Chapter 5
Estimating Soil Moisture Using Remote Sensing in Zimbabwe: A Review

Never Mujere and Hardlife Muhoyi

Abstract Soil moisture is an essential parameter for understanding the interactions and feedbacks between the atmosphere and the Earth's surface through energy and water cycles. Knowledge of the spatiotemporal distribution of land surface soil moisture for various environmental and socio-economic studies. Over recent past years, remote sensing using *electromagnetic spectra* from the optical/thermal to the microwave regions, have been intensively investigated for soil moisture retrieval, providing of several algorithms, models and products that are available for actual applications. However, the use of remote sensing technologies in estimating soil moisture is a challenge in low-income economies due to resource constraints. This present study gives a critical review of the remote sensing approaches applied in estimating soil moisture in Zimbabwe. The research findings show that remote sensing products have little been used in soil moisture monitoring in Zimbabwe.

Keywords GIS · Remote sensing techniques · Soil moisture · Zimbabwe

5.1 Introduction

At global scale, it is considered that at least 65% of precipitation returns to the atmosphere as green water while the remainder is either stored in the soil or become runoff (Bittelli 2011). Green water flow refers to water lost as actual evapotranspiration that is released back into the atmosphere via evaporation from both the soil, water bodies and transpiration from vegetation. Green water storage is also termed soil moisture or soil water. Soil moisture is the amount of water stored in the pore spaces between soil particles in the unsaturated soil zone or the vadose zone (Falkenmark and Rockström 2006). Soil moisture can also be grouped into surface soil moisture and root-zone

N. Mujere (✉)
Department of Geography Geospatial Sciences and Earth Observation, University of Zimbabwe, Harare, Zimbabwe
e-mail: nemuj@yahoo.co.uk

H. Muhoyi
Department of Geography and Geo-Information Sciences, Lupane State University, Bulawayo, Zimbabwe

S. K. Dubey et al. (eds.), *Soil-Water, Agriculture, and Climate Change*, Water Science and Technology Library 113, https://doi.org/10.1007/978-3-031-12059-6_5

soil moisture (Narasimhan and Srinivasan 2005). Surface soil moisture is the total amount of water found in the upper-most 10 cm of the soil profile. The water available in these first few centimetres of a soil layer is either stored or exchanged between the surface and atmosphere (Zhang et al. 2020). The amount of surface soil moisture determines how much rainfall is turned into runoff and, water movement and redistribution through infiltration, evaporation, percolation, and transpiration. Water available from the upper-most 200 cm of the soil profile is considered as root zone moisture. This is the water that is needed and available to be used by plants (Moran et al. 2004). Nevertheless, plants extract moisture from both the surface- and root-zone reservoirs through transpiration, but only the surface moisture zone is subject to evaporation. Vegetation growth development and their health are a function of the quantities of water as determined by the root zone moisture.

Soil moisture content is a soil property that is an essential parameter when it comes to appreciating the hydrological cycle and energy heat budget (Gumindoga et al. 2020; Zhang et al. 2020). It affects the critical hydrological, geomorphological, geological, ecological, and biogeochemical as well as the meteorological processes (Marumbwa et al. 2015). Knowledge of soil moisture variation in time and space is key in understanding both natural processes, water balance; and human activities e.g. irrigation scheduling. However, the concept of the term soil moisture varies depending on the area of application for example the farmer, water resource's manager and a meteorologist have got a different appreciation of the concept of soil moisture.

Therefore, depending on the field of specialisation and scale at which the measurements are taken, a calling for an accurate soil information forms part of the most important step for example in irrigation scheduling as in agricultural activities. When trying to maximise on food security, drought monitoring and yield forecasting as extrapolated from soil moisture modelling can promote economic and wise use of water, this is most relevant in the arid and semi-arid regions (Marumbwa et al. 2015). Moisture regimes affect the timing of irrigation, which must be applied at the right time, right place, and in the right amount for consistently high yields (Moran et al. 1994). Seed germination, plant growth, and plant nutrition require adequate amounts of soil moisture. Crop production in arid and semi-arid regions of the world, is determined by the available soil moisture either as derived from irrigation or precipitation (Marumbwa et al. 2015). Due to the high moisture content during the growing season which is mostly associated with rains or being supplemented by irrigation, crop yield has shown a linear relationship with soil moisture (Shafian and Maas 2015). It is from this understanding of the link between crop water requirement and crop productivity that accurate estimation of soil moisture is vital for activities such as irrigation scheduling.

