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A review of remote sensing of flood monitoring and assessment in southern Africa

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ABSTRACT

Southern Africa is one of the most vulnerable regions to flooding and this severely impacts its economic development, human livelihoods and ecosystem functioning. In this regard, there is need to identify strategies to monitor flood occurrence, to minimize effects. Remote sensing is one of the key data sources for natural hazards monitoring, over space and time. This paper therefore provides the state-of-the-art review on flood monitoring, using remote sensing in southern Africa, since the emergency of earth observation technologies. Specifically, the review focused on how southern Africa has embraced remote sensing for mapping flood extent, vulnerable areas and impacts, over time. The review also highlights available remote sensing data and products, to monitor floods, including their success, limitations, and prospects for improved flood monitoring in the region. Overall, there has been limited use of remote sensing data in flood monitoring in southern Africa, until 2010. Since then, there was an increase in the use of remote sensing data, for flood monitoring. Most of these studies used the freely available Landsat and MODIS datasets, and these studies focused more on mapping the extent of flooding. However, as much as considerable strides were made, there is still more work to be done. Future research needs to shift towards the use of new generation remote sensing data, including radar, as well as high spatial resolution drones, before, during and after flood occurrence. Advanced cloud-computing, such as Google Earth Engine and machine learning algorithms, also present opportunity for time series analysis of flooding.

1. Introduction

Floods are among the most hazardous hydrological extreme events, with devastating consequences across the globe (Haq et al., 2012; Feng et al., 2015). However, southern Africa is one of the most vulnerable and the most hit by floods (Revilla-Romero et al., 2015; Erena et al., 2018). The vulnerability of southern Africa to flood has been attributed to various natural and anthropogenic factors including poor drainage systems, lack of flood monitoring schemes and poor response strategies (Dalu et al., 2018; Douglas, 2017). Some of the factors which contribute to the vulnerability of southern Africa to flooding have been explored by Twumasi et al. (2017). These included the occurrence of El Nino, due to global climate change, topography, land degradation, sparse use of early warning systems and demography. Consequently, the region has so far experienced major floods, such as the two high-magnitude floods, in 2000 and 2013 in the Lower Limpopo Basin of Mozambique, the 2008/2009 in Namibia (Groeve, 2010), the Cyclone Eline floods in January and February in 2000 (Heritage et al., 2019) and the 2022 flood disaster which hit the province of KwaZulu Natal in South Africa. In addition, the research community has highlighted that floods are anticipated to increase in southern Africa, due to global climate change (Dalu et al., 2018) and this is evidenced in the frequency of their occurrence of late.

Flood results in devastating consequences, such that the majority of the countries in the region have not yet recovered from previous floods (Douglas, 2017; Mabuku et al., 2019). The effects of floods include the destruction of property, including homes, as well as loss of human life, livestock and wildlife. This has major implications to human livelihoods and the economy (*e.g.,* loss of wildlife affects the tourism industry). For example, approximately 700 lives were lost, 500 000 displaced and more than $400 million of property was damaged by the floodwaters in Mozambique (Asante et al., 2007). The occurrence of floods is also associated with health problems particularly, outbreak of waterborne diseases, as well as destruction of the health infrastructure (Schatz,

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2008; Mabuku et al., 2019). For example, the study by Schatz (2008) has reported considerable numbers of Cholera cases in Malawi, Mozambique and Zambia. Similarly, Mabuku et al. (2019) reported outbreak of pests and diseases, which affected livestock and human livelihoods in Zambia. In addition, destruction of ecosystems including functioning and species mortality, as well as land degradation were reported because of flooding. In this regard, floods alter ecosystem functions and, in some instances, cripple the ability of various ecosystems to provide goods and services. In this regard, the consequences of flood require detailed information about their occurrence and risk areas to implement or improve strategies.

