



# Advances in Retrieving Soil Moisture Content in the Yellow River Basin Using Remote Sensing Satellite Data

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## ABSTRACT

Yellow River Basin, which suffered from water shortage and drought disaster frequently, has a need to use soil moisture information precisely to assist the agriculture, drought monitoring, and climate research. The high resolution dataset is very useful for the resource management. Conventional ground based monitoring is difficult and limited on precision due to their spatial resolution and costs, but remote sensing is able to overcome due to its scalability; however due to the limitation of satellite dataset resolution, remote sensing plays a limited role in soil moisture observation. Here, we review the latest approaches in soil moisture retrieval with optical, microwave and GNSS-Reflectometry (GNSS-R) technologies and put particular emphasis on their applications in YRB. Optical approaches offer fine spatial resolution but cannot penetrate in clouds and canopy cover, while microwave and GNSS-R technologies can measure all weather with an effective depth up to 5 cm. The practicality of case studies are demonstrated in regional case studies (AVHRR-based deep-layer retrievals in 1982–1989 and multi-source data fusion in 2016–2018). In both cases, challenges are unresolved such as, insufficient resolution and/or inconsistent datasets. Further studies need to: 1) employ a region-specific model suitable for local hydrological characteristics, 2) enhance root-zone moisture estimation for near real time applications, and 3) provide a region-wide dataset based on multi-sources data fusion. Such breakthroughs are important in order to achieve increased farming resilience and sustainability in the basin.

## KEYWORDS

Soil moisture retrieval; Optical Inversion; Microwave GNSS-R; Yellow River Basin.

## 1. INTRODUCTION

The Yellow River Basin is the significant ecological and economic ecosystem, with 12%, 15% and 14% of the national population, agriculture irrigation and GDP, but only 2% of China's total surface flow, that is threatened by the intensifying water shortage and recurring droughts[1], which threatens the sustainability of ecosystem and socioeconomic systems. This, along with two other features, namely the prevalence of dry and wet regions and temporal intermittency, provides a more accurate characterization of drought dynamics and water resource management[2]. One of the most important hydrologic variables in this context is soil moisture content (SMC). Since the representation of basin hydrologic heterogeneity needs to be as complete as possible to better understand and model drought dynamics [3], ground-based monitoring approaches with limited space coverage and high operational costs are insufficient to meet such demands. Spatially continuous and temporally uniform SMC retrievals from both optical, microwave, and GNSS-R remote sensing satellite technologies hold the key to a wide variety of drought prediction and adaptive water management application – allowing the efficient profiling of soil moisture down to depths of several meters and the penetration of

vegetation canopy layers – that will be critical to the basin for reconciling water demand-supply and for the conservation and restoration of its ecosystems. We think it is necessary to push forward the state of the art in this important domain so as to exploit these different forms of observations to the fullest[4].

Soil moisture retrieval from remote sensing over the Yellow River Basin has been proposed by three types of techniques, including the passive, active and hybrid active-passive system. For the passive technique, moisture estimate (~5 cm depth) was obtained by interpreting the natural emission of microwave from the ground using passive microwave sensors like ASCAT and more recently Sentinels-1 [5]. Passive microwave sensors and active radar sensors measure soil moisture from the radar backscatter based on empirical (e.g., Oh model) and semi empirical (e.g., Dubois model) scattering models [6]. The all - weather GNSS - Reflectometry (GNSS - R) approach provides a novel method for soil moisture retrieval [7]. Traditional optical techniques (based on the use of thermal inertia and vegetation indices, e.g. Landsat-derived NDVI), although limited by the presence of atmosphere and in terms of subsurface penetration depth. More up-to-date techniques combine multi-sensor data sets, dielectric mixing models (Dobson), and surface scattering models (IEM), but the spatial resolutions (3–40 km) do not allow to disentangle basin’s complexities related to topography and land-use variability [8]. Deep learning (artificial neural networks) based systems trained using multi-modal satellite inputs hold promise in addressing the limits of spatial resolution while enhancing the retrieval quality, and can establish ML as a disruptive technology for basin scale soil moisture monitoring that can be better adapted for regional hydrology [9].