Excessive water application lowers yield since excess water promotes leaching. This leads to nitrates being carried below reasonable depths of root penetration, displacing available soil air hence causing a lack of oxygen to the roots. Low soil moisture for sustained periods results in drought, reduced crop yields and plant water deficit and can potentially lead to wildfires. Conversely, high soil moisture leads to an increased risk of floods (Bittelli 2011).

Soil moisture is an essential variable for predicting global climate change because it affects the flow of energy, greenhouse gases, and water among the atmosphere, vegetation, and soils (Klemas et al. 2014). Soil moisture aids the processes of water loss from both the abiotic earth's surfaces (evaporation) and plants through transpiration making it key in the study of meteorology—weather development and formation of rainfall. Simulations with numerical weather prediction models have shown that improved characterisation of surface soil moisture, vegetation cover, and temperature can lead to significant forecast improvements. Moisture also drives infiltration and runoff during heavy rain events, affecting the amount of precipitation that runs off into nearby streams and rivers. Large-scale dry or wet surface regions have been observed to impart positive feedback on subsequent precipitation patterns (Arnold and Laymon 2012). In addition, the evaporation rate is strongly correlated to soil moisture that makes a strong connection between the land surface and atmosphere (Koster et al. 2004).

In water resources management and hydrologic studies, the soil moisture content is a hydrological parameter useful in water quality management, reservoir management and flood control (Gumindoga et al. 2020). In semi-arid ecosystems, dynamic information on soil moisture is critical to understanding groundwater recharge and drought conditions (Dumedah et al. 2014). The amount of soil moisture content serves as a solvent and carrier of nutrients, regulates soil temperature, and empowers microorganisms to conduct their metabolic activities. Soil moisture gradients together with nutrient fertility are used to classify forest types (Southee et al. 2012; Arnold and Laymon 2012).

Depending on the soil characteristics and surface water content, extreme events such as rainstorms and hurricanes can lead to flooding and landslides (Klemas 2009). Soil erosion and transport depend on soil moisture together with other soil properties including soil type, grain size and composition. Conversely, high soil moisture leads to an increased risk of flooding and erosion. Having accurate soil moisture data may lead to better predictions of such hazardous events and proper geotechnical engineering structures (Ker ret al. 2010; Zhang et al. 2020).

Near accurate estimation of soil moisture data usually achieved via traditional methods such as field and laboratory approaches (both direct and indirect). These approaches include use of gravimetric method and soil probes, and they point based where areal representation is achieved through kriging (Moran et al. 2004; Wang et al. 2020). However, with the invention and advancement in technology use of remote sensing approaches has recently gained competitive advantages over traditional approaches. The use of both passive and optical remote sensing especially in the microwave band of the electromagnetic spectrum; has been used in soil moisture estimation. This includes satellite images from sensors such as Landsat (Castelli et al. 2000), MODIS (Wang et al. 2020) and Sentinel (Vogels et al. 2019; Yang et al. 2019). Some of these sensors provide very coarse resolutions that might not be applied to patches of land of less than 10 m. for example MODIS has got a minimum spatial resolution of 250 m (Van doninck et al. 2011) while Landsat usable spatial resolution of 30 m (Chander et al. 2009) and Sentinel has a spatial resolution of 10 m (Vogels et al. 2019). However, out of these only MODIS has a higher temporal resolution of a daily interval as opposed to Sentinel and Landsat (Van doninck et al. 2011). Therefore, it is not surprising that much research is restricted to handling soil moisture problems at a national, regional or global level to counter both spatial and temporal needs of the need for which soil moisture data is to be used (Bartsch et al. 2010a, b).

Even though many applications require soil moisture data, accurate assessment of this variable is difficult because typical field methods are complex and expensive. Also, local-scale variations in soil properties, terrain, and vegetation cover make the selection of representative field sites difficult if not impossible (Shafian and Maas 2015). Therefore, the purpose of this study is to review the remote sensing techniques applied in determining soil moisture with a particular focus on Zimbabwe, since the water for agriculture act as a key driver of its economic growth. Agriculture in the country is both rainfed and irrigated. Thus, there is a need for explicit soil moisture information in time and spatially, especially for irrigation scheduling.