Conventional methods are the primary sources of information in understanding, mapping and assessing floods vulnerability (Douglas, 2017). These methods primarily rely on ground-based surveys and meteorological observations, which are integrated in different models for flood modelling and monitoring (*e.g.* Dalu et al., 2018; Komi et al., 2017; Mkhandi et al., 2000) and qualitative approach, through the use of questionnaires (*e.g.*, Bola et al., 2014; Mabuku et al., 2019; Kienberger, 2014). These observations are coupled with hydrological models to characterize flood occurrence and for monitoring purposes (Paeth et al., 2011; Kienberger, 2014)). Different studies have used the conventional approach for flood monitoring (Hughes and Smakhtin, 1996; Dalu et al., 2018; Mabuku et al., 2019; Mkhandi et al., 2000). However, although ground-based conventional approach provides the most accurate data, there are considerable challenges associated with this approach, which were identified by previous studies (*e.g.* Cloete et al., 2018; Mabuku et al., 2019); thereby compromising flood monitoring in the region, over space and time. These challenges include resource constrains to conduct routine field-based surveys and equipment maintenance (Asante et al., 2007); data quality (Hughes and Smakhtin, 1996); lack of spatial representation of the data, as observation stations record point data (Moalafhi et al., 2017), as well as inaccessibility (Groeve, 2010). In this regard, remotely sensed data provides an effective means for flood monitoring and vulnerability over space and time.

Remote sensing and Geographic information system remain indispensable approach for effective flood mapping, vulnerability and impact assessment and monitoring, over space and time (Asante et al., 2007; Haq et al., 2012; Ticehurst et al., 2014; Hussein et al., 2019). As a recurring hydrological phenomenon, remote sensing offers data for continuous monitoring (Feng et al., 2015). This is facilitated by the temporal coverage of remote sensing datasets at various temporal scales. For example, the daily rainfall datasets provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor have been used to monitor the possibilities and flood prone areas across the globe (Ticehurst et al., 2014). In addition, remotely-sensed data can characterize factors associated with flood occurrence, including natural and anthropogenic, such as land use land cover, drainage network and topography (*e.g.* elevation and soil properties), which have been identified by different studies to have considerable effect on flooding (Dalu et al., 2018). Remote sensing also provides continuous data across national borders, which is fundamental when monitoring transboundary basins, spanning across different countries (Zhou et al., 2017). Some of the most critical basins in the region spans in different countries, which makes it difficult to access and integrate hydrological data for monitoring purposes. For example, the Limpopo basin includes Botswana, Mozambique, South Africa and Zimbabwe, whereas the Inkomati basin includes Mozambique, South Africa and Swaziland. The Zambezi basin is also a critical hydrological basin including Angola, Botswana, Malawi, Namibia, Mozambique, Tanzania, Zambia and Zimbabwe. Remotely sensed data thus allow monitoring of these areas over time, which is difficult to achieve, using the conventional approach. This notion was also emphasized by Asante et al. (2007). The study reported that accessing hydrological data from other surrounding countries for flood monitoring is a major challenge for Mozambique. They consequently recognized the value of across national borders.

In addition, advances in geospatial modelling algorithms enhance flood monitoring, prediction and vulnerability assessment (Samanta et al., 2018). These algorithms can integrate data from various sources, thereby providing remarkable potential for monitoring floods, identify risk areas and associated environmental variables, which facilitate flood occurrence. The application of these algorithms varied from using conventional approach to remote sensing approach. However, considering the effects of flooding in southern Africa, advances in remote sensing and geospatial modelling, there is a need to understand the state of this region in monitoring floods from space. This paper therefore provides an overview of the status of flood monitoring from space and application of advanced modelling in southern Africa. To achieve this, the review checked scientific scholarly publications which have used different remote sensing datasets to map flood extent, monitoring occurrence over time, and model vulnerable areas to flooding in southern Africa. In addition, the review provides the available remote sensing data and products for flood monitoring, their application and limitations, as well as provide trends in flood monitoring in the region based on available literature.