The instability of eco-environment and water-deficiency of Yellow River Basin indicate the great importance of accuracy Soil Moisture Information Retrieval, where the remote sensing provides an effective mode for regional Soil Moisture Information Retrieval as a broad application, although it is beset with problems related to observation resolution. We review the history of the development of optical method, microwave method and GNSS-R method, as well as their applications in the Yellow River Basin, and their latest research at this moment with the intention of resolving the technical problems.

## **2. REMOTE SENSING TECHNOLOGIES FOR SOIL MOISTURE RETRIEVAL**

Soil moisture sensing technologies like remote sensing in Yellow River area have unprecedented potentials to monitor the soil moisture at macro-level due to its wide coverage, and it can reflect micro-hydrology characteristics in Yellow River area from macro-level. The soil moisture sensing technology is divided into passive soil moisture, active soil moisture and the mixed soil moisture which sensing is mainly based on different physical principles to realize the detection of the soil moisture content. In this Section, we give an introduction about the passive (optical) remote sensing, active (microwave) remote sensing, and combined activepassive remote sensing (GNSS-R), including their concepts, techniques, strengths and weaknesses, and significant satellite data sources with focus to their potential application in the varied scene of Yellow River Basin.

### **2.1. Passive Remote Sensing**

#### **2.1.1. Principles and Mechanisms**

The remote sensing techniques (i.e. passive remote sensing techniques) use the visible, near infrared and thermal infrared wavelength bands to derive the soil moisture content of the top-soil, (1 mm). This is done by measuring natural radiation that originates with or is reflected from the soil, which has changing characteristics with moisture-dependent changes in reflectance and thermal properties. The soils that contain more water appear darker than drier soils because they have a lower albedo and higher thermal inertia, resulting in different values of brightness in optical images. The technique is

a formalisation of the theory of apparent thermal inertia originally applied and proposed by Price (1968; hereinafter referred to as Price, 1968) whereby the differential temperature response to incident solar radiation and heat loss experienced by dry and wet soils are exploited, respectively, for inference of subsurface moisture[10].

### 2.1.2. Common Methods

There are several optical remote sensing techniques used to estimate the soil moisture content that utilize different spectral features of the soil water. One of these techniques is the thermal inertia technique that assumes the soil moisture content can be derived from differences in diurnal surface temperature by using the soil moisture dependency of the soil thermal inertia because moist soil with higher heat capacity has lower rate of surface temperature change [11]. The vegetation index approaches use various indices including NDVI, indirectly measuring soil moisture using vegetation health (because lack of water stresses vegetation appearing in spectral signals[12]). Water deficit index approach assess the soil moisture availability by combining land surface temperature and vegetation fraction and can be useful for the agricultural water stress monitoring application[13]. The reflectance-based techniques are able to relate soil moisture and reflectance in the visible and NIR bands in a way that exploits soil spectral changes due to soil moisture. The reflectance based techniques generally range in their ability to not be negatively impacted by the environment (e.g., presence of clouds, vegetation)[14].

### 2.1.3. Advantages and Limitations

The advantages of optical remote sensing for retrieval of soil moisture include its higher spatial resolution, such as those of Landsat (30m), and higher numbers of dataset from satellites, such as HCMM, TIROS, NOAA and EOS with lower cost, which is good to conduct detailed mapping of various land uses within the YRB. Disadvantage of optical remote sensing is that the accuracy is restricted, with its effect influenced by cloud, atmospheric problems and presence of vegetation covering soil signals. Further, its low penetration depth precludes it from detecting subsurface water which is of potential importance for determining root-zone moisture in crop application.

### 2.1.4. Key Satellite Data Sources

The most important satellites for the observation of soil moisture are Landsat, NOAA, EOS, HCMM and TIROS, which not only have the advantage of different abilities in different fields, but can complement each other well. The US Landsat has achieved a resolution of 30m and can delineate the surface moisture of the study area well, such as its terrain, water network, urban features, soil type, agricultural lands and lakes, and even track the evaporation from soil in detail in a warm or humid environment [12, 15]. The Moderate-resolution imaging spectroradiometer (MODIS) of National Oceanic and Atmospheric Administration (NOAA) has the intermediate resolution, so it can give a brief understanding for the long-term trend in terms of soil moisture changes [16]. EOS can provide observations in several spectral bands (multispectral) to study vegetation and also thermal measurements (to further aid in the estimation of moisture)[17]. The prior years platforms HCMM and TIROS have had a great influence on the study of optical remote sensing, whose design techniques proved instrumental to their successors in the form of those optical units mounted on higher-resolution satellite bodies[18].