5.2 Description of the Study Area

Zimbabwe is a landlocked country, located in southern Africa with a total area of 390,760 km^2 (Fig. 5.1). The country is bordered by five countries namely; Zambia (to the north), to the east of it is Mozambique, South Africa in the south while Botswana and Namibia border it in the west. It has a population of about 13 million people and its economy is highly dependent on agriculture, mining and tourism (FAO 2016).

Zimbabwe lies almost entirely over 300 m above sea level. Its principal physical feature is the broad ridge running from southwest to northeast across the entire country, the central watershed The country has four major relief regions namely; the low veld (<600 m above mean sea level); middle veld (600–1,200 m); high veld (1,200–2,000 m); and eastern highlands (2,000–2,400 m). The highest point in the country lies at an altitude of 2,592 m along the eastern border with Mozambique.

Almost 70% of the country is covered by Precambrian Basement Complex and metavolcanic rocks. These rocks comprise gneisses and igneous rocks such as granite. Sedimentary rocks and metasediments occur in some parts of the country including the northwest (FAO 2016). Weathering of granite parent material resulted in residual soils including light sandy soils and -clays. Sands are highly leached and do not easily retain water because of their coarse texture. Except in areas where soils are of alluvial origin, soil depth is often less than 1 m (FAO 2016, 2020).

Zimbabwe has a tropical climate, with a dry season from April to October in which little rain falls and a rainy season that usually lasts from late November to March (FAO 2016). Mean annual ranges from less than 500 mm/year in the south and southwest; between 600 mm and 1,000 mm across much of the central part of the country to more than 1,000 mm in the eastern highlands. In Zimbabwe, rainfall amount increases from south to north as well as from west to east. The temperature gradient also tends to follow a west–east trend with temperatures getting lower as one moves from the south-eastern lowveld through the highveld to the east (FAO 2016).

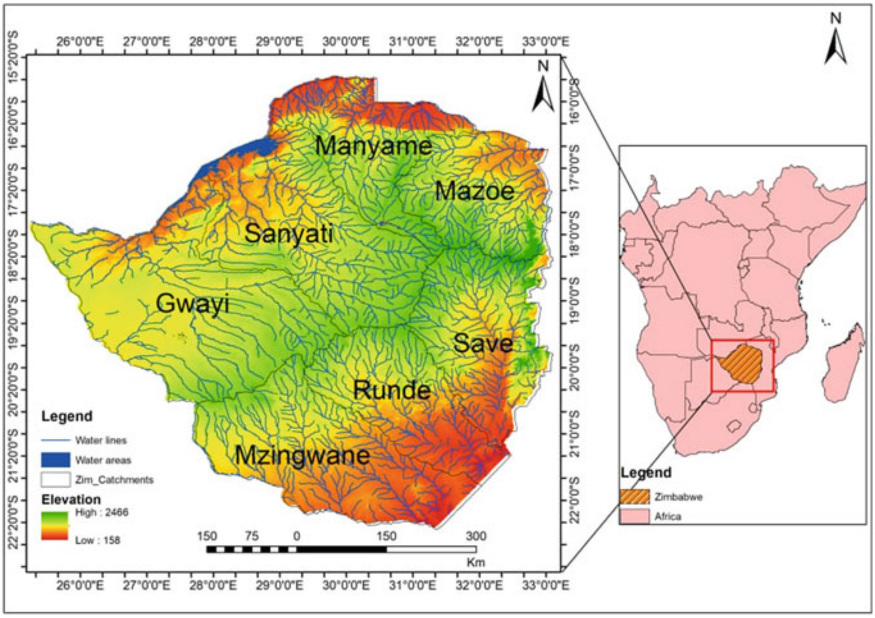

Fig. 5.1 Location of Zimbabwe in Africa and its river catchments

Vegetation of the country is predominantly tropical savanna comprising miombo and mopane trees with grasses. Tree growth is encouraged by the wet summers. Dry savanna with grass of up to 2 m height makes up a major part of Zimbabwe's landscape (FAO 2016).

5.3 Estimation of Soil Moisture

5.3.1 Field and Laboratory Methods

In situ manual measurements using the gravimetric method and soil moisture probe are arguably the most accurate and reliable ways to obtain soil moisture data (Wang et al. 2020). Both of these manual methods are labour intensive and can take an extremely long time to properly analyse moisture content in large areas.