2. Data and methodology

To achieve the objective of the study which is to determine the progress of the application of remote sensing in monitoring floods in southern Africa, scientific publications were searched using Google Scholar to access high-quality journal publications. The main search phrases were “remote sensing of floods in southern Africa”, “mapping flood extent in southern Africa” and “assessing flood risk in southern Africa”, flood vulnerability assessment in southern Africa” and “flood hazard in southern Africa”. This was intended to access different articles which have used different remotely sensed data to monitor flood occurrence, map flood extent, as well as in assessing areas vulnerable to flooding in southern Africa. The temporal coverage of the review was left open, to access different research articles conducted within southern Africa. The study area is presented in Fig. 1 and the data to produce the map was downloaded from the United Nations Office for the Coordination of Humanitarian Affairs website (https://data.humdata.org/dataset/east-and-southern-africa-administrative-1-boundaries?). These countries have significant transboundary basins which affect the

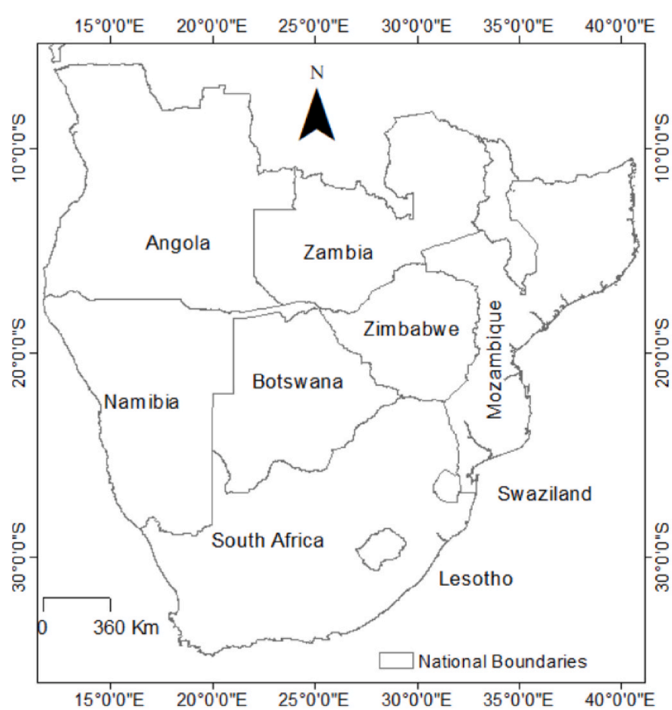

Fig. 1. Map of the study area illustrating southern Africa.

occurrence of floods in the region. In addition, these countries have been affected by floods with devastating impacts, hence the need to understand how remote sensing has been used to improve the understanding and monitoring of flooding.

3. Results and discussion

Remote sensing has been reported to be an effective data source for flood monitoring (Feng et al., 2015; Mind'je et al., 2019; Sanyal and Lu, 2004; Bangira et al., 2017). Different remote sensing datasets exist for flood monitoring in southern Africa. These include remotely sensed data and remotely sensed products, as well as ancillary spatial data such as digital elevation models (DEM), derived from advanced remote sensing techniques. Remotely sensed data include the use of low altitude airborne remote sensing and high-altitude space borne satellite remote sensing.

3.1. Low altitude airborne remote sensing for flood monitoring

Aerial reconnaissance is one of the recognized spatial data sources for determining the detailed spatial extent of flooding at high spatial resolution. This involves the use of aerial photographs taken before, during and after a flood event. Few studies have used aerial photographs to monitor floods in southern Africa. A limited number of scientific publications were found, which have used aerial photos to map flood extent, monitor their occurrence and to assess the vulnerability of areas to floods (Dalu et al., 2018; Heritage et al., 2019; Kabanda and Palamuleni, 2013). It was also noted that these studies have used aerial photographs with other data sources which included satellite images, DEMS and meteorological data. For example, the study by Dalu et al. (2018) used aerial photographs in assessing areas which were at high risk of flooding in eastern Cape of South Africa. Aerial photographs were integrated with land use and cover patterns and topographical maps. In a different study, Heritage et al. (2019) used aerial photographs coupled with Lidar data and DEM, to quantify the magnitude of floods in the Kruger National Park of South Africa. The study reported flood-induced significant changes to river morphology, vegetation communities and sediment flux, after the 2012 flood. The study also highlighted that the modelled results from remote sensing data performed well, when compared with field surveyed, simulated water surface slope and inundation patterns.

