Advancements In Remote Sensing and GIS for Groundwater and Water Resource Monitoring

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***Abstract*—Groundwater resources are increasingly threatened by population growth, urbanization, agricultural demand, and climate variability, making effective monitoring and management a global priority. Traditional hydrogeological methods, though reliable, are constrained by limited spatial coverage and high costs. Over the past two decades, advancements in remote sensing (RS) and geographic information systems (GIS) have transformed groundwater and water resource monitoring by providing scalable, cost-effective, and multi-temporal datasets. This review consolidates key developments up to 2021, highlighting the role of satellite missions, radar and LiDAR technologies, GIS-based modeling, and machine learning approaches.**

One of the most significant contributions has been the Gravity Recovery and Climate Experiment (GRACE) mission, which enabled large-scale groundwater storage anomaly detection and depletion mapping in stressed regions such as northern India and California. Complementing GRACE, the Soil Moisture Active Passive (SMAP) mission improved understanding of soil moisture dynamics and recharge estimation, while optical indices such as NDWI were used for vegetation water content and irrigation monitoring. Interferometric Synthetic Aperture Radar (InSAR) has become indispensable for detecting aquifer-system deformation and land subsidence linked to excessive pumping, with applications across Mexico, California, and Asia. At finer spatial scales, Light Detection and Ranging (LiDAR) datasets have supported recharge zone delineation and hydrogeomorphic studies, particularly in complex terrains. GIS has served as the integrative platform for these datasets, enabling groundwater potential mapping through multi-criteria decision analysis (MCDA). Techniques such as frequency ratio, certainty factor, and weights-of-evidence have been widely applied, while more recent works integrated machine learning and data mining algorithms to enhance predictive accuracy. Hybrid approaches linking RS datasets with hydrological models further improved aquifer monitoring in data-scarce regions.

Comparative analysis shows a progression from large-scale monitoring in the early 2000s (GRACE, GIS-based mapping), to detailed local studies in the 2010s (InSAR, LiDAR), and finally to advanced hybrid approaches combining RS, GIS, and machine learning after 2016. Despite these advances, challenges persist, including GRACE's coarse resolution, InSAR's atmospheric sensitivity, and the lack of robust validation for machine learning models. Moreover, many scientific outputs have yet to be fully integrated into water governance and management frameworks. Future efforts must focus on multi-sensor data fusion, downscaling techniques, UAV-based surveys, and stronger linkages between scientific tools and policy to ensure sustainable water resource management.

***Index Terms* - Groundwater resources, Remote sensing (RS), Geographic Information Systems (GIS), GRACE, SMAP, NDWI, InSAR, LiDAR, Groundwater monitoring, multi-criteria decision analysis (MCDA), Machine learning, Hydrological modeling, Aquifer deformation, Land subsidence, Recharge estimation, Multi-sensor data fusion, UAV-based monitoring, Water governance.**

I. INTRODUCTION

Water is one of the most essential natural resources that sustains life, agriculture, industry, and ecosystems. Among all freshwater sources, groundwater plays a particularly critical role, as it supplies nearly one-third of the world's total freshwater demand and serves as the primary source of drinking and irrigation water in many arid and semi-arid regions.

Globally, more than two billion people rely on groundwater as their main source of water supply, and its use continues to grow in response to rising population, urbanization, and agricultural intensification. However, the excessive and often unregulated extraction of groundwater has resulted in severe depletion of aquifers, declining water tables, deterioration of water quality, and in some cases, irreversible land subsidence. Coupled with the impacts of climate change—such as shifting rainfall patterns, prolonged droughts, and increasing evapotranspiration—groundwater resources face unprecedented stress. Effective monitoring and management of groundwater have therefore become a cornerstone of sustainable water resource planning.

Traditionally, groundwater assessment has relied on field-based hydrogeological surveys, pumping tests, and the monitoring of observation wells. While these methods provide accurate local-scale information, they are limited in spatial coverage, costly, and time-intensive. In many developing regions, monitoring networks are sparse or non-existent, creating large data gaps that hinder effective management. Furthermore, traditional approaches often fail to capture the temporal variability of aquifer dynamics over large regions, particularly in transboundary aquifers where coordinated monitoring is lacking. This has created a pressing need for innovative, scalable, and cost-effective tools that can complement and enhance conventional hydrogeological investigations.

Over the past two decades, remote sensing (RS) and geographic information systems (GIS) have emerged as transformative technologies for water resource research and management. Remote sensing, through satellite, airborne, and UAV platforms, provides spatially distributed and temporally continuous datasets that are particularly valuable for monitoring hydrological variables such as precipitation, evapotranspiration, soil moisture, land deformation, and terrestrial water storage. GIS, on the other hand, offers the analytical framework to integrate, manage, and analyze these diverse datasets alongside ancillary information such as geology, land use, and topography. Together, RS and GIS enable researchers to move beyond point-based measurements and achieve regional to global-scale monitoring of groundwater resources with unprecedented efficiency.