The soil moisture robe indirectly determines moisture content by the use of specialised probes that measure the electrical charge between two metallic hooks, thereby measuring the conduction of electricity in soil that can be translated to soil moisture. The gravimetric method directly estimates soil moisture content using a known volume of an undisturbed soil sample is collected from the field (using a ring, hovel, blade, plastic bag and a GPS) weighed, dried for 24 h at 105 °C, and then reweighed. The gravimetric soil moisture content is calculated as the net difference between the mass of wet soil and dry soil, divided by the mass of dry soil. Gravimetric soil moisture content can be converted to a percentage by multiplying with 100.

Direct and indirect field and laboratory measurements of surface soil moisture are difficult, and the available techniques are limited by environmental and socio-economic factors. It is from this background that there is a key need for surface soil moisture assessment approaches that have got an explicit coverage both in time and space. This is critical especially for irrigated areas where there is a need for irrigation scheduling. Thus, it is without a doubt that remote sensing approaches are most appropriate compared to traditional field-best techniques. Poonia (2022) criticised the use of conventional and in-situ approaches at a regional scale because they failed to capture precisely the spatio-temporal dynamics of soil moisture.

5.3.2 Satellite Remote Sensing of Soil Moisture

The need for continuous measurements of surface soil moisture with regional and global coverage is critical for hydrological, ecological and climatological studies. In contrast with field measurements which represent single point locations, and cover relatively short periods of observation, satellite remote measurements have broad spatial coverage and temporal continuity at relatively low cost (Ahmad et al. 2010). Satellite remote sensing developments for soil moisture estimation began in 1975 when NASA launched Landsat to collect data using a passive sensor (Ahmad et al. 2010). Since then, various passive and active remote sensing techniques (ground-based, aerial, and space platforms) have been used in determining soil moisture content in different areas across the world.

Over last 60 years, *electromagnetic spectra*, from the optical/thermal to the microwave regions, have been intensively used to provide a number of algorithms, models and products that are available for soil moisture retrieval (Poonia 2022). Because the microwave wavelength can penetrate through the atmosphere and vegetation, it is suitable to detect soil moisture even during cloudy conditions (Poonia 2022). Studies using remote sensing observations to evaluate soil moisture conditions by employing measurements from solar reflectance, thermal infrared wavelengths, and microwaves have shown lots of potential in this area. It is without a doubt that remote sensing approaches are better as compared to traditional field-based soil moisture estimation techniques (Ahmad et al. 2011; Li et al. 2021).

Remotely sensed observations depend on reflected and emitted electromagnetic to produce spatially comprehensive measurements of surface environmental conditions. By relating variations in measured electromagnetic emittance to surface moisture conditions, regional variations and local spatial heterogeneity of soil moisture conditions are determined (Shafian and Maas 2015). The use of satellite imagery in determining the surface soil moisture is based on the principle that surface soil moisture interrupts with the surface characteristics that later emit an electromagnetic wavelength than can be observed through remote sensing. These include biophysical factors such as vegetation cover, observed through vegetation indices (VI), and the surface energy balance, observed through surface temperature (T_S), is a good indicator of the energy balance on both regional and global scales. Surface temperature is one of the biophysical factors sensitive to soil moisture content. Stressed plants use a reflex through their stomata which close when maximising on water conservation while avoiding an accelerated transpiration hence results in a decreased latent heat flux. The energy flux balance is a function of an increase in sensible heat flux in association with warmer leaf temperatures and increased T_s. With decreasing soil moisture, VI decreases while T_s increases. Combining T_s and VI provides useful quantitative information for detecting the spatial and temporal distribution of soil moisture (Shafian and Maas 2015).

With remote sensing approaches, soil moisture data are retrieved from different from the electromagnetic spectrum (visible, infrared, thermal, and microwave) based on the sensitivity of the soil surface, the electromagnetic radiation as well as on the effectiveness of the reflected radiation from the soil surface that can be received by the sensor. Remotely sensed shortwave infrared transformed reflectance, the normalized difference vegetation index, and other such parameters are widely used to estimate soil moisture for drought detection or irrigation scheduling in low-income countries (Bartsch et al. 2010a, b; Marumbwa et al. 2015; Nhedzi 2008; Poonia 2022).