The use of drones or Unmanned Ariel Vehicles (UAVs) is also another approach which can be used for flood monitoring in southern Africa. The recent review by Iqbal et al. (2023) highlighted the potential of UAVs in mapping inundation and damage assessment. The use of drones has been reported to be more robust, efficient and associated with low cost. The review also noted that the use of drones is not yet fully explored, hence presents a valuable opportunity for future flood monitoring research. Drones have also shown their potential in assessing flood occurrence, before, during and after a flood event, beyond southern African region (Iqbal et al., 2023). In addition, some news reports have indicated the potential drones in showing live images of flood impacts as the events occurred.

However, although low altitude remote sensing acquires high spatial resolution data at a very close range that can be used to determine flood spatial extent, effects and vulnerability, this approach is applicable for relatively small geographical areas. For example, the study by Dalu et al. (2018) used aerial data for selected informal settlements of the Eastern Cape province of South Africa. In addition, the cost associated with this approach makes their application very difficult in southern Africa, from which the region is resource constrained. In addition, there are hardly aerial photographs to assess the historical occurrence or spatial extent of floods, for continuous monitoring. This has been indicated by limited studies conducted to determine the extent of flooding, using aerial photographs. The same applies with the use of drones. Although they provide high quality images in real time during, before or after a flood image, their implementation is very cost to have continuous monitoring of areas affected by floods and their impact.

3.2. Space borne multi-spectral remote sensing for flood monitoring

Different space borne sensors are currently in orbit, offering remote sensing data for flood monitoring in southern Africa. To monitor floods at regional scale, such as southern Africa, there is need to consider sensors availability, revisit frequency, geographical coverage and the spectral coverage. Table 1 provides the details of the currently available spaceborne multi-spectral datasets, which can be used for flood monitoring in southern Africa. Overall, most sensors are commercial data sources, which offer data at high spatial resolution, at small areal coverage (*e.g.* swath width between 10 km and 20 km). These sensors include the Worldview missions, GeoEye, Ikonos and Quickbird. In southern Africa, based on literature available, the application of these datasets has been limited so far (*e.g.* Kienberger, 2014). For example, the study by Kienberger (2014) used Quickbird with participatory GIS to assess flood risks in Munamicua, District of Búzi, in Mozambique. The study reported the validity of integrating high spatial remotely sensed data with ancillary data in assessing flood risks at community level.

The medium spatial resolution sensors also present a better opportunity to monitor flood occurrences. The Landsat series is one of the data sources that has gained considerable attention in monitoring floods in southern Africa (Awadallah and Tabet, 2015; Kabanda and Palamuleni, 2013; Twumasi et al., 2017; Zimba et al., 2018; Cai et al., 2017; Long et al., 2014). For example, Zimba et al. (2018) used Landsat to assess trends in flooding for the Barotse Floodplain of the upper Zambezi River Basin in the Western Province of Zambia. However, the study by Zimba et al. (2018) has noted considerable challenges associated with using Landsat 8 for flood monitoring. The study mentioned that although Landsat 8 had a relatively higher spatial resolution of 30 m when

Table 1
Spaceborne multispectral remote sensing data for flood monitoring.