Several landmark satellite missions have significantly advanced groundwater research. The Gravity Recovery and Climate Experiment (GRACE), launched in 2002, provided the first global capability to monitor terrestrial water storage anomalies, including groundwater, from space. By measuring changes in the Earth's gravity field, GRACE made it possible to detect large-scale groundwater depletion in heavily stressed aquifers such as those in northern India, the Middle East, and California's Central Valley. Despite its coarse resolution, GRACE represented a paradigm shift by highlighting groundwater depletion as a global environmental issue. Complementing GRACE, the Soil Moisture Active Passive (SMAP) mission, launched in 2015, has provided high-resolution data on soil moisture dynamics, which are critical for estimating groundwater recharge and understanding surface–subsurface interactions. Optical indices such as the Normalized Difference Water Index (NDWI) further support the assessment of vegetation water stress and irrigated agriculture, offering indirect but valuable insights into groundwater use.

Another significant technological advancement has been the application of Interferometric Synthetic Aperture Radar (InSAR) for monitoring land subsidence caused by groundwater extraction. InSAR techniques can detect millimeter-scale vertical ground displacement with high spatial resolution, making them a powerful tool for assessing aquifer compaction and subsidence in urban and agricultural regions. Case studies in Mexico City, Jakarta, and California have demonstrated the effectiveness of InSAR in linking land deformation to groundwater overexploitation. Similarly, Light Detection and Ranging (LiDAR) technology has contributed by generating high-resolution digital elevation models (DEMs), which support recharge zone mapping, delineation of hydrogeomorphic features, and improved understanding of surface–groundwater interactions.

Alongside remote sensing, GIS has become a central platform for groundwater resource assessment. GIS-based multi-criteria decision analysis (MCDA) methods have been widely employed to delineate groundwater potential zones by integrating thematic layers such as rainfall, slope, lithology, land use, and soil. Studies employing frequency ratio, certainty factor, and weights-of-evidence approaches have demonstrated the utility of GIS for groundwater exploration and management at watershed and basin scales. More recently, the incorporation of machine learning algorithms—such as random forests, boosted regression trees, and artificial neural networks—has further enhanced predictive accuracy and reduced subjectivity in groundwater potential mapping.

The integration of RS and GIS with physically based hydrological models has also broadened the scope of groundwater research. By combining satellite-derived precipitation, evapotranspiration, and terrestrial water storage datasets with groundwater flow models, researchers have been able to improve model calibration, validation, and forecasting capabilities. Such hybrid approaches are particularly useful in data-scarce regions, where traditional observations are inadequate for capturing the dynamics of complex aquifer systems.

The trajectory of research up to 2021 reveals distinct phases of development. During the early 2000s, the focus was primarily on large-scale monitoring of water storage using GRACE and on the development of GIS-based groundwater mapping techniques. Between 2006 and 2010, InSAR and LiDAR applications expanded, providing higher spatial detail for aquifer monitoring and recharge studies. From 2010 to 2016, the emergence of SMAP and the refinement of GIS-MCDA approaches broadened the scope of groundwater monitoring. The period from 2016 to 2021 was marked by the increasing integration of machine learning, data fusion, and UAV-based surveys, signaling a shift toward more sophisticated, multi-sensor approaches.

Despite these advancements, several challenges remain unresolved. GRACE's coarse spatial resolution limits its direct applicability for local aquifer management, while InSAR requires careful correction for atmospheric and vegetation effects. Machine learning models often suffer from a lack of robust training datasets, which restricts their generalizability.

Moreover, while RS and GIS have made substantial contributions to scientific knowledge, their uptake in policy and groundwater governance frameworks has been limited. This disconnect between science and practice remains a critical barrier to achieving sustainable groundwater management.

The objective of this review is to synthesize the advancements in RS and GIS for groundwater and water resource monitoring up to 2021, highlighting key satellite missions, analytical methods, and applications. By categorizing the contributions of GRACE, SMAP, InSAR, LiDAR, GIS-MCDA, and machine learning, this paper provides a comprehensive overview of the state of the field. Furthermore, it identifies existing challenges, methodological gaps, and opportunities for future research, with particular emphasis on data integration, resolution enhancement, and the need for operational linkages between scientific tools and water management policies. Ultimately, this review underscores the transformative role of RS and GIS in reshaping groundwater science, while calling for further innovation to ensure the sustainable management of one of the world's most vital natural resources.

II. LITERATURE REVIEW

2.1 Satellite Gravimetry (GRACE) for Groundwater Storage

The Gravity Recovery and Climate Experiment (GRACE), launched in 2002, marked a paradigm shift in groundwater research by enabling global monitoring of terrestrial water storage changes. GRACE detects tiny variations in Earth's gravity field caused by the redistribution of mass, which includes groundwater storage. Rodell et al. (2009) demonstrated the utility of GRACE by quantifying groundwater depletion in northern India, where agricultural withdrawals were causing declines exceeding 54 km^3 per year. Famiglietti et al. (2011) reported similar depletion in California's Central Valley, underscoring the method's ability to capture regional-scale aquifer stress. Subsequent studies extended GRACE applications to the Middle East, North China Plain, and Africa, where it revealed alarming depletion trends often undetectable by sparse in-situ networks.