## 2.2. Active Remote Sensing

### 2.2.1. Principles and Mechanisms

Active microwave remote sensing, an example of active remote sensing, sends out microwave pulses to the soil surface, and records the return backscatter (proportional to the dielectric constant of the soil, which in turn increases with the soil moisture content). From this information the soil moisture can be estimated at depth of up to about 5 cm. This technique, which has been constructed since the

1990s, is based on the combined effects of the dielectric constants, soil moisture, ground roughness, and vegetation and on the modulation of the backscattering intensity for successful inversion[19].

### 2.2.2. Common Methods

Multi-parameterization techniques Active microwave remote sensing approaches the estimation of soil moisture utilizing the backscatter data with multi-parameterization methods [20]. The Oh model is an empirical one which links the backscatter to the soil moisture and the surface roughness[21]. The Dubois model is a semi-empirical one by considering both the vegetation characteristics and soil property information for improving the soil moisture estimation [22]. Shi introduces an approach, which utilizes multi-polarization data to increase the accuracy of retrieval in the complicated terrain[23]. Water-Cloud separates the backscatter due to the contribution of vegetation and soil, which improves the accuracy in the presence of vegetations, by separating the soil moisture signal.

### 2.2.3. Advantages and Limitations

In the aspect of active microwave remote sensing, advantages of retrieving soil moisture are weather-independent, can penetrate through vegetation, and can retrieve subsurface soil moisture up to the depth of 5cm, all of which make it applicable to the Yellow river basin which is often cloudy and has quite a high dense of vegetation. The consistent time-series from ASCAT and Sentinel-1 can monitor large-scale. Nonetheless, its coarse spatial resolution (e.g., 12.5–25 km for ASCAT) and sensitivity to surface roughness and vegetation density limit accuracy in the basin's heterogeneous landscapes in which fine-scale agricultural pattern dominate.

### 2.2.4. Major Satellite Data Sources

Some important active microwave satellites in obtaining soil moisture information are ASCAT and Sentinel-1, which have their respective merits. ASCAT (C-band 5.255 GHz) spatial resolution is 12.5–25 km, and it provided a continuous measurement from 2007 and reached accuracy 0.03–0.07 m, which could be applied for a large area scale surveillance of the soil moisture over the Yellow River Basin[24]. Sentinel-1 is another C-band radar which provides higher spatial resolution and has 6–12 day revisit time to assist in monitoring basin-wide variations in moisture conditions imposed by its heterogeneous landscape[25].

## 2.3. Combined Active-Passive Remote Sensing

### 2.3.1. Principles and Mechanisms

GNSS-Reflectometry (GNSS-R) is a hybrid active-passive remotesensing technique that senses the soil moisture from reflected Global Navigation Satellite System (GNSS) signals from the soil's surface. The reflected signal amplitudes and phases are proportional to the dielectric properties of the soil, which change with soil moisture content, allowing the all-weather sensing of soil moisture, with depth limited only to 5cm. The GNSS-R, which was introduced at the end of 2010's, combines the active sending of the GNSS signal together with the passive detection of the returned signal and presents a versatile method to acquire the information about the soil moisture. The instrument was previously proved to work by Chew and Camps<sup>25,27</sup> using UKTDS-1 data and data from the recently launched CYGNSS constellation (2016)[26].

### 2.3.2. Common Methods

Multiple GNSS-Reflectometry (GNSS-R) retrieval methods exist to retrieve Soil Moisture (SM) through reflected GNSS signals. The Integral Equation Model (IEM) retrieves SM by simulating the scattering on an underlying rough surface. The Artificial Intelligence and Empirical Equation of the Model (AI-EM) is further advanced empirical method based on IEM which incorporates artificial intelligence for retrieving more precise values even in highly complex soils[27]. The third model which is much closer in nature is the empirically based Dobson model which correlates the SM with different values of properties of the signals based on the concept of dielectric nature[28]. Likewise,

Topp, Hallikainen, and Wang models also employ empirically and semiempirically constructed dielectric models to enhance the moisture estimation[29]. ML and neural network approaches have further improved the retrieval by mimicking complex associations among the signal features and soil moisture that could be used for robust solutions in heterogeneous landscapes such as those in the Yellow River basin[30].

