	6698	Gordon	Australia	OC	0.37, 208.54	12.40	278.00	311.42	145.979	−42.728
114	4964	Ujani	India	AS	0.055, 482.17	1.52	268.91	496.83	75.120	18.071
115	2312	Hondo	Argentina	SA	0.029, 266.72	1.74	330.00	276.36	−64.887	−27.524
116	4362	Ivankovo Reservoir	Russia	EU	0.018, 119.51	1.17	220.57	123.47	37.121	56.735
117	4702	Tarbela	Pakistan	AS	0.53, 351.46	13.69	250.00	483.55	72.691	34.091
118	4985	Nagarjuna	India	AS	0.29, 100.78	6.84	272.18	179.83	79.309	16.575
119	3070	Kallsjon	Sweden	EU	0.028, 387.52	6.14	189.74	392.80	13.342	63.433
120	4431	Karakaya	Turkey	AS	0.22, 631.76	9.50	298.00	697.54	39.135	38.229
121	4792	Beas	India	AS	0.20, 371.49	6.16	254.85	423.67	75.949	31.975
122	4047	Tshangalele	Congo	AF	0.031, 1119.03	1.06	225.65	1126.03	27.244	−10.753
123	4485	Finchaa	Ethiopia	AF	0.019, 2216.55	0.65	196.13	2220.26	37.363	9.558
124	4989	Almatti	India	AS	0.053, 504.12	3.11	293.42	519.60	75.888	16.333
125	4707	Mangla	Pakistan	AS	0.20, 320.13	9.12	251.00	370.60	73.643	33.145
126	4836	Ranapratap Sagar	India	AS	0.14, 324.74	1.44	197.66	352.81	75.580	24.916
127	3014	Bagre	Burkina Faso	AF	0.057, 223.54	1.70	255.00	238.12	−0.554	11.475
128	1991	Junin	Peru	SA	0.023, 4079.84	1.08	206.71	4084.62	−76.191	−10.980
129	4881	Bargi	India	AS	0.085, 401.51	3.18	236.24	422.76	79.928	22.945
130	6686	Great Lake	Australia	OC	0.40, 969.53	3.36	176.00	1040.54	146.730	−41.980
131	6800	Hawea	New Zealand	OC	0.15, 323.54	2.18	150.00	345.49	169.250	−44.609

Table A1. Cont.

Lake ID	GRanD ID	Name	Ctry	CONT	A–E Coeff. ¹ <i>a, b</i>	<i>V_c</i> ² (km ³)	<i>A_c</i> ² (km ²)	<i>E_c</i> ² (m)	Lon (°)	Lat (°)
132	3676	Albufeira da Quiminha	Angola	AF	0.13, 34.99	1.56	129.05	51.93	13.790	−8.963
133	6629	Eucumbene	Australia	OC	0.46, 1097.65	4.80	145.42	1165.24	148.617	−36.125
134	1320	Falcon	United States	NA	0.070, 71.74	3.88	311.84	93.48	−99.170	26.562
135	597	Powell	United States	NA	0.14, 1047.20	30.00	609.38	1127.76	−111.486	36.941
136	4463	Dukan	Iraq	AS	0.19, 462.68	6.97	270.00	513.69	44.955	35.958
137	1230	Cedar Creek	United States	NA	0.094, 85.92	0.80	133.03	98.15	−96.075	32.183
138	4041	Maga	Cameroon	AF	0.019, 309.63	0.68	148.72	312.50	15.050	10.829
139	5157	Pasak Chonlasit	Thailand	AS	0.053, 33.59	0.79	158.87	42.00	101.084	14.854
140	6594	Fairbairn	Australia	OC	0.13, 186.48	2.29	179.43	209.81	148.063	−23.650
141	6628	Hume	Australia	OC	0.15, 161.82	3.04	201.90	192.00	147.033	−36.108
142	4500	Kikuletwa	Tanzania	AF	0.10, 677.01	0.60	126.33	689.65	37.468	−3.821
143	4958	Nizam Sagar	India	AS	0.089, 419.96	0.50	92.75	428.24	77.929	18.203
144	6606	Victoria	Australia	OC	0.17, 7.53	0.68	122.00	27.73	141.275	−34.042
145	1869	Grenada	United States	NA	0.13, 49.35	1.54	128.29	65.53	−89.770	33.816
146	138	Canyon	United States	NA	0.69, 1300.94	1.61	108.39	1373.12	−121.091	40.179
147	4638	Aras	Azerbaijan	AS	0.12, 762.77	1.35	145.00	779.94	45.400	39.091
148	4481	Khashm el-Girba	Sudan	AF	0.093, 463.08	1.30	125.00	474.76	35.905	14.925
149	370	Lake Cascade	United States	NA	0.16, 1455.02	0.86	101.98	1471.57	−116.054	44.525
150	3695	Seitevare	Sweden	EU	0.63, 419.19	1.68	81.00	470.15	18.571	66.975
151	4484	Yardi	Ethiopia	AF	0.33, 533.59	2.32	104.87	568.25	40.538	10.233
152	119	Clear Lake	United States	NA	0.20, 1345.80	0.65	100.36	1365.84	−121.079	41.926
153	5196	Guanting Shuiku	China	AS	0.11, 465.09	4.16	130.00	479.09	115.600	40.233
154	2953	Barrage Al Massira	Morocco	AF	0.34, 241.41	2.76	80.00	268.54	−7.637	32.475
155	1319	Venustiano Carranza	Mexico	NA	0.095, 252.29	1.31	150.56	266.53	−100.616	27.512