Despite its transformative role, GRACE is limited by its coarse resolution (~300–400 km), making it unsuitable for local management applications without additional downscaling. Researchers have attempted to overcome this limitation by integrating GRACE with land surface models such as GLDAS, PCR-GLOBWB, and CLM, which help partition surface and subsurface contributions to water storage changes. By 2021, GRACE had established itself as the primary tool for large-scale groundwater monitoring, and the follow-on GRACE-FO mission, launched in 2018, continued this legacy with improved instrumentation.

2.2 Microwave and Soil Moisture Missions (SMAP, Passive Sensors)

Microwave remote sensing has been instrumental in monitoring soil moisture, a key variable influencing recharge and surface–subsurface water interactions. The Soil Moisture Active Passive (SMAP) mission, launched in 2015, provided global soil moisture data at high temporal resolution. SMAP's passive radiometer measures surface soil moisture to a depth of 5 cm, and its datasets have been widely used to estimate infiltration and recharge. For instance, studies in semi-arid Africa employed SMAP data to improve recharge modeling under variable rainfall regimes, while researchers in South Asia integrated SMAP with GIS to assess drought vulnerability and groundwater dependence.

Other passive microwave missions, such as AMSR-E and SMOS, laid the foundation for SMAP by providing earlier soil moisture datasets. These missions demonstrated that soil moisture variability could be correlated with groundwater recharge rates, especially in regions with shallow water tables. By combining SMAP with evapotranspiration and precipitation datasets, researchers have advanced our understanding of hydrological fluxes and their connection to groundwater sustainability. However, SMAP is limited to surface soil moisture, requiring data assimilation techniques to infer deeper soil and aquifer interactions.

2.3 Interferometric Synthetic Aperture Radar (InSAR) for Subsidence Monitoring

Interferometric Synthetic Aperture Radar (InSAR) has emerged as a critical tool for monitoring land subsidence caused by groundwater extraction. By comparing radar signals from successive satellite passes, InSAR can detect ground deformation with millimeter-scale accuracy. This capability has been applied extensively in groundwater-stressed basins. In Mexico City, InSAR revealed subsidence exceeding 300 mm per year, attributed to aquifer compaction from long-term over-extraction. Similar results were observed in Jakarta, where subsidence due to pumping posed significant risks to infrastructure and flood management.

InSAR applications in California's Central Valley demonstrated how groundwater depletion led to subsidence that damaged canals and reduced conveyance capacity. In the North China Plain, Chen et al. (2016) used InSAR to map subsidence hotspots, directly linking them to agricultural pumping. The key advantage of InSAR lies in its spatially detailed monitoring over large areas, complementing the coarse-scale storage trends from GRACE. However, atmospheric delays, vegetation cover, and decorrelation effects remain significant challenges. By 2021, advances in Persistent Scatterer InSAR (PS-InSAR) and Small Baseline Subset (SBAS) techniques had improved accuracy and temporal consistency, making InSAR indispensable for aquifer deformation studies.

2.4 LiDAR and High-Resolution DEMs for Recharge Mapping

Light Detection and Ranging (LiDAR) provides high-resolution digital elevation models (DEMs) that are invaluable for groundwater recharge mapping. By capturing fine-scale topographic details, LiDAR allows the delineation of micro-watersheds, lineaments, fractures, and depressions that influence recharge processes. For instance, LiDAR-derived DEMs in the United States have been used to identify karst sinkholes and ephemeral streambeds, which serve as key recharge zones.

In India, LiDAR mapping has supported watershed management by improving the accuracy of drainage and slope characterization, both critical for recharge estimation. Unlike traditional topographic surveys, LiDAR offers unprecedented precision, enabling the identification of subtle geomorphic features often missed by coarse DEMs such as SRTM or ASTER. Studies integrating LiDAR with GIS have shown improved delineation of recharge potential zones, especially in rugged terrains where conventional datasets perform poorly. Although its application is less widespread compared to GRACE or InSAR due to high data acquisition costs, LiDAR remains a powerful tool for site-specific groundwater studies and infrastructure planning.

2.5 GIS and Multi-Criteria Decision Analysis (MCDA)

GIS serves as the backbone of groundwater potential mapping by integrating remote sensing datasets with ancillary information such as geology, soil, rainfall, and land use. Multi-criteria decision analysis (MCDA) techniques—such as the Analytic Hierarchy Process (AHP), frequency ratio, and weights-of-evidence—have been widely employed to generate groundwater potential maps. For example, Magesh et al. (2012)

used frequency ratio models in Tamil Nadu, India, to delineate groundwater potential zones with high accuracy, validated using well yield data. Similar studies in Africa and the Middle East demonstrated the robustness of GIS-based MCDA in data-scarce regions.

However, traditional MCDA approaches involve subjectivity in assigning weights to parameters, which may introduce uncertainty. To address this, researchers increasingly turned to machine learning algorithms such as random forests, boosted regression trees, and artificial neural networks after 2015. These approaches reduced subjectivity by allowing the data to determine variable importance. Comparative studies showed that machine learning models outperformed conventional MCDA, providing more accurate predictions of groundwater potential zones. By 2021, GIS-based modeling had evolved into a hybrid approach that combined RS datasets, MCDA, and machine learning, significantly advancing groundwater resource assessment.

