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Review papers

Remote Sensing Technologies for Unlocking New Groundwater Insights: A Comprehensive Review

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ABSTRACT

This study examined recent advances in remote sensing (RS) techniques used for the quantitative monitoring of groundwater storage changes and assessed their current capabilities and limitations. The evolution of the techniques analyses spans from empirical reliance on sparse point data to the assimilation of multi-platform satellite measurements using sophisticated machine learning algorithms. Key developments reveal enhanced characterisation of localised groundwater measurement by integrating coarse-resolution gravity data with high-resolution ground motion observations from radar imagery. Notable advances include improved accuracy achieved by integrating Gravity Recovery and Climate Experiment (GRACE) and Interferometric Synthetic Aperture Radar (InSAR) data. Cloud computing now facilitates intensive analysis of large geospatial datasets to address groundwater quantification challenges. While significant progress has been made, ongoing constraints include coarse spatial and temporal resolutions limiting basin-scale utility, propagation of uncertainties from sensor calibrations and data merging, and a lack of systematic validation impeding operational readiness. Addressing these limitations is critical for continued improvement of groundwater monitoring techniques. This review identifies promising pathways to overcome these limitations, emphasising standardised fusion frameworks for satellite gravimetry, radar interferometry, and hydrogeophysical techniques. The development of robust cloud-based modelling platforms for multi-source subsurface information assimilation is a key recommendation, highlighting the potential to significantly advance groundwater quantification accuracy. This comprehensive review serves as a valuable resource for water resource and remote sensing experts, providing insights into the evolving landscape of methodologies and paving the way for future advancements in groundwater storage monitoring tools.

1. Introduction

Groundwater remains the primary water source in many parts of the world, enabling irrigation and rural socioeconomic endeavors Gleeson et al. (2012). It serves as the lifeblood of numerous ecosystems and sustains the livelihoods of billions of people worldwide (Fan et al., 2022). It is the ultimate natural freshwater reservoir, supporting approximately half of the world's drinking water, 40% of irrigated agricultural water, and 30% of industrial needs (Famiglietti, 2014). Groundwater plays a critical role in hydrological processes, water resource management, ecological sustainability, and climate change adaptation, thus necessitating a profound understanding of its dynamics (Fan et al., 2022; Li et al., 2023a; Petitta et al., 2023).

Understanding groundwater storage dynamics is essential in hydrology, as it governs the availability, quality, and sustainability of this resource (Groundwater, 2021). Furthermore, in the context of increasing anthropogenic activities and climate change impacts, an accurate and comprehensive assessment of groundwater storage variations is important for effective water resource management and climate adaptation strategies (Houben et al., 2022; Rahman et al., 2023;

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Saeedpanah and Azar, 2023a; Springer et al., 2023; Wunsch et al., 2022; Xie et al., 2022).

Groundwater storage modelling involves the development of models that calculate changes in groundwater storage based on the mass balance of fluxes and withdrawals (Scheidegger et al., 2021). This type of model faces challenges owing to limited observed data and poor quality, particularly in regions with weak observation facilities (Chi et al., 2022). Studies on groundwater storage dynamics models have historically presented challenges because of their hidden nature beneath the Earth's surface (Adams et al., 2022).

However, the complex nature of groundwater storage dynamics poses challenges that necessitate innovative approaches and advanced technologies (Lü et al., 2011; Sun et al., 2020; Wehbe, 2021). Traditional monitoring methods, such as wells and boreholes, often fall short in providing a comprehensive understanding, particularly in regions with weak observation facilities (Ahamed et al., 2022).

In recent decades, a paradigm shift has occurred with the advent of Remote Sensing (RS) technologies, offering a noninvasive and cost-effective alternative to overcome these limitations (Hasnat and Singh, 2018; Kyra et al., 2022; Ni et al., 2018; Bennett, 2024; Rampheri et al., 2023; Rodell et al., 2009; Atazadeh and Mahdavifard, 2021). This allows for a more holistic understanding of the complex interactions between the surface and subsurface hydrological compartments, contributing to a more accurate and reliable representation of the groundwater storage dynamics. The RS technologies provide a transformative means of monitoring hydrological parameters, including soil moisture, land surface displacements, and vegetation dynamics (Hilbich et al., 2022). Satellite-based sensors and airborne platforms offer a comprehensive understanding of the surface and subsurface hydrological compartments, significantly enhancing the representation of groundwater storage dynamics (Adams et al., 2022).

Recent studies (Ni et al., 2018; Sreekanth et al., 2023; Akhter et al., 2021) have underscored the effectiveness of remote sensing for quantifying groundwater changes, renewable groundwater stress, and evaluating groundwater sustainability globally. However, a comprehensive overview of remote sensing applications that specifically address groundwater storage anomalies is lacking, which highlights the need for this review. The review aims to thoroughly examine the applicability of various remote sensing methods employed in monitoring groundwater storage dynamics, from traditional monitoring approaches to cutting-edge data assimilation techniques and machine learning algorithms, with the following objectives: (1) To examine various remote sensing methodologies used in monitoring groundwater storage dynamics; (2) To evaluate the strengths and limitations of remote sensing technologies in capturing changes in groundwater storage; (3) To identify factors influencing groundwater storage dynamic models; (4) To explore the integration of remote sensing techniques with hydrological models; and (5) To highlight future directions and challenges of remote sensing applications for groundwater storage dynamics. Our overarching hypothesis is that "The integration of diverse remote sensing technologies offers a transformative approach to monitor groundwater storage dynamics, providing valuable insights for sustainable resource management and climate change adaptation." Drawing on case studies from diverse geographical contexts, this study synthesises the most promising avenues for future research by envisioning transformative impacts on groundwater management, sustainable resource allocation, and climate change adaptation strategies. The integration of RS technologies into hydrological analyses has redefined our capacity to observe, quantify, and interpret subsurface hydrological processes with unparalleled precision and scope. Through the deployment of satellite-based sensors and airborne platforms, researchers have gained access to a wealth of data, ranging from passive and active microwave sensors to Synthetic Aperture Radar (SAR) and gravity-based (GRACE missions), to capture soil moisture variability and thermal infrared imagery, revealing land surface displacements and uncovering complex subsurface features. This review provides insights into the current state of research, identifies gaps, and contributes to the development of effective RS approaches for groundwater storage dynamics.

In conclusion, this review aims to synthesise syntheses from the literature, state-of-the-art advancements beyond the conventional boundaries of groundwater storage, and identify literature gaps that contribute to the body of knowledge on the development of RS approaches for groundwater storage studies.

Among the range of techniques surveyed, particular emphasis was placed on the Gravity Recovery and Climate Experiment (GRACE) satellite mission, given its uniqueness in providing direct gravimetric observations of changes in total terrestrial water storage. With near-global coverage and coarse spatial resolution, GRACE delivers an integrated measure of groundwater mass fluctuations encompassing entire aquifer systems, a perspective that is unmatched by any other remote sensing platform (Rodell et al., 2009).

By synergizing GRACE's large-scale water storage anomaly information with other higher resolution satellite data and hydrological models, novel insights can be gained into surface–subsurface interactions governing groundwater behavior from local to regional scales (Bailing et al., 2019; Cornero et al., 2021; Famiglietti et al., 2011b; Gupta et al., 2022; Jha et al., 2006; Jothimani et al., 2022; Liu et al., 2019; Massoud et al., 2020; Massoud et al., 2022b; Massoud et al., 2021; Massoud et al., 2018; Sainju, 2021; Sun et al., 2023; Zhang et al., 2023b). Thus, GRACE merits a detailed examination given the transformative impact it continues to have across hydrological sciences and groundwater resource management. It is important to note that among the various RS technologies identified, GRACE was given more emphasis (Section 3.6) because of its data availability and accessibility, as well as its global coverage, which allows for groundwater studies to be conducted in any region.

2. Methodology

To address these objectives, a systematic bibliometric analysis was conducted across Web of Science, SCOPUS, and Google Scholar, utilizing search terms related to "remote sensing" and "groundwater." The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement guides the identification, screening, and inclusion criteria (Matthew et al., 2021).

The search terms used were " Remote sensing " AND "groundwater" along with related terms such as "satellite", "gravity", "electrical resistivity", etc. as follows: ("Remote Sensing" AND "Groundwater" OR "Remote Sensing" AND "subsurface water" OR "Interferometric Synthetic Aperture Radar" AND "Groundwater storage" OR "Gravity Recovery and Climate Experiment" AND "Groundwater storage" OR "Aquifer Storage" AND "Remote Sensing" OR "Electrical Resistivity Imaging" AND "Groundwater storage" OR "Ground-Penetrating Radar" AND "Groundwater storage" OR "Time Domain Reflectometry" AND "Groundwater storage" OR "Remote Sensing" AND "Groundwater Model" OR "Remote Sensing" AND "Groundwater Modelling"). The same search terms were used for all the three databases.

Fig. 1 depicts the detailed methodology used to refine the search results. The PRISMA-based identification, screening, eligibility, and inclusion criteria considered in the identification and selection of the specific literature included in this study are as follows:

a) Only titles that are directly applicable to assessing changes in groundwater storage.
b) Only technologies that have been validated and shown to provide accurate and reliable measurements of groundwater storage dynamics.
c) Only articles published in the last decade (2013–2023).
d) Only publications from high quality reputable indexed journals and Published in English Language.

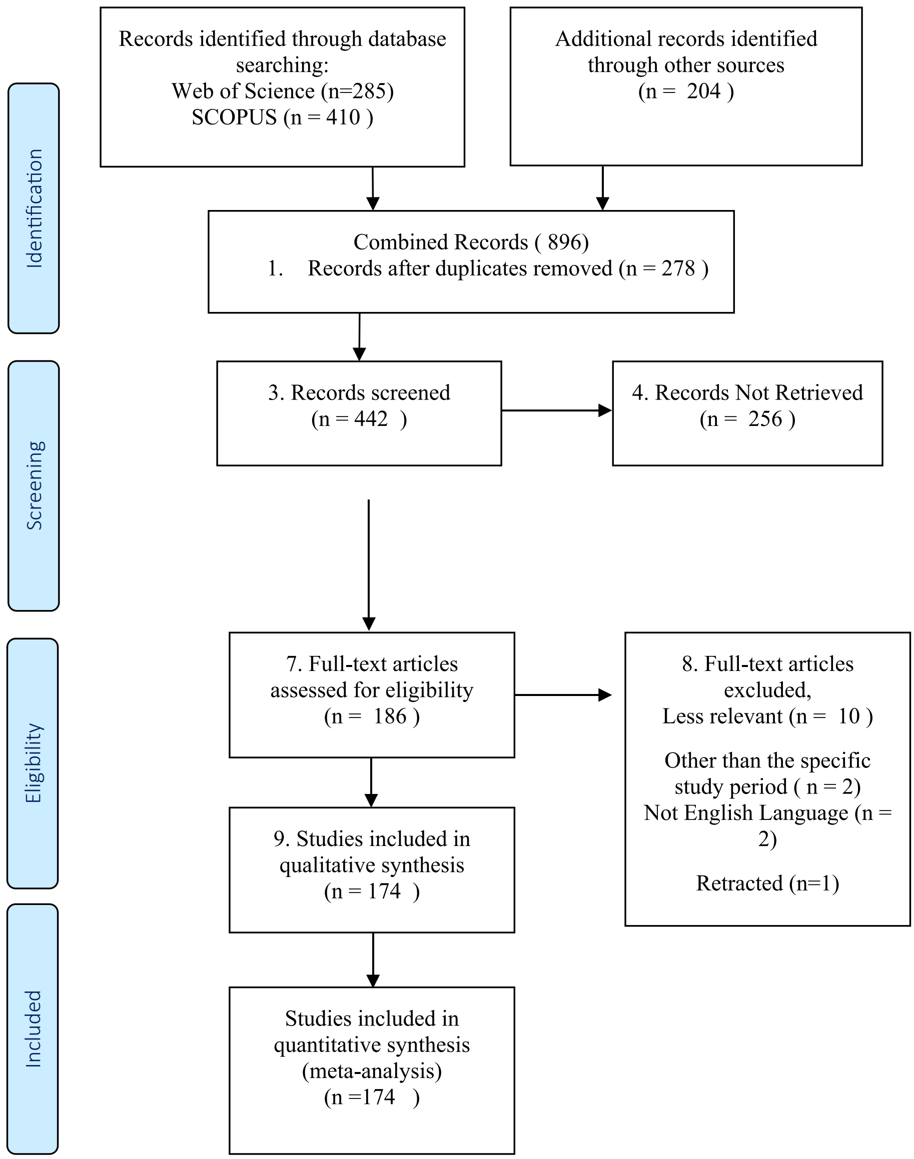

Fig. 1. Methodology flow Diagram based on PRISMA, adopted from Matthew et al., 2021.