Table A1. Cont.

Lake ID	GRanD ID	Name	Ctry	CONT	A–E Coeff. ¹ <i>a, b</i>	<i>V_c</i> ² (km ³)	<i>A_c</i> ² (km ²)	<i>E_c</i> ² (m)	Lon (°)	Lat (°)
156	4471	Hamrin	Iraq	AS	0.12, 80.23	4.61	228.00	107.50	44.967	34.116
157	4826	Matatila	India	AS	0.10, 297.22	0.71	112.07	308.46	78.371	25.099
158	1263	Twin Buttes	United States	NA	0.50, 576.78	0.23	29.47	591.37	−100.525	31.370
159	4997	Somasila	India	AS	0.17, 74.32	1.99	153.17	100.58	79.305	14.489
160	5183	Hongshan	China	AS	0.23, 422.08	2.56	66.90	437.64	119.696	42.751
161	6583	Ross	Australia	OC	0.11, 32.61	0.80	82.00	41.77	146.738	−19.411
162	4978	Yeleru	India	AS	0.59, 57.51	0.51	49.36	86.56	82.084	17.304
163	4696	South Surkhan	Uzbekistan	AS	0.34, 397.80	0.80	40.26	411.41	67.632	37.829
164	5287	Zhaopingtai	China	AS	0.0045, 312.77	0.71	46.50	174.27	112.771	33.733

* The 164 reservoirs include 13 regulated natural lakes, whose IDs are 1, 6, 20, 23, 33, 37, 44, 62, 73, 102, 131, 150, and 151. ¹ *a* and *b* are the coefficients used in the A–E relationship equation, $h = a * A + b$, where *h* and *A* are elevation (m) and area (km²), respectively. ² *V_c*, *A_c*, and *E_c* represent storage, area, and elevation values at capacity, respectively.