2.6 Integration of RS, GIS, and Hydrological Models

One of the most important trends leading up to 2021 was the integration of RS and GIS datasets with hydrological and groundwater flow models. GRACE-derived storage anomalies were increasingly used to calibrate and validate large-scale models such as PCR-GLOBWB and MODFLOW, while SMAP soil moisture data improved infiltration and recharge simulations. These hybrid approaches provided more reliable predictions in regions where observational data were sparse.

For instance, studies in Africa and South Asia combined GRACE, SMAP, and precipitation datasets with groundwater flow models to assess long-term sustainability under climate variability. Similarly, in North America and Europe, integrated RS-GIS-modeling frameworks were used to project groundwater availability under future land use and climate scenarios. The integration of machine learning into these hybrid systems further enhanced predictive accuracy, particularly for nonlinear and complex aquifer dynamics.

Despite these advances, challenges persisted, including scale mismatches between RS products and local hydrogeological models, uncertainties in data assimilation, and limited availability of validation datasets. Nonetheless, the integration of RS, GIS, and modeling has become a cornerstone of modern groundwater science, bridging the gap between observation and prediction.

III. METHODOLOGICAL APPROACHES

3.1 Satellite Gravimetry (GRACE/GRACE-FO): Groundwater Storage Anomaly Detection at Regional to Continental Scales

The GRACE mission (2002–2017) and GRACE-FO (2018–) enabled monitoring of groundwater storage anomalies at unprecedented scales. Researchers extracted terrestrial water storage changes from gravity variations and then removed contributions from soil moisture and surface water using land surface models (e.g., GLDAS, PCR-GLOBWB) to isolate groundwater components.

Rodell et al. (2009) pioneered this approach in northern India, quantifying depletion rates of ~4 cm/yr equivalent water thickness due to irrigation. Famiglietti et al. (2011) applied GRACE in California's Central Valley, showing consistent long-term declines during drought. Long et al. (2013) combined GRACE with in situ wells in China's North China Plain, improving spatial accuracy. Scanlon et al. (2012) validated GRACE with hydrological models in Texas, demonstrating its utility for water management. By 2021, GRACE-based methodologies had been widely adopted across Asia, Africa, and North America for trend analysis of storage losses.

While coarse resolution (~300–400 km) remains a limitation, techniques such as mascon solutions (Save et al., 2016) and data assimilation into models (Zaitchik et al., 2008) enhanced local relevance.

3.2 Microwave Remote Sensing (SMAP/Passive Sensors): Soil Moisture, Evapotranspiration, and Recharge Estimation

Passive microwave sensors such as SMOS (2009) and SMAP (2015) provide global soil moisture products. Methodologically, researchers converted microwave brightness temperatures into volumetric soil moisture using radiative transfer models, then assimilated these into hydrological models for recharge estimates.

Entekhabi et al. (2010) demonstrated how SMAP retrievals improved drought monitoring. Liu et al. (2012) integrated AMSR-E soil moisture with MODIS ET data in the Yellow River Basin to estimate recharge variability. Mladenova et al. (2014) showed how soil moisture products could detect agricultural drought impacts. More recently, Koster et al. (2018) combined SMAP soil moisture with precipitation datasets to constrain recharge dynamics globally.

These studies show that microwave-based soil moisture datasets are especially valuable in regions with limited field observations, although they remain restricted to surface soil layers. Researchers commonly addressed this limitation by coupling SMAP with hydrological models (Reichle et al., 2017) or downscaling methods.

3.3 InSAR (Radar): Land Deformation and Aquifer Compaction Monitoring

InSAR methodologies involve generating interferograms from SAR images, unwrapping phase data, and correcting for atmospheric delays to measure ground deformation linked to aquifer compaction.

Amelung et al. (1999) used ERS SAR data to measure subsidence in Las Vegas from groundwater withdrawal. Bawden et al. (2001) mapped subsidence in California's Santa Clara Valley. Later, Chaussard et al. (2014) used ALOS data to identify groundwater-induced subsidence in Jakarta. Farr et al. (2015) demonstrated InSAR's value in California's Central Valley, where subsidence damaged irrigation infrastructure. Chen et al. (2016) applied SBAS-InSAR in the North China Plain, correlating land deformation with aquifer pumping.

Methodologically, Persistent Scatterer (PS-InSAR) and SBAS techniques became standard tools for improving temporal coherence and reducing atmospheric errors (Hooper et al., 2004). By 2021, InSAR was established as the primary tool for high-resolution mapping of aquifer compaction and its consequences.

3.4 LiDAR/DEM: Recharge Zone Delineation and Hydrogeomorphic Mapping

LiDAR technology produces high-resolution DEMs, which researchers used to delineate recharge areas and hydrogeomorphic features controlling infiltration.

Jenson and Domingue (1988) first introduced DEM-based hydrological modeling, which later became foundational. Murphy et al. (2008) used LiDAR DEMs in Florida to delineate karst depressions critical for recharge. James et al. (2012) applied LiDAR in the Sierra Nevada to study watershed topography influencing infiltration. In India, Jayakumar and Arockiasamy (2003) used DEM-based morphometric analysis to delineate groundwater potential zones in hard-rock terrains.