The selected publications were analysed using selected bibliometric indicators, which provided insights into the influence of publications, interconnectivity of research areas, and emergence of new research topics.

3. Findings

An analysis of the literature reveals several key findings. First, research on RS technology applications in GWS studies has shown a significant increase in publication output over the past decade, indicating the growing importance of this topic.

3.1. Publication trends and sources

The initial search results yielded over 4000 publications, indicating a substantial body of remote sensing research applied to GWS studies. After careful screenings and exclutions, the number of publications narrowed to 173. Preliminary analysis of only the included articles showed an upward trend in yearly publications, from 7 publications in 2013 to 40 publications in 2023. This indicates the growing recognition of RS data and methods by the groundwater research community (Fig. 2).

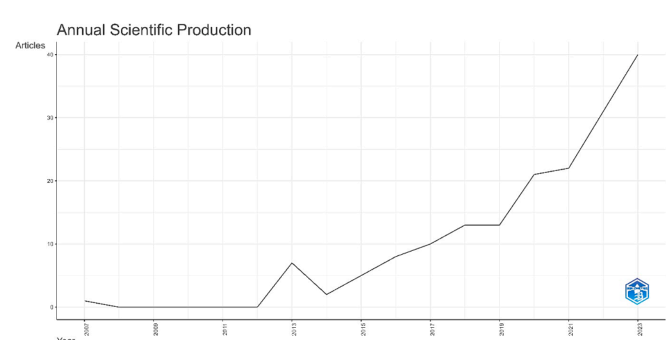

Fig. 2. Publication trends of RS techniques applications on GWS in last decade (2013–2023).

RS and groundwater literature is spread across journals spanning sustainable water resource management, hydrology, remote sensing, hydrogeology, and the Arabic Journal of Science, Water, and Applied

Geomatics. The top three publishing journals were Sustainable Water Resource Management, Remote Sensing, and the Arabian Journal of Geoseience (Fig. 3).

3.2. Remote sensing methods with key area of applications used in the surveyed litrature

Electrical resistivity imaging, ground-penetrating radar, time-domain reflectometry, airborne electromagnetics, LiDAR, Satellite multispectral/hyperspectral imaging, SAR, Gravity (GRACE mission) were the key methods commonly employed in the 173 selected articles. The key areas applied by these technologies include aquifer characterisation, groundwater exploration, monitoring water table levels, estimating recharge rates, mapping geology and hydrogeological properties, and measuring groundwater storage changes. Other methods applied in mapping geology and hydrological properties were further excluded.

3.3. Limitations and future outlook

Common challenges from the literature survey revealed includeSpatial and/or temporal resolution tradeoffs, complex data processing/analysis, site-specific factors affecting accuracy, and high costs for some methods, The accelerating publication rates and citations indicating that remote sensing will continue to grow as an integral tool for groundwater assessment and modelling in the coming decade. New satellite missions, improving sensors, expanding computing power, enabling better data processing, and increasing collaboration across domains will further advance the remote sensing capabilities for groundwater studies.

3.4. Types of remote sensing data

This section discusses the different types of remote sensing data used to model the groundwater storage dynamics. These data include land surface elevation, vegetation cover, and gravity data. Land surface elevation, a type of remote sensing data obtained from satellite altimetry, airborne laser scanning, and terrestrial laser scanning, can be used to measure changes in groundwater storage (Li et al., 2022; Liu et al., 2019; Massoud et al., 2021; Rodell et al., 2009). Although these data can provide valuable information about land surface elevation changes, they may not capture the full complexity of groundwater dynamics, as other factors, such as subsidence and tectonic activity, can also influence land surface elevation (Janardhanan et al., 2023; Zipper et al., 2022). These techniques provide valuable information regarding the vertical movement of the land surface, and can be used to infer changes in groundwater storage.

Vegetation cover is also a good indicator of groundwater availability, because plants rely on groundwater for growth and survival. Satellite imagery, airborne hyperspectral imagery, and ground-based measurements have been used to obtain vegetation-cover data (Jean et al., 2016). By analysing changes in vegetation cover over time, researchers can gain insights into changes in groundwater recharge. However, vegetation cover is also influenced by factors other than groundwater availability, such as the climate and land management practices.

Gravity data measure groundwater storage by detecting changes in the Earth's gravity field. These gravity changes are directly related to changes in surface mass, as described by (Lee et al., 2019). These data were captured using gravity gradiometry, airborne gravity surveys, and recent GRACE and GRACE-FO satellite missions. GRACE is a unique satellite mission launched in 2002 to measure the Earth's gravity field. This is the only satellite mission that is capable of accurately detecting changes in the gravitational field. This makes the GRACE data valuable for monitoring groundwater storage and other applications such as tracking ice sheet mass loss and climate change. Although gravity data alone may not provide detailed information regarding the spatial distribution of groundwater storage changes, additional data sources, such as hydrological models and in situ measurements, may be required to complement gravity data and improve the accuracy of groundwater storage estimates (Lee et al., 2019; Magnoni et al., 2020; Massoud et al., 2022a; Massoud et al., 2021; Massoud et al., 2018; Tolche, 2020).

3.5. Remote sensing methods for groundwater studies

This section discusses different methods that can be used to remotely sense groundwater, including ground-based, airborne, satellite-based, and gravity-based methods.

RS technologies use sensors to measure the energy reflected or emitted from Earth's surface (Sharad, 2021). This energy can take the form of visible light, infrared radiation, microwaves, or other wavelengths used to create images or maps of the Earth's surface from which geology, hydrology, and vegetation data are captured (Shandilya et al., 2013). These data can be used to identify areas with potential groundwater resources by capturing or sensing locations with appropriate hydrogeological features that influence GW storage, such as cracked bedrock or loose sediments, such as fissure rocks. RS can also detect regions with heavy precipitation or snowfall that can serve as recharge sources for GW aquifers. Various RS techniques have been employed for GW exploration, such as multispectral and hyperspectral RS, LiDAR, InSAR, GPR, and the recent GRACE and GRACE-FO mission data. Numerous RS technologies have been used for multiple applications in many disciplines. Fig. 4 depicts a summary of these technologies that can be applied to groundwater modelling and studies.

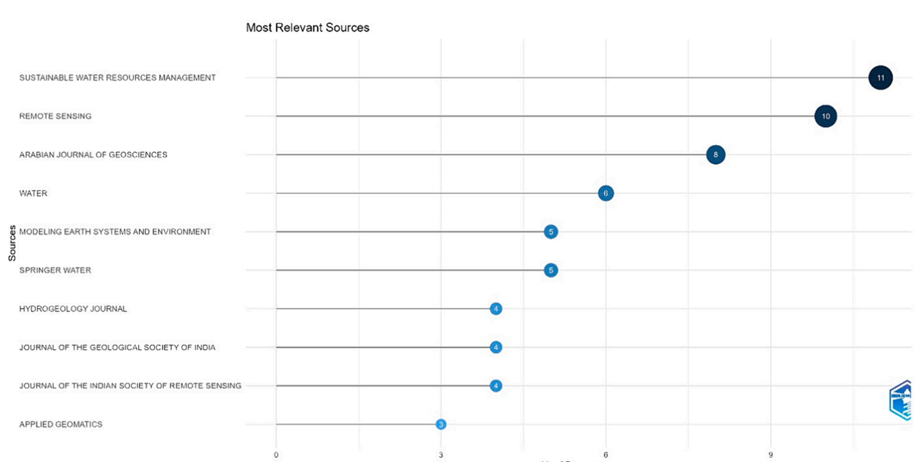

Fig. 3. Most relevant publication sources of the RS techniques applications on GWS in last decade (2013–2023).

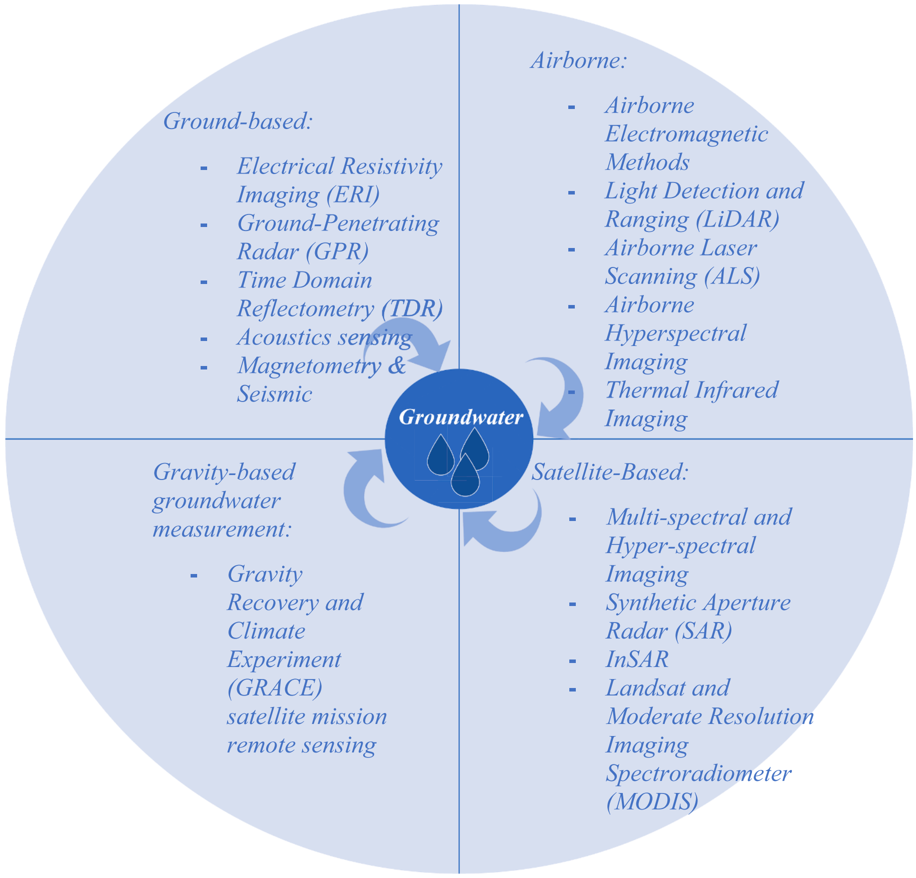

Fig. 4. Summary of RS technologies that can be applied to GW studies.

3.6. Ground-based remote sensing

Ground-based geophysical techniques such as electrical resistivity imaging (ERI), ground-penetrating radar (GPR), and time-domain reflectometry (TDR) offer subsurface imaging capabilities that can provide insights into the available moisture content and reveal potential indicators of groundwater resources. These methods provide high-resolution shallow subsurface characterisation without drilling or disturbance. However, care must be taken when interpreting subsurface signals from these techniques, as they may detect moisture in unsaturated soils above the water table, rather than directly measuring groundwater storage volumes or the water table surface. While the ground-based methods discussed in this section provide valuable subsurface data related to GWS, it is important to note that some may measure soil moisture content in the vadose zone rather than directly detecting the water table or quantifying groundwater storage volumes. Therefore, signals from electrical resistivity, ground-penetrating radar, and time-domain reflectometry should be interpreted carefully to differentiate between moisture originating from soil and moisture from underlying groundwater reservoirs should be done cauciousely. Additional data are required to confirm direct groundwater detection or quantification.