Appendix B

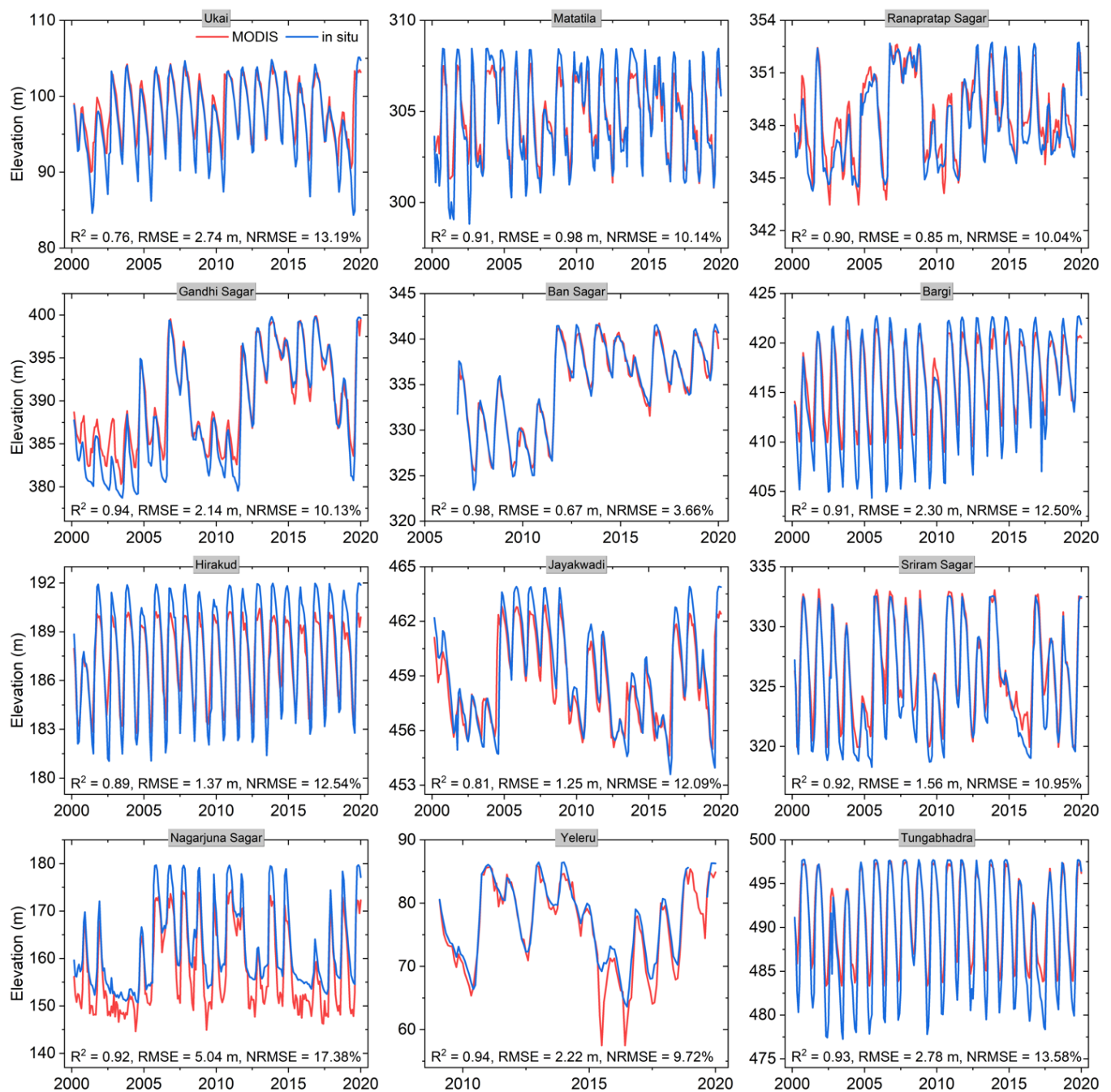


Figure A1. Validation of monthly elevation products for twelve Indian reservoirs from 2000 to 2019.