Measuring soil moisture using remote sensing at deep root zones below 5 cm from the surface is a challenge (Ahmad et al (2010). Surface soil moisture depth is determined based on satellites' sensor frequency on that respective piece of land. Soil moisture depth reachable by electromagnetic radiation is referred to as skin or surface soil moisture (e.g. only a few mm for the optical and thermal band) or near-surface soil moisture (e.g. a few cm for microwave sensors). Depths exceeding 30 cm are rarely reachable by satellite cameras. In order to access deeper root zone soil moisture, combined statistical techniques based on energy balance or simplified water balance approaches are used (Ahmad et al. 2010; Lu et al. 2011).

Several remote sensing techniques are used for regular monitoring of soil moisture at various spatial and temporal scales. The remote sensing approach specifications and utilities can be found in well-documented literature but not limited to e.g. (Bartsch et al. 2010a, b; Marumbwa et al. 2015; Nhedzi 2008; Poonia 2022). The techniques for soil moisture SSM estimation vary from empirical and mechanistic models while the widely used methods are through satellite remote sensing of the active and passive for both optical and microwave. These approaches usually employ the linear relationship between land surface reflectance and soil moisture content either directly or through the development of empirical spectral indices. However, because the microwave wavelength is unlimited by weather and vegetation cover then this makes the microwave band the most suitable for estimating soil moisture as it can penetrate through the atmosphere and vegetation to detect soil moisture in the surface layer (Poonia 2022). It is thus well documented that different soil-moisture evaluation methods have been introduced in different regions (Bartsch et al. 2010a, b; Lu et al. 2011; Van doninck et al. 2011).

Although, remote sensing techniques are plausible for surface soil moisture retrieval, however, they do not properly provide a pattern for surface soil moisture column. Therefore, appropriate input data be incorporated in hydrologic models to provide an estimation of the spatial distribution of moisture for water balance estimates of any area (Moran et al. 2004; Samboko 2016). While the Normalized Difference Vegetation Index (NDVI) is an effective indicator of vegetation conditions, it is a rather conservative indicator of soil moisture status because there is a time lag between the time observed for a change in soil moisture and that time change as observed in NDVI. Thus, NDVI-based methods may not be effective in the rapid monitoring of soil moisture conditions.

Several shortcomings can be observed from the current remote sensing products used to estimated soil moisture. ASTER, MODIS or Landsat products are of coarser spatial resolutions (>10 km) when it comes to their applicability at the watershed or regional scale as soil moisture is highly variable with space and time. Therefore, there is a need to downscale these soil moisture products to finer spatial resolution, which can also be done by developing models with several covariates like vegetation, slope, soil texture, or to use the potential of Sentinel -2 which has got a better spatial resolution of at 10 m (Poonia 2022). Moreso, it is additionally acknowledged that different land cover reduces the classification accuracy of soil-moisture retrieval (Notarnicola 2004; Scipal et al. 2005; Zwieback et al. 2013).

5.4 Designing the Search Strategy

A well-designed search strategy (i.e., specific, unbiased, reproducible and including subject headings along with a range of keywords/phrases for the concepts) was designed to capture as many studies from various online databases as possible that meet the criteria for this systematic review. The search strategy involved the use of Boolean logic, phrase searching and truncations (Lackey 2013). Using Boolean logic, the following words or phrases were searched; “soil moisture” AND “remote sensing” AND “Zimbabwe”, (soil moisture* OR soil water) AND “remote sensing” AND “Zimbabwe”. During phrase searching, specific phrases were typed and enclosed in quotation marks. The database searched for the words typed; “soil moisture”, “moisture”, “soil water”, “remote sensing”, “Zimbabwe”. Some words were truncated in order to search for their different forms using the asterisk * as the truncation symbol.

5.5 Findings on the Use of Satellite Remote Sensing in Estimating Soil Moisture in Zimbabwe

Bartsch et al. (2010a, b) estimated soil moisture dynamics using radar satellite technology to develop the soil moisture information system for the Southern African

Development Community in which Zimbabwe is located. Medium resolution soil data (1 km) were obtained from ENVISAT's ASAR sensor operated in global mode (GM) with METOP scatterometer sensors and, coarse resolution soil moisture data (25–50 km) were derived from backscatter measurements acquired with METOP scatterometers on-board of the satellites ERS-1 and ERS-2 in near real-time via EUMETCast). The synergistic use of both systems allows frequent, medium resolution monitoring of regional soil moisture dynamics in the uppermost soil layer (<5 cm). However, the ENVISAT ASAR Global Mode soil moisture data had higher noise compared to the coarse resolution soil moisture products.