3.6.1. Electrical resistivity imaging (ERI)

Recent literature on the use of ERI in groundwater storage studies emphasises its potential for capturing temporal and spatial variations in moisture content, understanding solute transport, and detecting leakage. Sebastian et al. (2017) Discussed how ERI can be used to monitor moisture dynamics during landslip reactivation. It was found that the ERI has the potential to capture temporal variations in moisture content, although there is a need for an accurate interpretation and the possibility of missing deeper groundwater storage. Acharya et al., (2017) and Jon et al., (2022) used time-lapse ERI to study soil moisture dynamics in various vegetation types, and emphasised the significance of ERI in evaluating the influence of biological processes on groundwater recharge and solute transport. However, the focus of this study on specific vegetation types may limit the generalisability of the findings. Bongkoch et al. (2022) discussed the application of ERI surveys in open dumpsites as well as the limitations of other geophysical methods, highlighting the benefits of ERI over seismic, electromagnetic, and ground-penetrating radar techniques; however, it may limit the applicability of the findings to other groundwater storage contexts. These studies demonstrate the diverse and promising applications of ERI in groundwater storage.

3.6.2. Ground-Penetrating radar (GPR)

GPR is a versatile and effective ground-based remote sensing technique that images the ground subsurface in various settings. It images subsurface features and detects changes in the properties of the ground materials using electromagnetic waves (Paz et al., 2017). High-resolution GPR images identify geological structures, soil layers, and groundwater levels (Paz et al., 2017). It is widely used in groundwater storage studies to map aquifer boundaries, detect sub-surface water flow patterns, and assess sediment layer thickness and properties (Alastair et al., 2012; Simon Damien et al., 2016).

Recent studies have shown that GPR can be used to characterise geological structures in various contexts. Joseph et al. (2020) used GPR to characterize the geological structures in crystalline rock formations. They identified and modelled groundwater-affected geological features using GPR and other geophysical and geological surveys. Tao et al. (2021) investigated karst unsaturated zones and groundwater dynamics using GPR, highlighting the need for multiple geophysical techniques to accurately assess the irregular distributions of soils and underlying fractures and also demonstrated the effectiveness of mapping shallow subsurface features of the karst critical zone by combining the utility of GPR and Electrical Resistivity Tomography (ERT) (Yang & Yunling, 2020). They used GPR to identify subsurface rock structures to understand geological formations and groundwater dynamics.

GPR is useful in geological and structural investigations. Soil type, moisture content, and antenna frequency influence the resolution and penetration depth. Data interpretation is complex and requires expertise in identifying and characterising subsurface features. This is also helpful for investigating the geological structure of the groundwater. It non-destructively images subsurface features, revealing the geological characteristics that affect groundwater flow and storage. Researchers can better understand the subsurface and manage groundwater resources by combining GPR with other geophysical and geological techniques. Huisman et al. (2003) reported a comprehensive review of methods to measure soil water content using ground penetrating radar including methods that use the reflected wave velocity and surface reflection coefficient.

3.6.3. Time domain reflectometry (TDR)

TDR operates based on the principle that the dielectric constant of a material such as soil is related to its water content. It works by sending an electromagnetic pulse along a transmission line, typically a coaxial cable, and measuring the time it takes for the pulse to travel back after being reflected by the soil–water interface (Topp et al., 2010). It is widely used for the remote sensing of groundwater storage and continuously monitors vadose zone moisture changes over time. This allows for a complete understanding of the GWS and flow dynamics.

TDR has been used in various studies to study water content, infiltration, and groundwater recharge across different geographical regions, and it has been used to study the characteristics of enhanced ground-penetrating radar wave images in carbonate rock formations (Ibrahim, 2023). It has been applied in both laboratory and field settings to investigate the dynamics of groundwater in karst regions (Li et al., 2023b). However, because TDR sensors are installed at shallow depths, they can miss groundwater storage in deeper layers, which could lead to the underestimation of groundwater storage (Yaara et al., 2007).

3.7. Airborne remote sensing

3.7.1. Airborne electromagnetic (AEM) methods

Airborne electromagnetic (AEM) methods use electromagnetic induction to measure the electrical conductivity of subsurface materials, thereby providing valuable information regarding groundwater storage and hydrogeological properties (Auken & Christiansen, 2004). AEM surveys employ a transmitter coil to produce an electromagnetic field and a receiver coil to measure the induced electrical response of the subsurface by analysing variations in electrical conductivity, which can assist in identifying aquifer boundaries and estimating groundwater storage (Kenneth & Russo, 2013). However, the electrical conductivity response measured by the AEM may also detect moisture in unsaturated soils above the water table. Care should be taken to differentiate between soil moisture and groundwater when interpreting AEM data. This technique has been successfully applied in several hydrogeological studies, including the mapping of saline intrusions, characterisation of aquifer properties, and assessment of GWS.

3.7.2. Light detection and ranging (LiDAR)

LiDAR measures the Earth's surface distance with laser pulses; objects reflect LiDAR sensor laser pulses back to the sensor and calculate the distance by timing the laser pulses to and from the objects (Lefsky et al., 2002). LiDAR data can be used to create detailed three-dimensional landscape models. These models can identify buildings, trees, faults, fractures, and aquifers, which are valuable for groundwater exploration studies (Maja & Jacek, 2021). The use of LiDAR for groundwater mapping is a relatively new field, but it has the potential to revolutionise our understanding and management of groundwater resources. Digital - Elevation Models (DEMs) derived from LiDAR technology exhibit superior resolution and vertical accuracy, than the LiDAR itself, thereby enabling a more dependable depiction of depressions and their hydrological importance (Saksena, 2015).

Although LiDAR models can identify potential aquifers, the technology itself only measures surface elevations and does not directly detect groundwater. Supplementary data may be needed to confirm the presence and depth of the groundwater resources.

3.7.3. Airborne hyperspectral imaging

Airborne Hyperspectral Imaging uses high-resolution images across a wide range of spectral bands to identify and characterise surface materials based on their unique spectral signatures (Jing et al., 2023). Hyperspectral imaging can reveal vegetation cover, soil moisture content, and mineralogy, which are important for groundwater storage and hydrogeological modelling (Jingjing et al., 2018; Pedram et al., 2017). This method has been used to map land cover, detect changes in vegetation health, and assess the impact of land use on groundwater resources (Pedram et al., 2017). Vegetation and soil moisture content revealed through hyperspectral imaging may indicate areas favourable for groundwater recharge but do not confirm the underlying groundwater resources. Additional hydrogeological data validation is advised when inferring groundwater from hyperspectral data, which may be further explored for groundwater dynamics studies.

3.8. Satellite-Based remote sensing

3.8.1. Multi-spectral and hyper-spectral imaging

Multispectral and hyperspectral imaging have been used to identify soil and rock types, vegetation cover, and other land features, all of which can be direct or indirect indicators of groundwater potential on Earth's surface. A research in India for instance, revealed that vegetation indices obtained from multi-spectral satellite images, might - be utilised to forecast groundwater potential (Kumar et al., 2022).

In Iran, Khodaei and Nassery (2013) used Landsat ETM, IRS (pan), SPOT data, and a Digital Elevation Model (DEM) to define the Groundwater Potential Index (GWPI), which was used for zoning and preparing the GWPI map of the region. They found that areas with high rates of groundwater depletion were characterised by low vegetation cover, high soil salinity, and high evapotranspiration rates.

Azimi et al. (2020) used data from the Soil Moisture Active and Passive satellite (SMAP) to map soil moisture. They found that soil water content can be used as a good indicator of groundwater potential and to map areas of high and low potential. This study was limited by the fact that the SMAP data were only available for 2015. However, they cannot be used to map earlier groundwater potential. Many researchers have used multispectral satellite images to identify areas of groundwater depletion across regions such as China (Akhter et al., 2021), Mexico (Olivares et al., 2019), and Nigeria (Epuh et al., 2020; Ogungbade et al., 2022).

In contrast, hyperspectral remote sensing offers more in-depth data on vegetation, soil, and rock types than does multispectral imaging. The key difference between the hyper and multi spectral is that Multispectral images typically have 3 to 15 spectral bands, whereas hyperspectral images have hundreds or even thousands of spectral bands (Chakravortty & Subramaniam, 2014). Hyperspectral imagery can also help identify minerals associated with groundwater sources (Peighambari & Zhang, 2021). Several studies have demonstrated the utility of hyperspectral imagery in identifying mineral deposits that are often associated with groundwater (Zheng et al., 2021).

Hyperspectral and multispectral data are often integrated in groundwater studies and have been extensively used for groundwater storage and exploration (Peighambari & Zhang, 2021; Zheng et al., 2021). However, there are many constraints to overcome, including the availability of data and costs associated with data collection and processing. Other multispectral technologies include the Visible and Infrared Imaging Radiometer Suite (VIIRS).

3.8.2. Synthetic Aperture radar (SAR)

Synthetic aperture radar (SAR) is an active remote sensing technology that utilises radar signals to generate high-resolution images of Earth's surface. It operates by transmitting radar signals from antennas mounted on moving platforms such as satellites, receiving reflected signals, and analysing properties such as intensity, phase, and polarisation to gather terrain information (Science., S. G., 2019).Specialised processing algorithms were then employed to enhance the image resolution beyond the antenna aperture limitations. Additionally, interferometric SAR (InSAR) involves the use of multiple SAR images to produce maps of surface deformation or digital elevation, enabling the monitoring of changes on the Earth's surface over time (Huizhang et al., 2021). Several studies have suggested the application of SAR to groundwater storage management. Engman (1994) highlighted the potential of SAR for groundwater studies because of its response to variations in soil moisture and snow properties, and its excellent spatial resolution. Amitrano et al. (2014) presented a pilot project in Burkina Faso that successfully used SAR to estimate the soil sedimentation rate and monitor water intake volume in small reservoirs. Jang et al. (2011) discusses the applicability of SAR for estimating reservoir storage, highlighting the limitations of SAR data and the need for alternative approaches to improve accuracy.

Recently, several studies have revealed how SAR datasets from the Sentinel-1 satellite estimate soil moisture content and monitor changes in groundwater storage; for example, Shashikant et al. (2023) predicted soil moisture content directly using PALSAR-2 (Phased Array type L-band Synthetic Aperture Radar-2) images of oil palm estate, and Liu et al. (2023) showed the potential of SAR for estimating reservoir storage and soil sedimentation rates related to groundwater. These studies have demonstrated the utility of SAR in retrieving soil moisture. Despite the potential of SAR in groundwater storage studies, its use in this field has been hampered by limitations, suggesting the need for further research and development in this area. Awasthi et al. (2022) used time-series Sentinel-1 data and InSAR measurements to analyse the impacts of urbanisation on groundwater stress and land deformation.

While SAR has shown promise for groundwater applications, studies have noted limitations related to accuracy and resolution. Further research and integration with other datasets can address these limitations.

3.8.3. Landsat and Moderate resolution imaging Spectroradiometer (MODIS)

Numerous groundwater studies have used Landsat and MODIS data (Muhammad Atiq Ur Rehman et al., 2022). Their benefits and drawbacks render them as complementary tools for this application. Landsat can map smaller features, such as individual wells and irrigation canals, owing to its higher spatial resolution (30 m), as well as soil moisture, vegetation health, and surface water extent, owing to its wider spectral range than MODIS (Joseph et al., 2013). However, MODIS data can track groundwater variables over time because they have a higher temporal resolution (1–2 days) than Landsat (16–18 days) and global coverage, which enables regional and global groundwater resource studies (Pinhas et al., 2012).