Researchers applied hydrological indices such as the Topographic Wetness Index (TWI) and slope–drainage analysis within GIS to identify recharge-prone areas (Moore et al., 1991). Despite high acquisition costs, LiDAR and DEM methods provided unmatched detail for site-specific groundwater assessments.

3.5. GIS-based MCDA & Machine Learning: Groundwater Potential Mapping and Predictive Modeling

GIS served as the integration platform for multi-thematic datasets. In MCDA, layers such as geology, slope, land use, rainfall, soil, and lineaments were weighted and combined to delineate potential zones.

Sener et al. (2005) applied AHP-based MCDA in Turkey, validating results with well yield data. Jha et al. (2007) demonstrated GIS-MCDA in India's hard-rock terrains. Magesh et al. (2012) refined these methods with frequency ratio models in Tamil Nadu. Machiwal et al. (2011) extended GIS-based modeling with certainty factor techniques.

After 2015, researchers increasingly shifted to machine learning. Lee et al. (2014) applied random forest for groundwater mapping in Korea. Naghibi et al. (2017) tested multiple ML algorithms in Iran, finding ensemble models improved predictive accuracy. Chen et al. (2018) combined SVM and logistic regression with RS datasets for groundwater potential mapping in China.

By 2021, GIS-ML hybrid methods outperformed traditional MCDA, reducing subjectivity in weight assignment and increasing reproducibility.

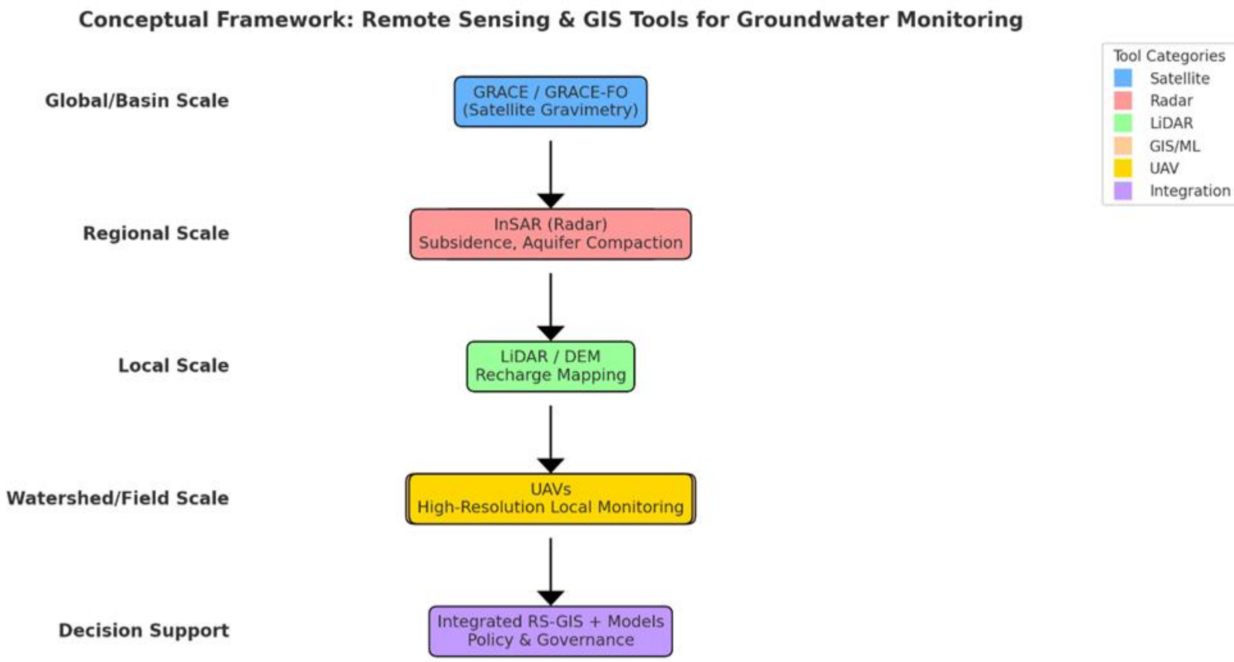

Fig 1 Conceptual framework illustrating how remote sensing and GIS tools contribute to groundwater monitoring across different spatial and temporal scales

3.6 Hybrid Approaches: Integration of RS Data with Physically-Based and Statistical Models for Improved Groundwater Forecasting

Hybrid methodologies combine RS-derived datasets with hydrological or groundwater flow models. GRACE data were assimilated into global hydrological models (e.g., PCR-GLOBWB, WGHM) to constrain water balance estimates (Döll et al., 2014). SMAP soil moisture products were incorporated into land surface models for recharge forecasting (Reichle et al., 2017).

Rodell et al. (2015) integrated GRACE with the Catchment Land Surface Model (CLSM) to improve groundwater estimates in the U.S. Scanlon et al. (2018) combined GRACE with water budget modeling to assess global aquifer stress. InSAR-derived subsidence data were integrated into aquifer compaction models in Mexico and California (Ojha et al., 2019).