Shoko et al. (2015) showed that remotely sensed shortwave infrared (SWIR) transformed reflectance (TRSWIR), the normalized difference vegetation index (NDVI), and other such can be successfully used to estimate soil moisture at the surface level for large areas in low-income economies. The products can also be applied in drought detection or irrigation scheduling. Nevertheless, higher precision techniques for measuring soil moisture are required at depths that are physically hidden from current satellite cameras.

Gumindoga et al. (2020) applied the Surface Energy Balance System (SEBS) and the TOPographic driven MODEL (TOPMODEL) to estimate the spatio-temporal variation of soil moisture over a district in northern Zimbabwe from 2008 to 2013. Estimates of soil moisture were obtained by multiplying the relative evaporation from the SEBS algorithm by the average soil porosity and field capacity. After calibrating the TOPMODEL rainfall-runoff model with land surface inputs obtained from remote sensing, the spatial and temporal soil moisture estimates were compared with in situ measured soil moisture from the fifty-two sampling sites. Results show that the SEBS approach shows spatial and temporal soil moisture variability across the district simulated with a strong relationship ($R^2 = 0.796$) between in situ-based soil moisture measurements and SEBS based techniques for the period of March to July 2013. The study further revealed that there is a fair relationship ($R^2 = 0.60$) between ground soil moisture measurements and hydrologically modelled using TOPMODEL).

Samboko (2016) used the Topographic driven rainfall-runoff model (TOPMODEL) whose land surface inputs were obtained from remote sensing techniques to simulate soil moisture patterns from September 2008 to August 2010. Model results showed high levels of soil moisture along river channels, valleys and floodplains in northern Zimbabwe. However, a 12% difference was observed between the point and pixel-based soil moisture simulated by the model and retrieved by the data logger.

In Zimbabwe, the widely used approach for soil moisture estimation is the field-based gravimeter method. This is adopted by many commercial farmers as well as government departments such as the Agricultural Rural Extension Services, Meteorological Services and Zimbabwe National Water Authority. The use of remote approaches is still in its infancy as illustrated by our literature review. In most cases, this is applied at the academic or research level where sharing of knowledge will focus on marketing the new technology. Table 5.1 is an illustration for the comparison of field-based and remote sensing approaches in which they are applied in soil moisture estimation.

Table 5.1 A comparison of remote sensing and conventional methods in soil moisture estimation (Moran et al. 2004)

Approach	Merits	Limitations
Optical remote sensing (Visible, Near Infrared, Short-wave Infrared)	Fine spatial resolution; broad coverage; multiple sensors including hyperspectral sensors	Weak estimation of surface moisture, works only on clear weather; affected by vegetation cover, issue of temporal resolution
Thermal Infrared	Fine spatial resolution with broad coverage; multiple sensors available	Minimal surface penetration, affected by high humid weather, vegetation and atmospheric gas density
Microwave remote sensing	Broad coverage; satellite sensors available; strongly related to surface moisture estimation; surface penetration up to 5 cm and it is insensitive to weather patterns and atmospheric conditions	Affected by vegetation cover and surface rough roughness; ideally has got a coarse spatial resolution of approximately 30 km
Field-based methods (combined)	Near accurate estimates, addresses one's needs at a time; depth depends on the need; insensitive to earth's roughness and atmospheric condition	Point-based; time consuming and laborious;

5.6 Conclusion and Future Needs

This present review has shown that soil moisture is of great importance in closing hydrologic budgets, assessing soil–plant water interactions, studying climate change, controlling and regulating the interaction between the atmosphere and the land surface. It controls the ratio of runoff and infiltration, energy fluxes and nutrients, vegetation development and then carbon cycle. Moreso, soil moisture is an important factor in animal and plant productivity and can even sustain the interaction between the natural system and anthropogenic activity. Therefore, the distribution pattern of soil moisture, both spatially and temporally, is the key to climate modelling. Moreover, a long-term soil moisture data set on a regional scale, therefore, provide valuable information for research such as climate change and global warming and then improve weather forecasting and water resources management.

The review has shown that few studies using a combination of geostatistical approaches, remote sensing and hydrologic models has been conducted in Zimbabwe. However, the use of remote sensing in measuring soil moisture is promising in such data-scarce and water-limited regions. The issue of intense vegetation in Zimbabwe is a challenge in some areas, especially where there are significant topographical changes. This is so because the most accurate results from remote sensing data are achieved when there is no or low soil cover and most importantly applicable where the area is flat. Thus, the interaction of the emitted or reflected radiation from a covered soil surface back to the remote sensor will no longer represent the actual soil surface-emission because part of the emitted/reflected radiation is either absorbed or enhanced by the soil cover.