3.9. Gravity-based groundwater measurement

Gravity-based groundwater measurement is an emerging technology that offers a cost-effective and efficient method for measuring groundwater. This technique relies on the principle that Earth's gravity field is affected by the underground mass of water. Changes in groundwater storage can be estimated by measuring changes in the Earth's gravity field. The most well-known gravity-based groundwater measurement mission is the Gravity Recovery and Climate Experiment (GRACE) launched in 2002. GRACE measures changes in Earth's gravity field with high accuracy and has been used to study groundwater storage changes in a variety of regions around the world. GRACE data have been successfully used in several studies worldwide (Liu et al., 2019), South Africa (Oke et al., 2019), Saudi Arabia (Algaydi et al., 2019; Mohammed et al., 2022), Pakistan (Ahmad et al., 2021; Mistry et al., 2019), China (Liu et al., 2020; Wang et al., 2020; Yin et al., 2021), India (Bhakar et al., 2021; Kalura et al., 2021; Swanand & Manjunatha, 2021; Verma & Patel, 2021; Wable et al., 2021), Morrocco (Al-Djazouli et al., 2020), Australia (Jasmine et al., 2021; Yin et al., 2020), Lebanon (Massoud et al., 2021), the Amazon (Massoud et al., 2022b), and many other regions. For example, Kaushik et al. (2021) used gravity-based methods to map groundwater storage changes in the Great Ark Basin. The study found that gravity-based methods can accurately map groundwater storage changes, even in areas with complex geology.

Gravity-based groundwater measurement is a promising new technology that has the potential to revolutionise the way groundwater is measured. Although this technology is still under development, it can provide a more accurate and cost-effective method for monitoring groundwater resources.

3.9.1. Gravity Recovery and climate Experiment (GRACE) satellite mission remote sensing

The Gravity Recovery and Climate Experiment (GRACE) satellite mission measures changes in the Earth's gravity field, which correspond to variations in the total Terrestrial Water Storage (TWS). TWS refers to the summation of all water resources on and beneath the land surface, including surface water, soil moisture, snow/ice, and groundwater (Famiglietti et al., 2011a). By observing changes in Earth's gravity field, GRACE provides the first opportunity to directly estimate GWS changes from space (Frappart & Ramillien, 2018; Rodell & Famiglietti, 2002). However, GRACE does not directly measure GWS changes. To estimate GWS changes from GRACE, TWS measurements must be combined with auxiliary data on other water budget components obtained from land surface models, remote sensing platforms, and ground-based observations (Long et al., 2015; E. Massoud et al., 2022; Massoud et al., 2021). Once these other components have been quantified, they can be subtracted from the TWS change to estimate the groundwater storage change.

Multiple studies have demonstrated a good correlation between GRACE-derived and in-situ observed groundwater storage changes when appropriate data integration is performed (Adams et al., 2022). However, data availability and processing can be challenging; therefore, validation of directly measured groundwater is still important (NASA, 2023).

$$\Delta \mathrm{TWS(t)} = \Delta \mathrm{SW(t)} + \Delta \mathrm{SM(t)} + \Delta \mathrm{SWE(t)} + \Delta \mathrm{GW(t)} \tag{1}$$

Where:

ΔTWS is the change in total water storage from GRACE, ΔSW is the change in surface water storage, ΔSM is the change in soil moisture storage, ΔSWE is the change in the snow water equivalent, and ΔGW is the change in groundwater storage.

By rearranging this equation and having data on the other terms, ΔGW can be estimated as

$$\Delta \mathrm{GW(t)} = \Delta \mathrm{TWS(t)} - \Delta \mathrm{SW(t)} - \Delta \mathrm{SM(t)} - \Delta \mathrm{SWE(t)} \tag{2}$$

Therefore, although GRACE provides unprecedented temporal resolution of TWS changes, its full value for groundwater assessment relies on its integration with other hydrological data sources (Alshehri & Mohamed, 2023; Liu et al., 2019; Long et al., 2015; Massoud et al., 2022b; Massoud et al., 2021; Massoud et al., 2018).

The GRACE mission is a joint project between NASA and the German Aerospace Center (DLR). The mission involves a pair of low-flying satellites orbiting the Earth in tandem and measuring the distance between them with high precision (NASA, 2018). These measurements are used to determine variations in the gravitational pull of Earth, which are caused by changes in the distribution of mass on and within the planet (Wang et al., 2020; Yan et al., 2022).

The GRACE mission was the first attempt to provide a novel remote-sensing dataset that provides temporal variations in terrestrial water storage (summation of water masses in the soil column and consists of surface water, soil moisture, snow, and groundwater) (Frappart & Ramillien, 2018). These masses can be easily used to determine the water stored beneath the Earth.

GRACE and GRACE Follow on (GRACE-FO) (the second mission to continue the project in 2018 after GRACE, known as the follow-on mission) revolutionised our view of groundwater dynamics and its storage variability on Earth, and eventually opened a new opportunity for many researchers. GRACE data offers opportunities to study groundwater anomalies unprecedentedly at global and regional scales, even in areas with little or no observed data.

The GRACE mission involves two identical satellites at an orbital altitude of approximately 450 km, separated by a distance of 220 km. The separation distance changes owing to the attraction of masses on and inside Earth's surface (NASA, 2023).

Groundwater storage dynamics have been extensively studied using gravity recovery and climate experiments (GRACE) and GRACE-FO (GRACE) technologies. Table 1 summarises the selected studies conducted using GRACE data.

4. Methodologies for modelling groundwater storage dynamics

4.1. Data preprocessing and calibration

Groundwater storage dynamics modelling involves several methods of data pre-processing and calibration. Atmospheric and topographic corrections are important in this regard. Atmospheric correction involves removing the effects of atmospheric interference from data to obtain accurate measurements of terrestrial (groundwater) storage. This correction is necessary because atmospheric conditions can affect the measurements of groundwater storage obtained from remote sensing satellites such as GRACE. Topographic correction involves correcting for the effects of topography. Topography can influence the distribution and movement of groundwater; therefore, it is essential to account for these effects in the modelling process (Troch et al., 2003).

Radiometric calibration ensures the accuracy and consistency of measurements obtained from remote sensing instruments. This involves calibrating the measurements to a known reference standard to eliminate systematic errors or biases (Christian et al., 2015).

4.2. Modeling approaches

Various modelling approaches have been used to simulate groundwater storage dynamics. These include empirical, analytical, numerical, statistical, and data-assimilation techniques.

Empirical models are based on observed data and relationships between variables (Massoud et al., 2018; Saeedpanah and Azar, 2023b). Although they are simple and quick to execute, they may need to be capable of adequately capturing complex processes (Sarkar et al., 2021).

Analytical models are based on mathematical equations that describe the physical processes governing groundwater storage dynamics (Christian et al., 2015). These models often involve simplifying assumptions and can provide insights into the fundamental mechanisms that control GWS. This can be derived from the principles of fluid mechanics and hydrogeology (Troch et al., 2003).

Numerical models: Numerical models are based on discretising the study area into a grid and solving the governing equations for the groundwater flow and storage in each grid cell. These models can simulate complex processes and interactions but require detailed input data and computational resources. Numerical models for groundwater storage dynamics can be developed using finite difference or finite element methods (Margaret & Brian, 2017). These models exploit high-resolution remote sensing data to delineate aquifer properties, thereby enriching our understanding of the spatial heterogeneity.

Statistical: Statistical methodologies provide a versatile lens for comprehending groundwater storage variations. Time-series analysis, spatio-temporal kriging, and machine-learning techniques have cast light on intricate temporal patterns and spatial trends. These methods exploit multidimensional RS data and reveal latent patterns that may elicit conventional interpretations (Sarkar et al., 2021).

Machine-learning (ML) approaches have gained popularity in recent years. ML algorithms learn patterns and relationships from data to make predictions or classifications. ML models for groundwater storage dynamics can be developed using techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), and Extreme Gradient Boosting (XGBoost) among others (Saskia, 2015). This approach has advantages over traditional methods, such as its ability to learn complex relationships, handle noisy data, and its applicability in various settings. However, it is prone to overfitting and requires a large dataset in addition to its inherent black-box nature.

Data Assimilation Techniques: The synergy between remote sensing observations and hydrological models is orchestrated using data assimilation techniques. Approaches such as Kalman filtering and Ensemble Kalman filters assimilate heterogeneous data, bridging the gap between the model predictions and actual observations. These methodologies not only enrich the accuracy of groundwater storage estimates but also mitigate the uncertainties inherent in both models and measurements (Gerlach et al., 2021).

Various modelling approaches have been used to simulate groundwater storage dynamics, each with its own strengths and weaknesses. Empirical models are simple and quick to execute; however, they may not adequately capture complex processes. Analytical models can provide insights into the fundamental mechanisms that control groundwater storage; however, they often involve simplified assumptions. Although numerical models can simulate complex processes and interactions, they require detailed input data and computational resources. Statistical approaches can be used to understand temporal patterns and spatial trends in groundwater storage, whereas machine learning approaches can learn complex relationships from data to make predictions. Data assimilation techniques can be used to combine RS observations with hydrological models to improve the accuracy of the GWS estimates.

The choice of the modeling approach depends on the specific problem being addressed. For example, empirical models may be sufficient for simple applications, whereas numerical models may be required for complex ones. Statistical and machine learning approaches can be used to complement numerical models by providing insights into the data and improving prediction accuracy. Data assimilation techniques can be used to improve the accuracy of groundwater storage estimates by combining the data from multiple sources.

It is promising that the future of GWS modelling lies in the use of integrated approaches that combine multiple modelling techniques. By combining the strengths of the different approaches, we can develop more accurate and reliable models that can be used to make informed decisions regarding the management of groundwater resources.

5. Strengths and limitations of remote-sensing technologies

Table 2 compares various remote sensing techniques and their strengths, weaknesses, and recommendations for the best application. Furthermore, spatial and temporal coverage, accuracy, uncertainty, and cost-effectiveness are discussed (section 5.1 to 5.3). The table shows opportunities to combine the strengths of multiple technologies for groundwater exploration. For example, GPR can be used to image the subsurface in areas where other remote sensing techniques are ineffective, and SAR data can be used to detect changes on the Earth's surface.

Table 1
Summary of the selected GRACE-based groundwater storage case studies.