Appendix C

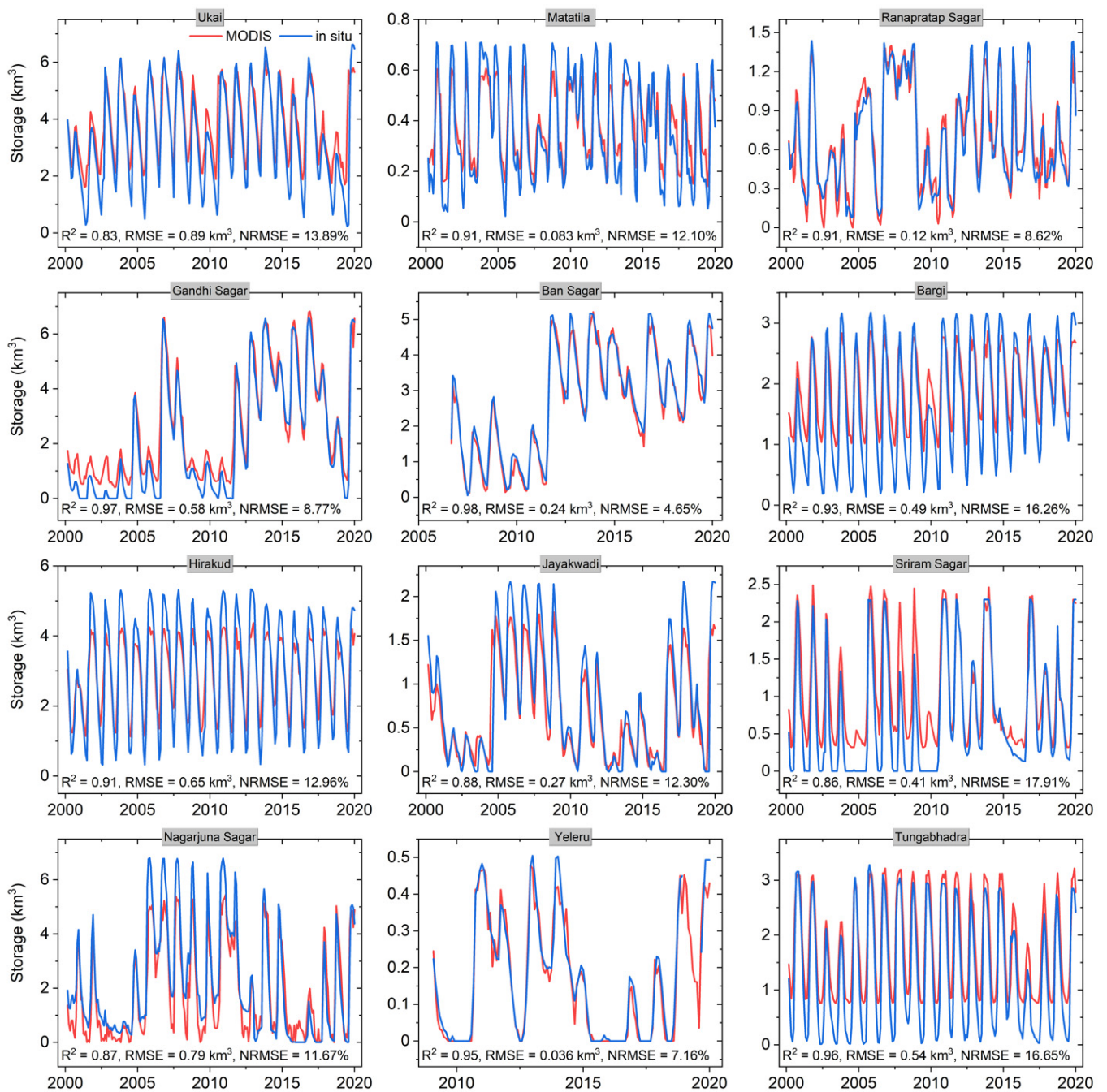


Figure A2. Validation of monthly storage products for twelve Indian reservoirs from 2000 to 2019.

Appendix D

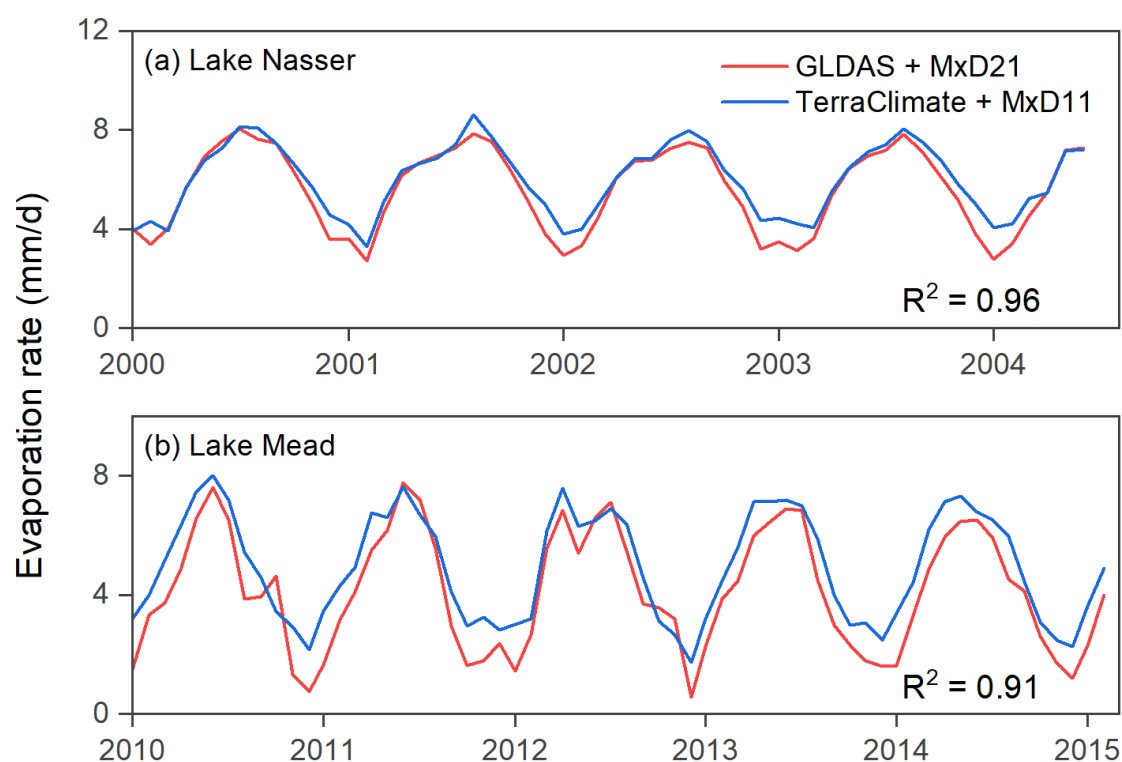


Figure A3. Comparisons of evaporation rates calculated from different datasets (GLDAS + MxD21 and TerraClimate + MxD11) for (a) Lake Nasser and (b) Lake Mead.

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