Acknowledgements The great work done by anonymous reviewers of this paper is greatly appreciated.

Declaration of competing interest The authors declare no conflicts of interest.

References

Ahmad S, Kalra A, Stephen H (2010) Estimating soil moisture using remote sensing data: a machine learning approach. Adv Water Resour 33:69–80

Ahmad A, Zhang Y, Nichols S (2011) Review and evaluation of remote sensing methods for soil-moisture estimation. Society of photo-optical instrumentation engineers (SPIE). https://doi.org/10.1117/1.3534910. Downloaded From: https://www.spiedigitallibrary.org/journals/SPIE-Reviews. Accessed 4 Jan 2022

Arnold JE, Laymon C (2012) NASA Soil moisture study. http://wwwghcc.msfc.nasa.gov/landprocess/lp_home.html.

Bartsch A, Sabel D, Pathe C, Sinclair C, Vischel T, Doubkova M, Wagner W, Pegram G (2010a) Soil moisture dynamics from synthetic aperture radar for hydrometeorological applications in the southern African development community. International hydrological programme (IHP) and UNESCO, France

Bartsch A, Doubkova M, Wagner W (2010b) ENVISAT ASAR GM soil moisture for applications in Africa and Australia. In: Earth observation and water cycle science. Presented at the ESA SP-674, ESA SP-674, Italy, p 6

Bittelli M (2011) Measuring soil water content: a review. Hort Techno 21:293–300. https://doi.org/10.21273/HORTTECH.21.3.293.

Castelli RM, Chambers JC, Tausch RJ (2000) Soil-plant relations along a soil-water gradient in Great Basin riparian meadows. Wetlands 20:251–266

Chander G, Markham BL, Helder DL (2009) Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. Remote Sens Environ 113:893–903. https://doi.org/10.1016/j.rse.2009.01.007

Dumedah G, Walker JP, Chik L (2014) Assessing artificial neural networks and statistical methods for infilling missing soil moisture records. J Hydrol 515:330–344

Gumindoga W, Murwira A, Rwasoka DT, Jahure FB, Chikwiramakomo L (2020) The spatio-temporal soil moisture variation along the major tributaries of Zambezi River in the Mbire District. Zimbabwe. J Hydrol Reg Stud 32:100753. https://doi.org/10.1016/j.ejrh.2020.100753

Falkenmark M, Rockström J (2006) The new blue and green water paradigm: breaking new ground for water resources planning and management. J water resour plann manage 132(3):129–132

FAO (2016) The state of world fisheries and aquaculture. Contributing to food security and nutrition for all. Rome (200 pp)

FAO (2020) Crop and food security assessment mission to Zimbabwe. FAO Harare

Kerr YH, Waldteufel P, Wigneron JP, Delwart S, Cabot F, Boutin J, Mecklenburg S (2010) The SMOS mission: new tool for monitoring key elements of the global water cycle. Proc IEEE 98(5):666–687

Klemas VV (2009) The role of remote sensing in predicting and determining coastal storm impacts. J Coast Res 25(6):1264–1275

Klemas V, Finkl CW, Kabbara N (2014) Remote sensing of soil moisture: an overview in relation to coastal soils. J Coast Res 30(4):685–696

Koster RD, Dirmeyer PA, Guo Z, Bonan G, Chan E, Cox P, Gordon CT, Kanae S, Kowalczyk E, Lawrence D, Liu P, Lu CH, Malyshev S, McAvaney B, Mitchell K, Mocko D, Oki T, Oleson K, Pitman A, Sud YC, Taylor CM, Verseghy D, Vasic R, Xue Y, Yamada T (2004) Regions of strong coupling between soil moisture and precipitation, Sci 305:1138–1140. https://doi.org/10.1126/science.1100217,6969,-06981

Li X, Du Z, Huang Y, Tan Z (2021) A deep translation (GAN) based change detection network for optical and SAR remote sensing images. ISPRS J Photogramm Remote Sens 179:14–34