SN	Paper Title & Author	Objective	Methodology	Key Findings	Recommendation	Comment
1.	"Development of a simple groundwater model for use in climate models and evaluation with Gravity Recovery and Climate Experiment data," (Niu et al., 2007)	To develop a simple groundwater model (SIMGM) for use in climate models and evaluate its performance using Gravity Recovery and Climate Experiment (GRACE) data.	The study develops the SIMGM by representing recharge and discharge processes of water storage in an unconfined aquifer. The model is added as a single integration element below the soil of a land surface model. The SIMGM is evaluated against GRACE terrestrial water storage change (DS) data.	The study found that the SIMGM, when evaluated against GRACE DS data, shows good agreement with the observed groundwater storage changes. The model successfully captures the temporal variations in groundwater storage and demonstrates the potential for incorporating groundwater dynamics into climate models.	The authors recommend further research to validate the SIMGM using additional independent data sources and in different hydrogeological settings. They also suggest exploring the potential of incorporating the SIMGM into climate models to improve the representation of groundwater dynamics.	This work addresses the important issue of incorporating groundwater dynamics into climate models. The development of the SIMGM provides a valuable tool for representing groundwater storage changes in climate models. The evaluation of the model using GRACE data demonstrates its potential for capturing groundwater dynamics. However, further research is needed to validate the model using additional data sources and in different hydrogeological settings. The incorporation of groundwater dynamics into climate models is crucial for improving the accuracy of water resource assessments and climate change impact studies
2.	"Global-scale modeling of groundwater recharge," (Petra & Kristina, 2008)	To develop a global-scale model for estimating groundwater recharge.	The study uses a global hydrological model, WaterGAP, to simulate GW recharge at global scale. The authors incorporate various data sources, including climate data, soil data, and land cover data, into the model to estimate groundwater recharge. They validate the model results using available groundwater recharge observations and evaluate the spatial patterns and temporal variability of groundwater recharge.	The study provides estimates of global-scale groundwater recharge and highlights the spatial patterns and temporal variability of recharge. The authors find significant spatial variability in groundwater recharge, with higher recharge rates in humid regions and lower recharge rates in arid and semi-arid regions.	The authors recommend: further research on improving the accuracy of global-scale groundwater recharge estimates. They suggest incorporating more ground-based observations to validate and refine the model results. The authors also emphasize the need for considering climate change impacts on groundwater recharge and the development of sustainable water management strategies.	The study contributes to our understanding of global-scale groundwater recharge. The use of the WaterGAP model allows for the estimation of groundwater recharge at a global scale and provides insights into the spatial patterns and temporal variability of recharge. The findings highlight the significant spatial variability in groundwater recharge and emphasize the importance of considering climate change impacts. However the study has limitations such as the reliance on model-based estimates without extensive validation with ground-based observations.
3.	"Drought indicators based on model-assimilated Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage observations" (Ibrahim et al., 2012)	To develop drought indicators based on model-assimilated Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage (TWS) observations.	The study utilizes a data assimilation framework to assimilate GRACE TWS observations into a land surface model. The authors use the assimilated TWS data to develop drought indicators, including the Standardized Precipitation Evapotranspiration Index (SPEI) and the Standardized Soil Moisture Index (SSI). The drought indicators are validated against observed drought events	The study found that the assimilated GRACE TWS data improves the accuracy of drought indicators compared to using precipitation and temperature data alone. The developed drought indicators, SPEI and SSI, show good agreement with observed drought events and perform well in capturing the spatial and temporal variability of drought conditions. The findings highlight the potential of GRACE TWS data assimilation for	The study made following recommendations: To explore the uncertainties associated with GRACE measurements and data processing techniques in the context of drought monitoring. Incorporating error estimates into the assimilation framework to account for the uncertainties in the GRACE TWS data.	The study addresses the important issue of developing drought indicators based on model-assimilated GRACE TWS observations. The assimilation of GRACE data into the land surface model improves the accuracy of drought indicators, enhancing the representation of water storage dynamics. The validation of the drought indicators against observed drought events adds confidence to the accuracy of the results.

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Table 1 (*continued*)

SN	Paper Title & Author	Objective	Methodology	Key Findings	Recommendation	Comment
			and compared with other drought indices.	drought monitoring and assessment.		However, it is important to acknowledge the limitations of the study, such as the focus on model-assimilated GRACE TWS data without considering the uncertainties associated with the GRACE measurements themselves. Future research should explore the impact of GRACE measurement errors and data processing techniques on the accuracy of drought indicators.
4.	"Groundwater depletion in the Middle East from GRACE with implications for transboundary water management in the Tigris-Euphrates-Western Iran region" (Voss et al., 2013)	The main goal of the study is to assess groundwater depletion in the Middle East using GRACE satellite data and to evaluate its implications for transboundary water management in the Tigris-Euphrates-Western Iran region	The authors analyze the GRACE data to assess the magnitude and spatial patterns of groundwater depletion in the region. They also examine the implications of groundwater depletion for transboundary water management in the Tigris-Euphrates-Western Iran region.	The study shows a significant groundwater depletion in the Middle East, particularly in the Tigris-Euphrates-Western Iran region. They pointed out the implications of groundwater depletion for transboundary water management, including the potential for conflicts over water resources.	Further research on the impacts of groundwater depletion on transboundary water management in the Middle East. The need for improved monitoring and management of groundwater resources, as well as international cooperation to address the challenges of groundwater depletion is needed.	The findings highlight the challenges of groundwater depletion in the Tigris-Euphrates-Western Iran region and emphasize the need for sustainable water management strategies and international cooperation. However, the study rely on satellite data without extensive validation with ground-based observations, thereby poses some limitations.
5.	Global-scale assessment of groundwater depletion and related groundwater abstractions: Combining hydrological modeling with information from well observations and GRACE satellites" (Döll et al., 2014)	The study aims to improve the understanding of groundwater depletion and its causes, and to distinguish between groundwater depletion due to climatic reasons and human water abstractions.	Combines hydrological modeling with information from well observations and GRACE satellites. They also incorporate information from well observations to validate the model results. they utilize GRACE satellite data to assess groundwater storage changes at a global scale. The GRACE data is combined with model-based estimates of soil and snow storage to derive groundwater depletion.	GRACE data can contribute to a better understanding of groundwater depletion and its causes. The ability of GRACE data to distinguish between groundwater depletion due to climatic reasons and human water abstractions as highlighted. and The study emphasizes the usefulness of GRACE data in monitoring groundwater depletion, particularly in regions where groundwater and surface water withdrawals are high and not well monitored.	The study suggests exploring alternative methods to derive groundwater depletion from GRACE data, such as incorporating additional data sources or refining the modeling approaches. The authors also emphasize the need for more localized studies to capture the spatial variability of groundwater dynamics. Future research could focus on specific regions or aquifer systems to provide more detailed insights into groundwater depletion processes	A strength of the study is the integration of multiple data sources and modeling approaches to assess groundwater depletion. The combination of hydrological modeling, well observations, and GRACE satellite data provides a comprehensive understanding of groundwater dynamics. The study also highlights the importance of distinguishing between climatic reasons for groundwater storage decreases and groundwater depletion due to human water abstractions. This distinction is crucial for effective groundwater management and sustainable water resource planning Döll et al. (2014). However, the study relied on model-based estimates of soil and snow storage to derive groundwater depletion from GRACE data. Nevertheless, the author acknowledged that the approach has been used in most studies but may introduce uncertainties in the estimation of groundwater depletion.

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Table 1 (*continued*)

SN	Paper Title & Author	Objective	Methodology	Key Findings	Recommendation	Comment
6.	"Monitoring groundwater storage changes in complex basement aquifers: An evaluation of the GRACE satellites over East Africa" (Nanteza et al., 2016)	The focused on evaluating the suitability of GRACE data for monitoring groundwater storage changes in areas where traditional monitoring methods may be limited.	the study utilizes carefully processed data sets, including GRACE data, lake altimetry, and model soil moisture, to evaluate groundwater storage changes in East Africa. They employed a combination of these data sources to reduce scaling factor bias and compare the GRACE-derived groundwater storage changes with in situ groundwater observations. They also consider the impact of surface water storage on the accuracy of the GRACE data and evaluate the correlation between GRACE-derived groundwater storage changes and in situ measurements	The work highlights the importance of considering the impact of surface water storage on the accuracy of the GRACE data and emphasize the need for cautious processing techniques. The study demonstrates a strong correlation between GRACE-derived groundwater storage changes and in situ groundwater observations, indicating the potential of GRACE data for monitoring groundwater dynamics in complex basement aquifers	the authors recommend further research on the application of GRACE data for monitoring groundwater storage changes in other regions and aquifer systems. They suggest expanding the evaluation to different hydrogeological settings to assess the generalizability of the findings.	The findings have implications for water resources management in areas where traditional monitoring methods may be limited. However, future studies are needed to expand the evaluation to other regions and aquifer systems, and to explore the potential limitations or uncertainties associated with the GRACE data itself.
7.	Relative contribution of monsoon precipitation and pumping to changes in groundwater storage in India (Akarsh et al., 2017)	The main goal of the study is to assess the relative contributions of monsoon precipitation and pumping to changes in groundwater storage in India	The authors analyze the GRACE data to assess the spatial and temporal patterns of groundwater storage changes. They also examine the relationship between groundwater storage changes and monsoon precipitation, as well as the impact of pumping on groundwater depletion.	The study made the following findings: Both monsoon precipitation and pumping contribute to changes in groundwater storage in India. Observed a strong correlation between monsoon precipitation and groundwater storage replenishment, indicating the importance of monsoon rainfall for groundwater recharge. That pumping for irrigation and other purposes leads to significant groundwater depletion, particularly in regions with high pumping rates.	The study recommends further research on the impacts of monsoon variability and pumping on groundwater storage in India. Suggest the need for improved monitoring and management of groundwater resources, as well as the implementation of sustainable irrigation practices to reduce excessive pumping. The authors also Emphasized the importance of integrating satellite data with ground-based observations to improve the accuracy of groundwater storage assessments.	The findings highlight the importance of considering both natural factors and human activities in understanding groundwater dynamics. However, it is important to acknowledge the limitations of the study, such as the reliance on satellite data without extensive validation with ground-based observations. Future research should focus on incorporating more ground-based data to enhance the accuracy of groundwater storage estimates and to understand better the complex interactions between climate, pumping, and groundwater resources in India.
8.	"Evapotranspiration depletes groundwater under warming over the contiguous United States," (Laura et al., 2020)	To investigate the impact of warming on groundwater depletion through changes in evapotranspiration over the contiguous United States	The study combines satellite observations, climate model simulations, and groundwater model simulations to assess the relationship between warming, evapotranspiration, and groundwater depletion. The authors use GRACE satellite data to estimate changes in total water storage, including groundwater storage, and validate the results with in situ groundwater observations.	IT is revealed that warming leads to increased evapotranspiration, which depletes groundwater storage. The authors observed a significant increase in groundwater depletion over the contiguous United States due to warming-induced changes in evapotranspiration.	Recommend further research to assess the impact of warming on groundwater depletion in other regions and to explore the potential of incorporating climate change projections into groundwater models. They also suggest the need for improved monitoring and management of groundwater resources in the face of climate change.	This study addresses an important aspect of the impact of warming on groundwater depletion through changes in evapotranspiration. The integration of satellite observations, climate model simulations, and groundwater model simulations provides a comprehensive understanding of the relationship between warming, evapotranspiration, and groundwater depletion. The findings highlight the need for sustainable water management strategies to mitigate the impacts of climate change on groundwater

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Table 1 (*continued*)