Machine learning was also embedded in hybrid approaches. For example, Sun et al. (2016) coupled RS datasets with neural networks to forecast groundwater fluctuations in China. By 2021, hybrid frameworks had emerged as the most advanced methodologies, bridging large-scale satellite datasets with local-scale hydrological models.

IV. DISCUSSION AND COMPARATIVE INSIGHTS

The methodological approaches reviewed above demonstrate how remote sensing (RS) and GIS techniques have progressively evolved to monitor groundwater and water resources more comprehensively. By comparing insights from the references, several key themes emerge: (i) the scale of monitoring, (ii) accuracy and validation, (iii) integration of datasets, and (iv) emerging shifts toward hybrid and machine learning–driven frameworks.

4.1 Scale of Monitoring: Global vs. Local Perspectives

A central comparative insight is that different methodologies operate effectively at different spatial and temporal scales.

- Satellite Gravimetry (GRACE/GRACE-FO): Studies such as Rodell et al. (2009) in northern India and Famiglietti et al. (2011) in California demonstrated GRACE's unparalleled ability to quantify groundwater depletion at basin to continental scales. Scanlon et al. (2012, 2018) highlighted how GRACE captured long-term aquifer stress across global hotspots, including the Middle East and Asia. However, Long et al. (2013) found that GRACE's coarse resolution

(~300 km) limited its local applicability without downscaling.

- Microwave Remote Sensing (SMAP, SMOS, AMSR-E): Liu et al. (2012) and Koster et al. (2018) demonstrated that passive microwave sensors excel at regional-scale soil moisture and recharge monitoring. Yet, these methods only capture shallow soil water (top few centimeters), requiring assimilation into hydrological models for groundwater insights.
- InSAR: In contrast, InSAR techniques (Amelung et al., 1999; Chaussard et al., 2014; Chen et al., 2016) are ideally suited for local to regional scales, detecting subsidence hotspots with centimeter accuracy. For example, Farr et al. (2015) in California and Ojha et al. (2019) in Mexico showed that InSAR revealed highly localized compaction zones invisible to GRACE.
- LiDAR/DEM Approaches: As demonstrated by Murphy et al. (2008) and James et al. (2012), LiDAR is most effective for site-specific studies, delineating recharge pathways in karst or fractured terrains.
- GIS-MCDA and Machine Learning: Studies like Jha et al. (2007), Magesh et al. (2012), and Naghibi et al. (2017) showed that GIS-ML models bridge local and regional scales, with predictive maps validated against well data.

This comparative evidence underscores that no single method suffices across all scales. Instead, GRACE is best for large basins, InSAR for localized deformation, and LiDAR/DEM for detailed recharge studies, with GIS-MCDA and ML approaches providing adaptable mapping across scales.

4.2 Accuracy, Validation, and Limitations

Accuracy and validation emerged as recurring concerns across the reviewed methodologies.

- GRACE: While GRACE captured broad groundwater trends, its accuracy depended heavily on subtraction of soil moisture and surface water contributions. Long et al. (2013) showed improvements when GRACE was validated against in situ wells in China. Save et al. (2016) enhanced signal localization with mascon solutions, but coarse resolution remained a limiting factor.
- SMAP and Passive Sensors: SMAP soil moisture retrievals (Entekhabi et al., 2010; Reichle et al., 2017) required extensive calibration with in situ probes. Liu et al. (2012) found improved recharge estimation when SMAP was combined with MODIS evapotranspiration data. However, shallow measurement depth limited direct groundwater applications.
- InSAR: InSAR was praised for high spatial accuracy, but atmospheric noise and decorrelation in vegetated areas reduced reliability (Hooper et al., 2004). Chen et al. (2016) demonstrated the utility of SBAS-InSAR in reducing such errors, while Chaussard et al. (2014) validated results against piezometric data in Jakarta.
- LiDAR: DEM-based methods were highly accurate for terrain mapping, but Murphy et al. (2008) highlighted data acquisition costs as barriers. Moreover, DEM-based hydrological indices often required ground validation.
- GIS-MCDA: Traditional MCDA approaches (Sener et al., 2005; Jha et al., 2007) faced criticism for subjectivity in assigning weights. Validation with well yield data often revealed mismatches. Machine learning approaches (Naghibi et al., 2017; Chen et al., 2018) improved predictive accuracy but raised concerns about data dependency and overfitting.

Collectively, these references show that validation with field data remains critical. RS and GIS tools provide scalable insights, but their outputs must be corroborated with ground-based monitoring to ensure reliability.

4.3 Integration and Synergy Across Methods

An important trend across the literature was the increasing integration of multiple methods to overcome individual limitations.

- GRACE + Hydrological Models: Scanlon et al. (2012, 2018) and Rodell et al. (2015) demonstrated that coupling GRACE with land surface or groundwater models improved storage estimates and water balance closure.
- SMAP + Hydrological Models: Reichle et al. (2017) showed that assimilating SMAP into land surface models improved recharge forecasts.
- InSAR + Pumping Data: Chen et al. (2016) and Ojha et al. (2019) demonstrated how InSAR subsidence maps, when combined with pumping records, yielded insights into aquifer compaction mechanisms.