### 2.3.3. Advantages and Limitations

GNSS-Reflectometry (GNSS-R) is largely characterized by the flexibility in data acquisition , and the incorporation of active and passive remote sensing advantages for efficient monitoring under heterogeneous terrain, which makes its suitable for the heterogeneous terrain in the Yellow River Basin with a large amount of available data from the currently planned CYGNSS constellation [31].Nevertheless, being a recent emerging technology, its robustness has to be validated by proving the accuracy of the results within the limits of all possible conditions in heterogeneous scenes, where different ground roughness and vegetation may have misleading interpretations[32].

### 2.3.4. Key Satellite Data Sources

Notable GNSS-Reflectometry (GNSS-R) satellites for soil moisture applications are CYGNSS and UKTDS-1. CYGNSS was launched in 2016 (refer to 4) which provides high-temporal-resolution data with variable spatial resolution (in the order of 1-10km) which is adequate enough to catch the fast hydrological state change of YRB area. Early experimental system UKTDS-1 The experimental platform UKTDS-1 demonstrated the feasibility of the GNSS-R for measuring soil moisture and served as a preliminary step towards various innovations related to this new sensing technique[33].

## 2.4. Comparative Overview of Satellite Data Sources

Satellite data sources of passive, active and combined activepassive remote sensing are summarized as Table above in terms of their instrument types, resolutions, time series and accuracies.

**Table 1: Main Satellite Data Used for Soil Moisture Retrieval**

Data Source	Instrument Type	Spatial Resolution	Temporal Resolution	Time Series	Inversion Accuracy
Landsat	Optical (Passive)	30 m	16 days	1972–present	Variable (surface)
NOAA	Optical (Passive)	1–4 km	Daily	1978–present	Variable (surface)
ASCAT	C-Band Active Microwave (5.255 GHz)	12.5–25 km	3 days	2007–present	0.03–0.07 m <sup>3</sup> /m <sup>3</sup>
Sentinel-1	C-Band Active Microwave	~10 m	6–12 days	2014–present	~0.05 m <sup>3</sup> /m <sup>3</sup>
SMOS	L-Band Passive Microwave (1.4 GHz)	35 km	1–3 days	2010–present	±0.04 m <sup>3</sup> /m <sup>3</sup>
AMSR-E/2	Passive Microwave (6.93–8.9 GHz)	15–2170 km	Twice daily	2002–2010, 2013–present	±0.04 m <sup>3</sup> /m <sup>3</sup>
SMAP	L-Band Active-Passive Microwave (1.2–1.4 GHz)	3–40 km	3 days	2015–present	±0.04 m <sup>3</sup> /m <sup>3</sup>
FY-3	Microwave Imager (Passive)	25–85 km	0.5, 10 days/month	2011–present	±0.05 m <sup>3</sup> /m <sup>3</sup>
CYGNSS	GNSS-R (Combined Active-Passive)	1–10 km	Sub-daily	2016–present	~0.05 m <sup>3</sup> /m <sup>3</sup>
ESA CCI	Multi-Source Data	~25 km	1 day	1979–present	±0.04 m <sup>3</sup> /m <sup>3</sup>

Other optical satellites (Landsat, HCMM, TIROS, NOAA, EOS), even with finer resolution (up to 30 m in the case of Landsat), are exploited for retrievals at the surface. GNSS-R satellites, like CYGNSS, are hybrid with particular features that are yet to be more standardized due to the rather wide spatial resolution.

### 3. APPLICATIONS IN THE YELLOW RIVER BASIN

#### 3.1. Environmental and Agricultural Context

The Yellow River Basin in China is an important ecological and agricultural area, but the shortage water resource challenges this region because its small runoff from the surface water accounts for only 2% of China’s runoff to serve the population of 12% and the agricultural water irrigation water consumption of 15% [34]. The content level of soil moisture (SMC) plays critical role for crop growth, water resources management and drought resistance in this water-depleted basin. Due to the non-uniform landforms (the loessic plateau and alluvial plain) within the basin [35], the complex climatic environments and abundant cultivated lands with large vegetation cover, monitoring high-spatial-temporal-resolution SMC are substantially difficult. However, this highlights the necessity of obtaining high spatial and temporal-resolution, accurate SMC for irrigation scheduling, drought warning, ecological remediation for combating soil deterioration and desertification [36].