SN	Paper Title & Author	Objective	Methodology	Key Findings	Recommendation	Comment
						resources. However, it is important to consider the regional variability in groundwater dynamics and to expand the research to other regions to obtain a more comprehensive understanding of the impacts of warming on groundwater depletion.
9.	"Estimating the Spatiotemporal of GRACE/GRACE-FO derived groundwater storage and depletion and validation with in-situ measurements of water level and quality (Yazd Province, Central Iran)," (Amiri et al., 2023)	To estimate the spatiotemporal variations of groundwater storage and depletion in Yazd Province, Iran, using GRACE/GRACE-FO data and to validate the results with in-situ measurements.	The study used GRACE/GRACE-FO data to estimate the spatiotemporal variations of groundwater storage in Yazd Province from 2003 to 2020. The results were then validated with in-situ measurements of water level and quality.	The study found that groundwater storage in Yazd Province has been decreasing since 2003. The depletion is most pronounced in the central and southern parts of the province. The results were validated with in-situ measurements, which showed good agreement with the GRACE/GRACE-FO data.	Recommend further research to investigate the causes of groundwater depletion in Yazd Province.	The study provides valuable insights into the spatiotemporal variations of groundwater storage in Yazd Province.
10	"Groundwater recharge and water table levels modelling using remotely sensed data and cloud-computing" (Magnoni et al., 2020)	To assess the suitability of using remotely sensed data to estimate monthly groundwater recharge (GWR) and water table depths (WTD) in a representative area of the Guarani Aquifer System.	Used actual evapotranpiration, surface runoff, and precipitation data from the FLDAS drought monitor extracted using Google Earth Engine. Models GWR using a water budget equation and WTD using an adapted Water Table Fluctuation method.	Good agreement found between FLDAS precipitation data and rain gauge measurements. Accounting for recharge delay improves correlation of modeled GWR with reference GWR WTD model shows better performance for shallow wells.	Recommends exploring incorporation of remotely sensed data into groundwater models in data scarce regions using cloud computing tools like Google Earth Engine. Suggests using the uncertainty analysis framework for decision making where validation data is not available.	This study demonstrates the potential for using remotely sensed data and cloud computing tools to model groundwater parameters. The uncertainty analysis provides a means to evaluate model utility even when validation data is scarce. Findings are promising for expanding groundwater modeling to data deficient regions.
11	"Information content of soil hydrology in a west Amazon watershed as informed by GRACE" (E. C. Massoud et al., 2022)	To quantify the capability of GRACE terrestrial water storage (TWS) data to inform and constrain key soil hydrologic processes like soil moisture, plant available water, root depth, and groundwater recharge.	Uses a reduced-complexity physically based hydrologic model calibrated using Bayesian inference against GRACE TWS data over the Amazon. Quantifies information gain on model parameters and water cycle components based on prior and posterior distributions.	Data-constrained model captures basic hydrologic cycle physics and TWS variability over study period. Shows 2–85 % reduction in uncertainty across key process parameters. Accurately simulates impacts of major droughts on TWS.	Results demonstrate potential of using GRACE data to identify and constrain uncertain parameters related to soil hydrology. Can lead to improved representation of terrestrial water dynamics in models.	Leverages GRACE observations to reduce parametric uncertainties in hydrologic modeling. Well constrained models can better simulate water storage changes and inform water resource management.
12	Groundwater Depletion Signals in the Beqaa Plain, Lebanon: Evidence from GRACE and Sentinel-1 Data" (Massoud et al., 2021)	To quantify groundwater storage changes and depletion rates in the Beqaa Plain, Lebanon using multiple data sources.	Combines GRACE TWS data with hydrologic components from GLDAS and reservoir data to estimate groundwater storage changes. Validates using Sentinel-1 subsidence rates and ground measurements.	Results show groundwater depletion rates ranging from −1.10 to + 0.08 cm/year across different districts. Sentinel-1 and wells confirm strong depletion signals in areas of heavy pumping.	Recommends combining remote sensing and ground data for monitoring groundwater resources. Further integration of data sources can provide higher resolution depletion estimates.	Study provides robust evidence of unsustainable groundwater usage in the Beqaa Plain from multiple data streams. Framework demonstrated has value for water management in data scarce regions.
13	"Projecting Groundwater Storage Changes in California's Central Valley" (Massoud et al., 2018)	To develop an aggregated groundwater storage model for California's Central Valley to estimate past and project future changes.	Uses annual water supply/demand data and precipitation to build empirical relationships and water balance model Calibrates model against USGS and GRACE groundwater storage change estimates from 1981 to 2014.	Model matches historic groundwater depletion trends reasonably well (RMSE = 6.8 km3). Projects continued future groundwater declines without changes in water management.	Model provides a useful tool for assessing impacts of climate variability and water management decisions on groundwater resources.	Study demonstrates potential value of parsimonious models that integrate multiple data sources for providing insights on water resource systems.
14	"Monitoring Groundwater Change in California's Central Valley Using Sentinel-1 and GRACE Observations" (Liu et al., 2019)	To use Sentinel-1 InSAR and GRACE data to analyze spatiotemporal groundwater variability and land subsidence in	Processes Sentinel-1 interferograms to generate high resolution ground deformation maps and time series. Combines GRACE TWS	InSAR shows land subsidence up to ~ 25 cm/year during recent drought, higher than previous drought. Strong correlation found	Recommends integrating InSAR deformation mapping and GRACE water storage data for improved	Study demonstrates how satellite datasets can provide complementary information to characterize groundwater system dynamics over a

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Table 1 (*continued*)

SN	Paper Title & Author	Objective	Methodology	Key Findings	Recommendation	Comment
		California's Central Valley.	anomalies with hydrologic components to isolate groundwater signals.	between GRACE groundwater depletion and InSAR subsidence trends.	spatiotemporal groundwater monitoring.	range of spatial and temporal scales.
15	"Cascading Dynamics of the Hydrologic Cycle in California Explored through Observations and Model Simulations" (Massoud et al., 2020)	To explore the temporal co-evolution of components of California's hydrologic cycle from 2002 to 2018 using satellite, model, and observational data.	Combines GRACE total water storage data with NLDAS outputs and reservoir storage records to analyze soil moisture, snowpack, reservoir levels, and groundwater.	Majority of total water storage loss attributed to groundwater depletion, especially during droughts Snowpack and soil moisture impacted earlier and recover faster than surface and groundwater reserves Clear cascading effect occurs over 8–16 month period.	Quantifying lag times and linkages between hydrologic components can improve drought characterization and water management. Further analysis of process interdependencies could provide additional insights.	Leverages multiple data streams to demonstrate and quantify the cascading nature of California's hydrologic cycle across wet periods and droughts.

This combination of technologies can provide a more comprehensive picture of the subsurface and help to identify areas of groundwater potential. In addition to combining multiple technologies, it is also important to use data from multiple sources. For example, ground-based data can be used to validate remote sensing data.

The integration of GRACE and InSAR technologies with data from in situ wells has garnered significant attention from researchers owing to its potential to enhance the understanding of subsurface processes. Liu et al. (2019) and Massoud et al. (2021) have specifically delved into the exploration of combining these technologies to enable comprehensive monitoring of groundwater levels and land surface deformation. This integrated approach provides valuable insights into hydrological processes and subsurface dynamics, ultimately contributing to improved accuracy of GWS exploration. By leveraging the strengths of multiple technologies and integrating data from various sources, it is feasible to identify areas of groundwater potential that would otherwise be challenging to detect. Studies by Liu et al. (2019) and Massoud et al. (2021) underscore the significance of data fusion in achieving enhanced accuracy and reliability in groundwater exploration, emphasising the pivotal role of integrated technologies in advancing our understanding of subsurface dynamics.

5.1. Spatial and temporal coverage

Remote sensing provides extensive spatial and temporal coverage in various applications. For example, the GRACE satellite mission was used to estimate the mass trends over Antarctica (Jianli et al., 2006). The mission covers the entire continent and provides a comprehensive image

Table 2
Comparison of various remote sensing techniques, strengths, weaknesses, and recommendations for the best application.

Remote Sensing Technologies	Strength	Weaknesses	Recommendation	Reference
Ground-based remote sensing:				
Ground-penetrating radar (GPR)	GPR Images ground subsurface can be used to identify groundwater features, such as aquifers and fractures.	It is limited by the depth of ground penetration.	Use GPR to image the subsurface in areas where other remote sensing techniques are not effective.	(Francisco et al., 2021)
Time domain reflectometry (TDR)	TDR measure the electrical properties of the subsurface, which can be used to identify groundwater features.	TDR can be affected by soil moisture and other factors.	Use TDR to measure the electrical properties of the subsurface in areas where groundwater exploration is warranted.	(Yaara et al., 2007)
Electrical resistivity imaging (ERI)	ERI map the electrical resistivity of the subsurface, which can be used to identify groundwater features.	Can be affected by soil moisture and other factors.	Use ERI to map the electrical resistivity of the subsurface in areas where groundwater exploration is warranted.	(Sebastian et al., 2017)
Airborne remote sensing:				
Airborne electromagnetic (AEM) methods	Map the electrical conductivity of the subsurface, which can be used to identify groundwater features.	Expensive to acquire and process.	Use AEM methods to map the electrical conductivity of the subsurface in areas where groundwater exploration is warranted.	(Kenneth & Russo, 2013)
Light detection and ranging (LiDAR)	LiDAR create detailed three-dimensional models of the landscape, which can be used to identify groundwater features.	Expensive to acquire and process.	Use LiDAR data to create detailed maps of the landscape, which can be used to identify groundwater features.	(Maja & Jacek, 2021)
Satellite-based remote sensing:				
Multispectral and hyperspectral imaging	Can be used to identify vegetation, soil, and rock types, all of which can be indicators of groundwater potential.	Can be affected by atmospheric conditions, such as cloud cover and haze.	Use multiple sensors to collect data in different spectral bands.	(Peighambari & Zhang, 2021)
Synthetic aperture radar (SAR)	Can be used to detect changes in the Earth's surface, which can be used to identify areas of groundwater storage and recharge.	Can be affected by atmospheric conditions, such as cloud cover and haze.	Use SAR data to identify areas of groundwater storage and recharge.	(Jang et al., 2011)
Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS)	Can be used to identify vegetation, soil, and rock types, all of which can be indicators of groundwater potential.	Can be affected by atmospheric conditions, such as cloud cover and haze.	Use Landsat and MODIS data to identify vegetation, soil, and rock types, which can be used to identify groundwater potential.	(Rehman at al., 2022)
Gravity-based groundwater measurement:				
Gravity Recovery and Climate Experiment (GRACE)	It can be used to measure changes in groundwater storage over time.	It can be affected by other factors, such as changes in precipitation and evaporation.	Use GRACE data to identify areas where groundwater storage is changing, which can be used to identify areas where groundwater exploration may be warranted.	(Rodell, 2013)

of surface mass trends, which allows for the exploration of prominent features such as regions of mass loss and accumulation. Moreover, satellite remote sensing, including sensors onboard aircrafts and space-based platforms such as Landsat, offers large spatial and frequent temporal coverage (Belachew et al., 2016). These technologies provide valuable data for monitoring and managing various environmental phenomena including forest health (Marion et al., 2016), drought (West et al., 2019), and agricultural processes (Valentina et al., 2019).

5.2. Data resolution and accuracy

The resolution and accuracy of remote sensing data vary with data resolution and accuracy, thereby enabling a variety of applications. Resolution is a key factor influencing the accuracy of remote sensing data. Higher spatial resolution data provide more detailed information about Earth's surface, allowing for better classification and analysis. For example, high-resolution remote sensing data classification methods based on spectrum sharing have been shown to improve the accuracy of data classification and image fusion (Duan & Duan, 2021). The improved resolution allows for better differentiation of features, increased texture, and prominent edges, which are critical for accurate classification. However, the classification accuracy of traditional pixel-based methods may be limited because of the large amount of data and inability to meet the requirements of high-resolution images (Guan et al., 2022). To overcome this limitation, many researchers have embraced machine learning and deep learning techniques, such as Convolutional Neural Networks (CNNs), which have shown powerful feature extraction and expression capabilities that do not rely on multidomain expert knowledge and can achieve high model accuracy (Cao et al., 2022). For example, the use of CNNs for multilevel cloud detection in high-resolution RS imagery improves accuracy (Chen et al., 2018).

In addition to data resolution, data accuracy is another important aspect of RS technology. Accurate classification and detection of features, such as clouds and wetlands, are critical for various applications, including resource surveying and groundwater monitoring (Guan et al., 2022). However, achieving high accuracy in remote sensing data processing remains challenging, particularly when dealing with multilevel cloud detection using satellite imagery that contains only visible and near-infrared spectral bands (Chen et al., 2018). Nevertheless, advancements in RS technologies, such as the use of multiple CNNs and attention mechanisms, have shown promise in improving the accuracy of scene data augmentation and feature extraction (Cao et al., 2022).

5.3. Cost-Effectiveness

The cost-effectiveness of RS technologies in groundwater studies is a topic of significant interest and debate in the scientific community. While it is true that RS missions such as GRACE involve substantial costs and long planning periods, it is essential to consider the broader context in which remote sensing technologies are deemed cost-effective.

RS techniques, including satellite imagery and signals, offer distinct advantages over traditional ground-based methods (Tracey et al., 2018). Despite the substantial initial investment in satellite missions, the ability to collect data over large and often inaccessible areas provides a cost-effective solution for monitoring and evaluating various environmental phenomena (West et al., 2019). This is particularly valuable in regions where obtaining field measurements and allometric models is challenging owing to geographical remoteness, lack of capacity, data paucity, or armed conflicts, as noted by Rodriguez-Veiga et al. (2017) and West et al. (2019).

It is important to acknowledge that the cost-effectiveness of remote sensing technologies should be evaluated in the context of their ability to provide comprehensive and continuous data collection over vast and often challenging terrains. While the initial investment in satellite missions is substantial, its global applicability and long-term benefits of continuous data acquisition, especially in regions where ground-based observations are impractical, may pose a RS technology a cost-effective solution for acquiring essential data, particularly in the academic research community, as highlighted by (Rodriguez-Veiga et al., 2017).