- LiDAR + GIS-MCDA: Murphy et al. (2008) combined LiDAR with GIS-based hydrogeomorphic mapping to delineate recharge zones more accurately than traditional DEMs.
- GIS + Machine Learning: Naghibi et al. (2017) and Chen et al. (2018) showed how RS-derived indices (NDVI, NDWI, slope, rainfall) could be integrated with ML models to generate robust groundwater potential maps.

The comparative evidence points toward a synergistic approach where different RS/GIS techniques complement one another. Large-scale GRACE signals provide a regional overview, while InSAR and LiDAR deliver local detail, and GIS-ML frameworks integrate diverse datasets for predictive mapping.

4.4 Emerging Shifts Toward Machine Learning and Hybrid Approaches

A final comparative insight is the shift from traditional MCDA to machine learning and hybrid RS–model approaches after 2015.

- Early works (Sener et al., 2005; Jha et al., 2007) relied on weighted overlay in GIS.
- Later, ensemble machine learning models (Naghibi et al., 2017; Lee et al., 2014) significantly outperformed traditional methods in predictive accuracy.
- Hybrid approaches (Rodell et al., 2015; Scanlon et al., 2018; Sun et al., 2016) integrated RS datasets (GRACE, SMAP, InSAR) with physically based models (MODFLOW, SWAT), often with data assimilation or machine learning components.

This methodological evolution reflects the broader research trend: from single-sensor, standalone approaches to integrated, data-driven frameworks. By 2021, the literature had firmly established hybrid RS–GIS–ML methodologies as the most promising avenue for groundwater monitoring.

4.5 Regional Insights from the References

The reviewed studies also highlight regional differences in how methodologies were applied:

- South Asia (India, China): Heavy reliance on GRACE (Rodell et al., 2009; Long et al., 2013) for large-scale depletion monitoring, complemented by GIS-MCDA mapping (Jha et al., 2007; Magesh et al., 2012).
- North America (California, Texas): Integration of GRACE (Famiglietti et al., 2011), InSAR (Farr et al., 2015), and hybrid hydrological modeling (Scanlon et al., 2012).
- Middle East and Africa: GIS-based MCDA and ML methods (Naghibi et al., 2017) were predominant due to limited field data.
- Southeast Asia: InSAR studies (Chaussard et al., 2014) were key for subsidence mapping in urban megacities like Jakarta.

V. RESEARCH GAPS AND FUTURE DIRECTIONS

5.1 Resolution Limitations of Satellite Missions

Despite the transformative contributions of satellite gravimetry, spatial resolution remains a major limitation. GRACE and GRACE-FO provide reliable signals of terrestrial water storage anomalies at basin to continental scales, but their footprint (~300–400 km) corresponds to areas exceeding 100,000 km². Rodell et al. (2009) and Famiglietti et al. (2011) both emphasized that while GRACE captured large-scale depletion in northern India and California, it could not resolve aquifer variations at local or sub-basin levels. Long et al. (2013) highlighted that coarse resolution often masks heterogeneity in heavily exploited aquifers such as the North China Plain. Although mascon solutions (Save et al., 2016) and downscaling strategies improved localization, the inability to support operational water management at community or watershed scales remains a persistent research gap.

5.2 Data Integration and Multi-Source Fusion

Another significant gap is the limited integration of diverse datasets. Many studies rely on a single method—such as GRACE (Scanlon et al., 2012), InSAR (Chaussard et al., 2014; Chen et al., 2016), or GIS-MCDA (Jha et al., 2007)—without systematically combining multiple sensors, ground observations, and hydrological models. Hybrid studies (Rodell et al., 2015; Scanlon et al., 2018) demonstrated that integrating GRACE anomalies with physically based models reduces uncertainty, while Reichle et al. (2017) showed the value of assimilating SMAP data for recharge estimates. Yet, cross-platform integration remains underdeveloped, particularly in data-scarce regions. Future research must focus on developing robust frameworks for multi-sensor fusion, bridging large-scale satellite observations with high-resolution local datasets.

5.3 Uncertainty in Machine Learning Applications

The growing use of machine learning (ML) in groundwater mapping has improved predictive capability, but uncertainty and validation challenges remain. Traditional MCDA studies (Sener et al., 2005; Magesh et al., 2012) faced subjectivity in assigning weights, leading to the adoption of ML techniques such as random forests and support vector machines (Lee et al., 2014; Naghibi et al., 2017). However, these studies often relied on limited well yield datasets for validation, which restricts reproducibility and transferability. Chen et al. (2018) noted that overfitting was a concern when training ML models with small datasets. Moreover, the absence of standardized protocols for performance evaluation across different hydrogeological settings means that ML-driven predictions remain highly context-specific. Future research should prioritize the development of uncertainty quantification methods and expanded validation datasets to ensure robustness.