Lu H, Koike T, Gong P (2011) Monitoring soil moisture change in Africa over past 20 years with using passive microwave remote sensing. In: 2011 19th international conference on geoinformatics. Presented at the 2011 19th international conference on geoinformatics, IEEE, Shanghai, China, pp 1–5. https://doi.org/10.1109/GeoInformatics.2011.5980961

Marumbwa FM, Murwira A, Madamombe EK, Kusangaya S, Tererai F (2015) Remotely sensing of irrigation water use in Mazowe Catchment. Zimbabwe 5:11

Moran MS, Clarke TR, Inoue Y, Vidal A (1994) Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. Remote sens environ 49(3):246–263

Moran MS, Peters-Lidard CD, Watts JM, McElroy S (2004) Estimating soil moisture at the watershed scale with satellite-based radar and land surface models 30:23

Narasimhan B, Srinivasan R (2005) Development and evaluation of Soil Moisture Deficit Index (SMDI) and Evapotranspiration Deficit Index (ETDI) for agricultural drought monitoring. Agric Meteorol 133:69–88. https://doi.org/10.1016/j.agrformet.2005.07.01

Nhedzi E (2008) Assessment of a catchment water balance using GIS and remote sensing techniques: Mazowe, Zimbabwe (MSc). ITC, Netherlands

Notarnicola C (2004) Bayesian iterative inversion algorithm applied to soil moisture mapping using ground-based and airborne remote sensing data. In: Posa F (Ed), Presented at the remote sensing, Barcelona, Spain, p 116. https://doi.org/10.1117/12.514413

Poonia RC (2022) Deep learning for sustainable agriculture. Deep learning for sustainable agriculture. Elsevier, India, pp 143–168

Samboko H (2016) A remote sensing based approach to determine evapotranspiration in the Mbire District of Zimbabwe (MSc). University of Zimbabwe, Harare

Scipal K, Scheffler C, Wagner W (2005) Soil moisture-runoff relation at the catchment scale as observed with coarse resolution microwave remote sensing. Hydrol Earth Syst Sci 5:11

Shafian S, Maas SJ (2015) Index of soil moisture using raw Landsat image digital count data in Texas high plains. Remote Sens 7(3):2352–2372

Shoko C, Dube T, Sibanda M, Adelabu S (2015) Applying the Surface Energy Balance System (SEBS) remote sensing model to estimate spatial variations in evapotranspiration in Southern Zimbabwe. Trans Royal Soc South Africa 70(1):47–55

Southee FM, Treitz PM, Scott NA (2012) Application of lidar terrain surfaces for soil moisture modeling. Photogram Eng Remote Sens 78(12):1241–1251

Van doninck J, Peters J, De Baets B, De Clercq EM, Ducheyne E, Verhoest NEC (2011) The potential of multitemporal Aqua and Terra MODIS apparent thermal inertia as a soil moisture indicator. Int J Appl Earth Obs Geoinformation 13:934–941.https://doi.org/10.1016/j.jag.2011.07.003

Vogels M, de Jong S, Sterk G, Douma H, Addink E (2019) Spatio-temporal patterns of smallholder irrigated agriculture in the horn of Africa Using GEOBIA and sentinel-2 imagery. Remote Sens 11:143. https://doi.org/10.3390/rs11020143

Wang C, Xie Q, Gu X, Yu T, Meng Q, Zhou X, Han L, Zhan Y (2020) Soil moisture estimation using Bayesian Maximum Entropy algorithm from FY3-B, MODIS and ASTER GDEM remote-sensing data in a maize region of HeBei province. China. Int J Remote Sens 41:7018–7041. https://doi.org/10.1080/01431161.2020.1752953

Yang L, Feng X, Liu F, Liu J, Sun X (2019) Potential of soil moisture estimation using C-band polarimetric SAR data in arid regions. Int J Remote Sens 40:2138–2150. https://doi.org/10.1080/01431161.2018.1516320

Zhang D, Zhan J, Qiao Z, Župan R (2020) Evaluation of the performance of the integration of remote sensing and Noah hydrologic model for soil moisture estimation in Hetao irrigation region of inner Mongolia. Can J Remote Sens 46:552–566. https://doi.org/10.1080/07038992.2020.1810003

Zwieback S, Dorigo W, Wagner W (2013) Estimation of the temporal autocorrelation structure by the collocation technique with an emphasis on soil moisture studies. Hydrol Sci J 58:1729–1747. https://doi.org/10.1080/02626667.2013.839876