Therefore, the cost-effectiveness of remote sensing technologies in groundwater studies should be viewed from a holistic perspective, considering the long-term benefits of continuous data acquisition over large and inaccessible areas, global applicability, data access costs, and challenges associated with traditional ground-based methods.

5.4. Integration with Ground-Based observations

Integrating Remotely sensed data with ground-based observations improves data accuracy and reliability (Congalton, 1991). Ground-based observations provide valuable data that can help constrain and validate the estimations derived from remote sensing data (Janardhanan et al., 2023). Eddy covariance measurements, physically based model simulations, meteorological forcings, and remote sensing datasets can improve evapotranspiration and ecosystem respiration estimations (Chen et al., 2021).

Several studies have highlighted the importance of combining remote sensing data with ground-based observations to comprehensively investigate and account for the dynamics of groundwater storage in regional aquifer systems (Chen et al., 2021; Janardhanan et al., 2023; Marion et al., 2016). The integration of remote sensing with ground-based observations has several advantages.

First, it provides a more comprehensive understanding of groundwater storage dynamics by combining data from different sources and at different scales (Hoff et al., 2019). RS provides a broad-scale view of the Earth's surface, whereas ground-based observations offer detailed information at specific locations, allowing us to obtain a more complete picture of groundwater storage changes and gain a better understanding of the underlying processes (McStraw et al., 2021).

Second, the integration of RS and ground-based observations can help improve the accuracy and reliability of GWS estimation. RS data such as satellite imagery and radar measurements can provide spatially extensive coverage; however, they may need to be improved in terms of their resolution and accuracy (Wang et al., 2022). However, ground-based observations provide high-resolution data, which are often used to validate and calibrate RS estimations. This provides an opportunity to reduce the uncertainties and improve the overall accuracy of groundwater storage models when these two data sources are integrated. However, the integration of remote sensing and ground-based observations has been limited. One limitation is the spatial and temporal mismatch between the two types of data. RS data are typically collected at regular intervals and cover large areas, whereas ground-based observations are often limited to specific locations and may have irregular sampling intervals (Wang et al., 2022). This mismatch can make it challenging to integrate the data and derive consistent estimations of GWS changes.

Another limitation is the need for careful calibration and validation of the remote sensing data using ground-based observations. Remote sensing data may require correction and calibration to account for atmospheric effects, sensor characteristics, and other sources of errors. Ground-based observations can provide reference data for this calibration process; however, they require careful analysis and validation to ensure the accuracy and reliability of integrated data (Nansen et al., 2023b).

Hence, integrating remote sensing and ground-based observations is essential for modelling groundwater storage dynamics. This allows for a more comprehensive understanding of groundwater systems and improves the accuracy and reliability of estimations. Despite the challenges associated with integration, future research should focus on addressing these challenges and developing robust methods for integrating remote sensing and ground-based observations to improve our understanding of groundwater resources.

5.5. Limitations and uncertainties

One of the main limitations of satellite-based remote sensing technologies like GRACE in groundwater monitoring and modelling is their relatively coarse spatial resolution, which hampers their accuracy in smaller study areas (Yilmaz & Murat, 2016). However, InSAR has emerged as a valuable complementary technology in this regard, offering very high spatial resolution ground displacement information that can be used to infer localised changes in groundwater storage (Massoud et al., 2021). By integrating InSAR-derived ground motion data with large-scale GRACE measurements, recent studies have achieved improved characterisation of groundwater dynamics, even in regions smaller than the native resolution of GRACE (Massoud et al., 2021).

Another challenge, although not exclusive to groundwater storage studies, is the estimation of deep subsurface moisture dynamics using spaceborne methods limited to surface observations. However, recent advances in parsimonious hydrological modelling using GRACE have shown promise in constraining root zone moisture and vegetation water availability in deeper soil layers in the vadose zone (Massoud et al., 2022a). Such data assimilation techniques can help to extend the reach of remote sensing to deeper vadose zone moisture monitoring. Moreover, ground-based geophysical techniques, such as electrical resistivity tomography (ERT), can directly image deeper vadose zone moisture distributions through field surveys (Acharya et al., 2017).

There are also inherent uncertainties associated with remote sensing retrievals and their integration into hydrological models. Key sources include measurement calibration limitations, fusion of multi-source datasets, and structural deficiencies in the models themselves (Dabboor & Brisco, 2019; Ruggieri et al., 2021). However, recent studies have formulated rigorous uncertainty analysis frameworks to quantify errors from individual sources and propogate them through modelling sequences (Massoud et al., 2020). Such efforts towards transparent quantification and reporting of uncertainties can significantly improve the reliability of RS products in hydrological studies.

It is noteworthy that advances in multimodal data fusion and uncertainty analysis are helping address some of the key limitations of remote sensing for groundwater applications. However, meticulous preprocessing, validation against in situ data, and interpretation by domain experts remain vital for generating actionable information (John et al., 2016). The unique strengths and weaknesses of different RS technologies (Table 2) highlight the need for a tailored, fit-for-purpose approach in applying them for GWS monitoring and modelling.

6. Factors influencing groundwater storage dynamic models

In this section, the factors influencing the GWS dynamics are discussed. Climatic variations, geology, anthropogenic activities, water allocation, and land use are the main factors influencing groundwater storage (Asoka & Mishra, 2020; Jin et al., 2021; Kevin et al., 2019; Lähivaara et al., 2019; Massoud et al., 2018; Thomas & Famiglietti, 2019).

6.1. Climate change

Climate changes, such as precipitation and temperature variations, significantly impact groundwater storage dynamics (Famiglietti, 2014; Famiglietti et al., 2011b). Climate-driven alterations in recharge patterns and evapotranspiration rates lead to fluctuations in groundwater storage levels and overall aquifer response to external factors. For example, groundwater storage levels are typically high in areas with high rainfall and typically low in areas with low rainfall. Asoka et al. (2017) observed that climate variability directly affects groundwater through changes in recharge and abstraction during droughts. Changes in surface water storage, such as lakes and reservoirs, and soil moisture also affect terrestrial water storage, including groundwater (Zhang et al., 2023a). Akarsh and Vimal (2020) studied the influence of climate change and agricultural expansion on groundwater storage in the Amur River Basin, and found that changes in climate and land use have significant impacts on groundwater storage.

6.2. Geology and lithology

Aquifer geology can also significantly impact groundwater storage. The rock type, porosity, and permeability of an aquifer affect the amount of water that can be stored and the ease of movement through the aquifer(José et al., 2013). For example, sandstone aquifers are typically more permeable than limestone aquifers; therefore, they can store and transmit more water (Yin et al., 2021). Understanding geology is essential for accurately estimating groundwater storage changes using remote sensing techniques such as GRACE-based. However, the interpretation of GRACE-based estimates of groundwater depletion is specific to the geological characteristics of the study area. This is because the geological heterogeneity of aquifers can affect the hydraulic connection between groundwater and streams, leading to discrepancies between recession-based approaches and GRACE-derived groundwater estimates (Frédéric and Guillaume, 2018; Sun et al., 2020).

Similarly, the lithology of an area influences the groundwater recharge and discharge (Frappart & Ramillien, 2018). This is a key factor in GRACE-based groundwater storage estimates (Wang et al., 2023). For example, permeable rocks, such as sand and gravel, are more likely to store groundwater than impermeable rocks, such as shale. Vegetation can also influence the groundwater storage by increasing infiltration and reducing evaporation. In addition to lithology, land cover, and structure, other geological features such as lineaments and drainage patterns can also influence groundwater storage. Lineaments are linear subsurface features caused by faults, fractures, or other geological processes (Sander, 2007).

Overall, geology and lithology influence groundwater storage measurements. For example, gravity-based measurements affect the local mass distribution and the resulting variations in the gravitational force, which are detected by GRACE satellites. By analysing GRACE data in conjunction with geological information, researchers can gain valuable insights into groundwater dynamics and their relationship with geologic settings, providing essential information for water resource management and geological studies.

6.3. Aquifer properties and structure

The physical characteristics of aquifers play a significant role in the groundwater storage dynamics. Porosity, hydraulic conductivity, and storage coefficient directly influence the rate of groundwater flow and the amount of water that the aquifer can store (Bonì et al., 2016); (McMahon & Peterson, 1992). These properties are fundamental in determining the response of an aquifer to external stresses and changes in groundwater levels. Hydraulic properties are used to estimate the transmissivity and storage coefficient of an aquifer and are parameters that describe how easily water can flow through and be stored in an aquifer. These parameters were used to improve the accuracy of GRACE-based groundwater storage estimates by accounting for the spatial distribution of groundwater storage within an aquifer. Hydrogeological information was used to develop a model of groundwater flow in an aquifer in the Nubian Sandstone of African Sahara (Egypt, northern Sudan, and eastern Libya), which was then used to interpret GRACE data (Gossel et al., 2004).

However, the aquifer structure significantly influences groundwater flow and storage (Pinder and Celia, 2006). An aquifer with a well-developed network of fractures is more permeable than an aquifer with more uniform aquifer structures that act as preferential flow paths or barriers, thereby affecting the overall storage behaviour (Renard & Allard, 2013).

6.4. Topography

The topography of the land surface strongly influences groundwater flow paths and storage patterns. Groundwater tends to flow from areas of higher elevation to lower elevations following the hydraulic gradient. Topographic data, often derived from digital elevation models (DEMs) obtained through remote sensing techniques, are critical inputs for dynamic groundwater storage models.

6.5. Land Use, land cover (LULC) and groundwater pumping

Human anthropogenic activities, such as urbanisation, agriculture, and deforestation, can alter groundwater storage dynamics (Scanlon et al., 2005). Changes in land use and land cover can affect the amount and rate of recharge, as well as the availability of natural discharge areas, thereby impacting groundwater storage patterns. Excessive groundwater abstraction through pumping can lead to a decline in the groundwater level and reduced storage capacity (Groundwater, 2021) the pumping rate and sustainable yield of an aquifer are critical considerations for understanding the dynamics of groundwater storage (Massoud et al., 2018).

6.6. Recharge and discharge rates

Groundwater recharge and discharge rates are key factors shaping the dynamics of groundwater storage. Recharge processes, such as rainfall infiltration and surface water seepage, replenish aquifers (Sophocleous, 2002). Discharges include groundwater pumping and natural outflow to rivers and lakes (Wang and Du, 2016). Understanding these processes is vital for accurate modelling of groundwater storage variations (Massoud et al., 2018).

The groundwater recharge and discharge can be estimated using various methods and models. One common approach is to use a soil-–water model, such as the Soil Conservation Service (SCS) model or Soil and Water Assessment Tool (SWAT) model. These models use a variety of factors such as rainfall, soil type, and vegetation to estimate the amount of water that infiltrates the ground (Mohsenifard et al., 2023). SCS method, also known as the Curve Number (CN) method, is a commonly used empirical approach for estimating the surface runoff that indirectly contributes to groundwater recharge. Although the SCS method primarily focuses on surface runoff estimation, it can be used to infer groundwater recharge and discharge patterns to some extent (Karki et al., 2021). However, it is less comprehensive than hydrological models such as SWAT in explicitly estimating groundwater processes. SWAT considers land use changes, soil properties, and other factors to estimate the recharge content.

Researchers have demonstrated several methods that successfully estimate groundwater recharge and discharge (Liao et al., 2023; Mohammed et al., 2022; Nansen et al., 2023a; Nolte et al., 2021; Zhu et al., 2021) for example, the WetSpass (Water and Energy Transfer between Soil, Plants, and Atmosphere under Steady-State Conditions) model which considers factors such as soil texture, land use, slope, and meteorological variables to estimate groundwater recharge accurately (Albadry & Shamkhi, 2021). These models integrate surface runoff models with soil moisture and evaporation models to obtain sequential estimates of direct groundwater recharge from meteorological data (Mohammed et al., 2022).