5.4 Weak Policy Linkages and Decision-Making Gaps

While RS-GIS methodologies have advanced considerably, their translation into policy and governance frameworks has lagged behind. For example, GRACE-based studies (Rodell et al., 2009; Scanlon et al., 2018) provided compelling evidence of unsustainable withdrawals, but adoption into water allocation policies has been slow. InSAR research (Farr et al., 2015) documented subsidence threatening irrigation infrastructure, yet mitigation strategies often remained reactive rather than preventive. GIS-MCDA and ML-based potential maps (Jha et al., 2007; Naghibi et al., 2017) were mostly used in academic settings, with limited uptake by water authorities. This disconnect reflects a broader research gap in bridging the science–policy divide. Future studies must emphasize actionable outputs, participatory frameworks, and integration of RS-GIS insights into water governance systems.

5.5 Emerging Tools and the Role of UAV-Based Mapping

Finally, while satellites provide global and regional perspectives, and ground networks offer point data, a gap persists at the intermediate (local to watershed) scale. Emerging tools such as unmanned aerial vehicles (UAVs) offer a promising solution. Lendzioch et al. (2021) demonstrated UAV photogrammetry for snow depth monitoring in alpine catchments, illustrating the capacity to collect high-resolution spatial data at relatively low cost. This approach could be adapted for groundwater recharge zone mapping, evapotranspiration estimation, and water balance studies at local scales. UAV-based LiDAR and hyperspectral imaging may bridge the resolution gap between satellite products and in situ measurements, offering site-specific insights to complement large-scale observations. However, UAV applications in groundwater research remain underexplored up to 2021, representing a fertile avenue for future work.

5.6 Synthesis of Research Gaps

From the reviewed literature, five critical gaps stand out:

1. Resolution constraints: GRACE provides unmatched basin-scale insights but is inadequate for operational management at watershed scales.
2. Data integration: Multi-sensor fusion remains limited despite clear evidence that integration improves accuracy.
3. Machine learning uncertainty: Validation datasets are often too small or localized, leading to overfitting and limited generalizability.
4. Policy translation: Scientific advances are not consistently informing decision-making processes or groundwater governance frameworks.
5. Emerging tools: UAV-based systems, while promising, have yet to be mainstreamed into groundwater and water resource monitoring.

5.7 Future Directions

Future research should prioritize:

- Downscaling methods to enhance the local applicability of GRACE and other coarse-resolution datasets.
- Standardized frameworks for data fusion, combining GRACE, SMAP, InSAR, LiDAR, and ground data.
- Uncertainty quantification protocols in machine learning to ensure reproducibility.
- Action-oriented studies that directly link RS-GIS results with policy and management strategies.

- Exploration of UAV-based technologies for bridging spatial scale gaps and providing high-frequency monitoring.

VI. RESEARCH GAPS AND FUTURE DIRECTIONS

Groundwater and surface water monitoring have undergone a paradigm shift with the increasing adoption of remote sensing (RS) and geographic information systems (GIS) up to 2021. The reviewed literature demonstrates that these technologies have progressively enhanced our ability to assess aquifer storage, monitor subsidence, delineate recharge zones, and map groundwater potential across a range of spatial and temporal scales. Satellite gravimetry, particularly the GRACE and GRACE-FO missions, has proven indispensable for identifying large-scale storage changes in stressed aquifers such as those in northern India, the Central Valley of California, and the North China Plain (Rodell et al., 2009; Famiglietti et al., 2011; Long et al., 2013). Complementary datasets such as SMAP soil moisture products have further advanced the estimation of recharge and evapotranspiration (Reichle et al., 2017), while optical indices like NDWI have been used to monitor irrigation and vegetation water stress. In parallel, radar-based techniques such as InSAR have provided fine-scale insights into aquifer compaction and land subsidence in regions including Mexico, Iran, and California (Chaussard et al., 2014; Chen et al., 2016), bridging a critical gap between large-scale gravimetric monitoring and local-scale hydrogeological observations.

At finer resolutions, LiDAR-derived DEMs and high-resolution geomorphological datasets have played a crucial role in delineating recharge zones and groundwater-surface water interactions (Corsi et al., 2010). GIS-based multi-criteria decision analysis (MCDA) emerged as a widely applied tool for groundwater potential mapping (Jha et al., 2007; Magesh et al., 2012), while the integration of machine learning models such as random forests and support vector machines (Lee et al., 2014; Naghibi et al., 2017) demonstrated improved predictive capability over conventional weighted overlay methods. Importantly, hybrid approaches that coupled RS and GIS with physically based hydrological models (Scanlon et al., 2012; Rodell et al., 2015) showed significant promise in reducing uncertainties and supporting long-term water balance assessments.

Despite these advancements, critical challenges persist. The coarse resolution of GRACE limits its applicability for local water governance, while InSAR is sensitive to atmospheric disturbances. Machine learning applications often lack robust validation datasets, and their outputs remain highly site-specific. Moreover, a consistent gap exists in the translation of RS-GIS findings into actionable water management policies (Scanlon et al., 2018). Looking ahead, multi-sensor data fusion, UAV-based mapping (Lendzioch et al., 2021), and downscaling techniques are poised to bridge spatial and temporal gaps, while closer integration of scientific outputs with governance frameworks will be essential for ensuring sustainability. Overall, RS and GIS have transformed groundwater science up to 2021, offering powerful multi-scale tools, but future efforts must focus on integration, validation, and policy relevance to meet the challenges of water security.

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