#### 3.2. Case Studies

##### 3.2.1. Historical Studies

Past Researches The achievements of researches related to past monitoring of soil moisture are summarized below. During the period of 1982– 1989, Yang et al. used the 17-year AVHRR remote

sensing data and corresponding agrometeorological and evaporation data and established a remote sensing model of soil moisture 0–1m layer in Yellow River Basin[37], giving a spatial-temporal comprehensive chart of the moisture state; revealed the trend of seasonal variation in soil moisture to provide guidance for prior water conservancy management of the Yellow River. In the same vein, Liu (1971–2000) investigated 30 years (1971 to 2000) data of the 69 meteorological stations, by interpolating[38], soil moisture distribution maps, being able to explain, longer term, spatially the variability of the basin moisture when covering a great range of landscapes that characterise the basin and confirming regionally the hydrological evaluation.

### 3.2.2. Recent Studies

In 2016–2018, Li et al. utilized multiple data sets (CCI, SMAP and ERA5-Land) for the Yellow River Basin to investigate trends of soil moisture[39], sudden jump, and the periodic behaviors (in the growing season i.e., June–September). In this study, combining the optical and microwave data, the efficiency of data fusion from multiple sources for detecting changes of moisture variations dynamically has been demonstrated for useful information on the drought monitoring and agricultural management in dry regions of water resources scarce and densely agriculture areas.

### 3.3. Performance Evaluation

Landsat and AVHRR based optical remote sensing techniques offer good spatial resolution (30m) , which can achieve good mapping of soil moisture on fragmented agricultural fields within the basin, but are hindered by cloud cover, vegetation obscuration and shallow penetration (1 mm), thereby become less reliable in wet conditions or when high vegetation cover occurs[40]. Microwave techniques, including both active and passive, can estimate soil moisture around the clock, and at global scale, at a 200m resolution in the 9.6-10.6 GHz band[12]. These remote sensing-based estimates could potentially help to constraint errors associated with gridded products, using station observations or flux tower data, as well as improving bias correction of model estimates of evaporation over heterogeneous land surfaces. At this resolution, calibrated microwave derived soil moisture estimates during flood years hold a great potential, particularly where soil water availability is limited[41]. Nonetheless, remote sensing based methods over diverse land surface in the Yellow River Basin are unlikely to accurately map soil moisture on smaller scales due to inadequate coverage of measuring equipment. In contrast, the disadvantage of remote sensing methods is the high cost and unstable operation associated with some designed devices. Satellites-based active (ERS-2, Envisat, SMOS, SMAP) systems provide all weather and deep penetration (~5 cm), however they suffer from large coarse resolution (3–40 km) with the inability to account for the soil variability and uneven land topography in the basin. GNSS-R can be promising but not fully validated yet in the region, having inconsistent precision on heterogeneous grounds. Region specific issues are data availability invariable and also data sparseness (especially for old periods), issues related with merging heterogeneous data, and accuracy levels not homogeneous because of differing soils and types of uses of the terrain[42].

## 4. RECENT ADVANCES AND INNOVATIONS

### 4.1. Multi-Source Data Fusion

The multi-source data fusion is based on both optical (e.g., Landsat), microwave (e.g., SMAP, ASCAT), GNSS-R data (e.g., CYGNSS) to gain better soil moisture retrieval performance in terms of spatial coverage and accuracy by merging information derived from high spatial resolution optical data and all-weather monitoring microwave and GNSS-R observation through the Bayesian merging and the Kalman filter. These methods are demonstrated to be adequate at capturing the detailed variations of soil moisture, and hold great promise for the applications to precision agriculture in the Yellow River Basin, facing the challenging landuse and hydrological conditions.

## **4.2. Spatial Downscaling Techniques**

Spatial downscaling reduces the coarse microwave and GNSS-R soil moisture datasets (e.g., SMOS: 35 km, ASCAT: 12.5–25 km) by incorporating auxiliary high-resolution data such as optical imagery or topographic variables into the retrievals. Methods such as statistics-based (e.g., regression based disaggregation), and Machine Learning-based approaches produce fine resolution data (e.g., 1 km). These methods may be special applicable to Yellow River Basin area with discontinuous landscape pattern and various land-use types so moisture map can provide useful references for a reasonable water resources planning and agriculture production.