Overall, the estimation of groundwater recharge and discharge involves the use of models such as SWAT and WetSpass as well as water balance models and tracer techniques. These models consider factors such as land use, soil properties, meteorological data, and groundwater-surface water interactions to provide estimates of groundwater recharge and discharge. However, further research is needed to improve the accuracy and reliability of these estimations, and to establish a consensus on the most effective methods for estimating groundwater recharge and discharge.

6.7. Groundwater-Surface water interactions

Interactions between groundwater and surface water bodies such as rivers and lakes influence both groundwater levels and surface water flow patterns (Chavoshi & Danesh-Yazdi, 2022; Massoud et al., 2022a). These interactions are essential for determining the overall water balance and storage dynamics of aquifer systems. Mackay et al. (2014) highlighted the importance of understanding groundwater travel time distributions, which provided insights into the subsurface mixing behaviour and hydrological response of a groundwater system. Existing large-scale models often exclude or oversimplify GWS dynamics and their contribution to surface water availability (Condon et al., 2020). Therefore, it is important for future studies to consider these interactions to improve modelling accuracy.

7. Future directions and challenges

7.1. Improved data fusion and integration

One of the most important directions for future groundwater modelling is the development of improved data fusion and integration techniques. A number of studies stressed the need for data fusion (Dube et al., 2023; Hosseini & Kerachian, 2019; Langevin & Panday, 2012; Massoud et al., 2018; Rehman et al., 2022; Porter et al., 2000; Zhang et al., 2023c). This is because groundwater systems are complex and involve a wide range of interacting processes that can be difficult to represent using a single remote-sensing data source. By fusing data from multiple sources, it is possible to improve the accuracy and reliability of groundwater storage modelling (Sutanudjaja et al., 2014). Su et al. (2022) proposed a groundwater-weighted fusion model (GWFM) based on an Extended Triple Collocation (ETC) method to increase the precision of groundwater storage estimates. The GWFM was evaluated using in-situ groundwater level measurements, and the outcomes demonstrated significant improvements in the correlation coefficient (CC) and Nash-Sutcliffe efficiency coefficient (NSE) compared to the original outcomes.

Several different data fusion and integration techniques can be used for groundwater modelling. A common approach is to use multivariate statistical analysis to combine the data from different sources. This involves identifying the relationships between different datasets, and then using these relationships to combine the data into a single, more comprehensive dataset.

Another approach to data fusion involves the use of data assimilation techniques (Xiao et al., 2021). Data assimilation involves iteratively updating a groundwater model using new data. This can be achieved using a Kalman filter or particle filter to assimilate groundwater table depth measurements into a hydrological model using the Localized Ensemble Kalman Filter (LEnKF). The assimilation of groundwater data improves the performance of hydrological models and reduces errors in simulating groundwater dynamics (Li et al., 2023b).

Assimilating GRACE data has been found to mitigates model deficiencies in groundwater simulations and leads to major improvements in storage estimations (Tian et al., 2017). However, the assimilation of TWS does not guarantee an accurate estimation of surface soil moisture and vice versa (Tian et al., 2017). Additionally, the benefits of GRACE data assimilation may vary depending on the region and the specific characteristics of the groundwater system (Girotto et al., 2017; Li et al., 2019).

7.2. Advancements in Machine learning algorithms

In recent years, machine learning (ML) algorithms have increasingly been used in groundwater studies. ML algorithms analyse large amounts of data, identify patterns, and make predictions based on the relationships between different variables (Ed-Daoudi et al., 2023). Integrating ML algorithms with remote sensing data promises enhanced accuracy and efficiency of groundwater modelling (Haggerty et al., 2023). ML algorithms are now used to extract information from remote sensing data, such as land surface temperature, vegetation index, and rainfall, to improve our understanding of groundwater storage dynamics (Ahmadi et al., 2022). For example, Ed-Daoudi (2023) investigated the potential of ML algorithms in improving crop yield predictions in Morocco (Ed-Daoudi et al., 2023). This study compared the performance of different ML algorithms, including Decision Trees, Random Forests, and Neural Networks, with that of traditional statistical models. The results demonstrated that ML algorithms outperformed statistical models in predicting crop yields (Ed-Daoudi et al., 2023). Similarly, Vito (2018) highlighted the use of multivariate ML analysis techniques for flood risk prevention (Vito, 2018).

One of the most promising advances in ML algorithms for groundwater studies is the use of deep learning. Deep learning algorithms can learn the complex relationships between the input and output variables, which can be used to improve the accuracy of groundwater models. For example, Sahoo et al. (2017) used a deep learning algorithm to predict groundwater level changes in agricultural regions in the United States. The study found that the deep learning algorithm could predict groundwater levels with high accuracy, even in areas with limited data, whereas another promising advance in ML algorithms for groundwater studies is the use of ensemble methods. Ensemble methods combine the predictions of multiple ML algorithms to improve the overall accuracy of the predictions (Martínez-Santos & Renard, 2019).

These studies indicate the potential of ML algorithms as a promising approach for improving the accuracy of future groundwater modelling and analysis.

7.3. Enhanced spatial and temporal resolution

Satellite gravimetry data from the GRACE mission provide invaluable large-scale terrestrial water storage anomaly information, including groundwater storage changes. However, its coarse spatial resolution (~150,000 sq km) limits its utility for localised groundwater monitoring (Hilbich et al., 2022; Mohammed et al., 2022).

On the other hand, satellite radar interferometry (InSAR) can map centimeter-scale ground surface displacements induced by subsurface water loss and recharge (Massoud et al., 2021). Though InSAR has limited penetration depth, by correlating measured subsidence rates to the governing hydrogeology, it can serve as a valuable proxy for highly localized groundwater storage variations (Massoud et al., 2021; Wang et al., 2023).

Thus, integrating InSAR and GRACE through data fusion and downscaling techniques can overcome the limitations of both techniques (Agarwal et al., 2020; Liu et al., 2019; Massoud et al., 2022a; Massoud et al., 2021). The fusion enhances GRACE's coarse resolution of GRACE by incorporating high-resolution subsurface information from InSAR. This produces downscaled GRACE GWS anomaly estimates at finer resolutions, which are more suitable for basin/aquifer-scale analyses (Massoud et al., 2021).

However, differences in measurement depth, spatial coverage, and the choice of suitable data integration approaches present additional research challenges. Therefore, further work is needed to develop robust frameworks and standardised methods for fusing multisensor data to fully harness the synergies between InSAR and GRACE (Elubid et al., 2020). There is also a need for more in situ validation experiments to evaluate the accuracy of the downscaled GRACE products and their applicability across hydrogeological regimes (Chen et al., 2016). Addressing these research gaps would help cement the viability of joint InSAR-GRACE analysis for operational groundwater monitoring and modelling applications.

7.4. Standardization of remote Sensing-Based groundwater monitoring

The use of remote sensing to monitor groundwater storage has grown in recent years because of the availability of high-resolution satellite data, and the development of new remote sensing techniques and data, such as GRACE and GRACE-FO, has made it possible to map and monitor groundwater at a regional scale. However, to harness the full potential of remote sensing as a routine tool for groundwater monitoring, standardisation of remote sensing methods is needed. Currently, there is no universally accepted method of using remote sensing to monitor groundwater storage. This makes it difficult to compare the results from different studies and to interpret the results from a single study.

Several factors must be considered when standardising RS methods for groundwater monitoring. These include the type of remote sensing data used, the processing methods applied, and how the results are interpreted. The following two methods have been proposed to address this challenge.

i. Developing a set of guidelines that could include recommendations based on these factors, among others, to use remote sensing to monitor groundwater storage.
ii. Develop a set of standard data products. These data products are produced using a consistent set of methods, and are available to researchers and practitioners.

The development of standardisation guidelines and data products would help improve the quality and comparability of remote sensing-based groundwater storage monitoring. This would make it possible to use remote sensing as a routine tool for groundwater monitoring, and it would also help improve our understanding of groundwater storage dynamics.

8. Recommendations

This study explored diverse RS tools for assessments of GWS qantifications. From these studies, it was found that remote sensing technologies are increasingly advanced and have been applied extensively in groundwater storage studies, further identifying data scarcity, the need for robust modelling, and remote sensing data fusion as key challenges faced by many researchers (Ahamed et al., 2022; Akhter et al., 2021; Mohamed et al., 2022).

Leveraging cloud platforms such as Google Earth Engine (GEE) and Planetary Computer from Microsoft can significantly enhance research capabilities (Magnoni et al., 2020). GEE, a cloud-based platform for planetary-scale geospatial analysis, harnesses Google's massive computational capabilities for extensive data processing and analyses. Similarly, the Planetary Computer, a Microsoft initiative, offers a cloud-based approach for handling large-scale environmental data.

Future research should explore the potential of these cloud computing platforms to address challenges identified in groundwater studies, such as data scarcity, robust modelling, and remote sensing data fusion. Researchers should consider integrating these cloud platforms to improve groundwater storage modelling accuracy by developing innovative methods for data integration and enhancing the precision of field data collection. This approach aligns with the evolving landscape of remote sensing technologies, ensuring accurate and reliable assessments in groundwater storage studies.

9. Summary and conclusion

This review thoroughly examines various RS technologies that model the groundwater storage dynamics. These technologies include satellite-based measurements like GRACE the Gravity Recovery and Climate Experiment (GRACE), Interferometric Synthetic Aperture Radar (InSAR), other geophysical methods, and land-based observations. The strength of remote sensing technologies lies in their ability to provide large-scale and continuous monitoring of groundwater storage changes, thereby offering insights into regional trends. However, limitations, such as spatial resolution and susceptibility to errors due to land cover changes and atmospheric conditions, must be considered. This review delved into the methodologies employed for groundwater storage modelling using remote sensing data. These methodologies include numerical models, data-assimilation techniques, statistical and machine learning approaches. Various factors influencing groundwater storage dynamics, such as climate variability, land use changes, recharge and discharge rates, lithology, and geological and hydrogeological properties, have been explored in relation to modelling accuracy.

This review was synthesised from several case studies showing the application of remote sensing technologies in groundwater storage modelling. These cases demonstrate valuable insights gained in diverse hydrogeological settings, aiding in understanding regional variations in groundwater storage and the appropriate remote sensing tools used to achieve these goals. The review emphasised the potential of integrating remote sensing data with other sources, such as hydrological models, well measurements, and geological data. This integrated approach can enhance the accuracy and reliability of groundwater storage modelling, contributing to a more comprehensive understanding of groundwater dynamics. Future directions in this field were identified, including the need for improved data fusion techniques to effectively combine multiple data sources. Enhanced spatial and temporal resolution of remote sensing data is critical for capturing finer-scale groundwater storage changes. Standardised monitoring protocols and data-sharing mechanisms are necessary for consistent and comparable assessment. By integrating remote sensing data with other information, there is a significant potential to advance the management of groundwater resources. This integration can aid policymakers and decision makers in making informed choices regarding sustainable groundwater management strategies. This review highlights specific research directions and recommendations. These suggestions were aimed at researchers, policymakers, and decision-makers and provided guidance for further investigations in sustainable groundwater management. The ultimate goal is to preserve and effectively utilise groundwater resources. This review provides a comprehensive overview of the role of remote sensing technologies in groundwater storage dynamics, addressing the strengths, limitations, methodologies, case studies, integration prospects, challenges, and future directions in the field.

CRediT authorship contribution statement

Abba Ibrahim: Conceptualization, Data curation, Formal analysis, Funding acquisition, Writing – original draft, Writing – review & editing. **Aimrun Wayayok:** Conceptualization, Project administration, Resources, Software, Supervision, Validation, Writing – review & editing, Funding acquisition. **Helmi Zulhaidi Mohd Shafri:** Conceptualization, Supervision, Writing – review & editing. **Noorellimia Mat Toridi:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

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Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used 'Grammarly' for grammar correction. After using this tool/service, the author reviewed and edited the content as needed and took full responsibility for the content of the publication.

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