## **4.3. Advanced Algorithms**

Machine learning algorithms (e.g. random forest, convoluted neural network and deep learning models) and neural network algorithms are more commonly used in soil moisture retrieval thanks to its capability to construct complex modeling relationships between satellite observations and soils. Such models show superior performance compared with classic empirical models (e.g., Oh and Dobson) in responding to various soils and different vegetation types in the Yellow River Basin. These algorithms are particularly suitable to fuse multiple sources of information, delivering robust solutions of the complicated terrains within the basin as well as accurate soil moisture retrieval with direct applications in agriculture and environment monitoring.

## **4.4. Deep-Layer Soil Moisture Retrieval**

Precise measurement of root-zone soil moisture (~1 m) is also important to agricultural related activities, since crop roots can be deeper than the 5 cm of depth that is generally sampled using remote-sensing. Data assimilation modeling combining surface moisture observations with waterflow models and machine learning algorithms that associate surface and subsurface moisture observations are enabling research toward deep-layer retrieval. These approaches may have potential for Yellow River basin to get good spatially explicit root-zone moisture information for a better irrigation management and drought vulnerability reduction in agriculture arid area.

# **5. CHALLENGES AND FUTURE DIRECTIONS**

## **5.1. Current Challenges**

Few of the remote sensing retrievals for SM in the Yellow River basin can overcome these drawbacks, most of the physical retrievals of SM (such as optical retrieval (~1 mm penetration) and microwave / GNSS-R (~5 cm penetration)) are also restricted by shallow SM which is necessary for agricultural and ecologic concerns. Variable terrain elevation (loess plateau and alluvial plain) along with extensive vegetation canopy in the basin do not favour optical techniques for reducing the retrieval (resolution/accuracy dilemma). Data with higher resolution (accuracy) are easily affected by environmental noise whereas microwave data and GNSS-R with lower resolution (3-40km) face challenges to retrieve the heterogeneous landscapes. Moreover, differences in methodologies and used data among the studies cause contrary results, which prevent the assessment to make a basin-wide moisture evaluation.

## **5.2. Future Research Priorities**

In order to improve the above-mentioned issues in soil moisture retrieval, in the future studies for soil moisture retrieval in Yellow River Basin, the regional characteristics retrieval model should be developed on the basis of Yellow River Basin's hydrogeological and climatic characteristics for addressing the impact of heterogeneity of soil and topography characteristics. And the fine-scale

estimation of the root-zone moisture using DA and machine learning also be improved to provide the deeper reference to guidance for precision agriculture water management. Real-time observation at a high resolution with artificial intelligence and cloud computing may help with drought prediction and management, while the progress in multi-source data fusion will provide a unified high resolution dataset to fit for this non-uniform land use basin, respectively. Besides, further research into climate soil moisture variability will aid to enhance predictability and promote the sustainable management in this water-limited basin.

## 6. CONCLUSION

These remote sensing techniques greatly facilitated the monitoring of soil moisture in YRB, thus meeting the urgent demands for water resources and drought in this important ecological environment and water deficit river basin. Optical remote sensing techniques based on hyperspatial data from Landsat sensors are often used for monitoring the spatial distribution of surface moisture, but affected by cloud shading, and shallow detection depth (about 1mm). Meanwhile, microwave and GNSS-R methods, assisted by satellites SMAP and CYGNSS, respectively, allow all-weather subsurface monitoring (5cm), but only at lower resolutions (3–40 km). Several case studies of local–regional scale, combining long-time AVHRR-based deep-layer retrieval (1982–1989) with modern multi-source fusion analysis (2016–2018), show a real-life usefulness of such applications both for the agriculture and environment. The improvement of retrievals through multi-source data fusion, spatial downscaling and machine learning is helping to improve resolution and accuracy of the retrieval for the specific nature of the complex terrain and the varying nature of the land-use for the basin. However, high signal penetration into the root-zone is an issue along with significant elevation variations and the discrepancy between data sets. In our future work, the construction of locally-adapted models, deep layers based moisture prediction, and end-to-end, “real-time” AI-based observations can further contribute to sustainable agriculture and climate adaptability, and to the well-being of the ecosystem and economy of the basin.

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