Sensor	Spatial resolution (meters)	Spectral coverage	Revisit Time (days)	Swath width (km)
IKONOS	0.82; 3.28	Panchromatic; Visible; Near InfraRed	3	11.3
Quick-Bird	0.65; 2.62	Panchromatic: Visible; Near InfraRed	1 to 3.5	16.5
GeoEye-1	0.46; 1.84:	Panchromatic; Visible; Near InfraRed	2 to 8	15.2
WorldView 1, 2, 3 & 4	0.46, 0.31, 0.5	Panchromatic; 8 MS (Red, Blue, Green, 2 Near InfraRed, RedEdge, Coastal blue, Yellow), ShortWaveInfraRed; 12 CAVIS Bands	1 to 5	16.4, 13, 17
SPOT 5, 6 & 7	5/2.5; 10; 20	Panchromatic; MS; ShortWaveInfraRed	1–5	60
Sentinel 2	10; 20; 60	Blue; Green; Red; Near infrared, Shortwave InfraRed NIR, Red Edge	5–10	295
Landsat series	15, 30; 100	Blue; Green; Red; Near infrared, Shortwave InfraRed; Panchromatic, Cirrus, Thermal InfraRed	16	185
ASTER	15; 60; 90	Red; Green; Blue; Near InfraRed, Shortwave infrared, Thermal InfraRed	16	60
ENVISAT MERIS	300	Blue; Green; Red; Near infrared	3	1150
MODIS	250, 500, 1000	36 spectral bands in the Visible, Near InfraRed, Shortwave infrared, Thermal InfraRed	1 to 2	2330
NOAA AVHRR	1100	Visible, Near InfraRed, Shortwave infrared, Thermal InfraRed	Twice/day	2900

compared to MODIS, its 16-day revisit frequency proved difficult for adequate time-series analysis. In addition, very few cloud-free images were available during the flooding period and those images available during the flood season had considerable different acquisition dates. The study further used MODIS, to compensate for this limitation.

The availability of low spatial resolution sensors provides another opportunity for the monitoring of floods in southern Africa. These include MODIS, the Advanced Very High-Resolution Radiometer (AVHRR) and ENVISAT MERIS. These datasets, particularly MODIS has daily revisit frequency which allows monitoring flooding extent continuously. The study by Zimba et al. (2018) has emphasized the importance of MODIS temporal resolution in flood monitoring. They reported that MODIS enabled a daily comparison of flooding across the period under study. In addition, these sensors allow for the monitoring of flooding for large geographical areas, due to their large swath width (*e.g.*, 2330 for MODIS and 2390 for AVHRR). In addition, the free-accessibility, global coverage and open data policy make MODIS and AVHRR data more appropriate for continuous monitoring of floods in the region. However, Revilla-Romero et al. (2015) emphasized the need to evaluate the reliability of the data for disaster response purposes. Similarly, Zimba et al. (2018) noted that MODIS can be used with Landsat especially for validation of its performance.

Although a wide range of multispectral optical datasets are available for flood monitoring (Table 1), their application for flood monitoring has been used with some challenges, particularly in terms of their data acquisition approach. For example, these multispectral optical and passive sensors are limited by cloud coverage as their data acquisition approach cannot penetrate clouds. Landsat 8 at 16 days temporal resolution presents a considerable challenge in mapping flood, assess vulnerable areas or understanding the impacts of flood (Mehmood et al., 2021). The availability of images from Landsat can further be compromised by cloudy cover, especially during rain/summer period (Mehmood et al., 2021). In this regard, data acquired by these sensors during cloud coverage are difficult to use due to the presence of clouds. This becomes the major challenge for the application to monitor flood occurrence during flood events. In this regard, active sensors provide an indispensable data source for flood monitoring.

The development of active radar sensors marks an advanced monitoring of flood. Radar altimeters can directly measure water variations for large river. On the other hand, airborne LIDAR can be used to determine water depths of inundated areas; hence can be used to monitor the occurrence of flood. Active synthetic aperture radar systems can penetrate clouds hence allowing for monitoring of flood occurrence before, during and after a flood event. Recently, the study by Anusha and Bharathi (2019) emphasized the advantage of SAR data when compared to optical passive datasets, for flood monitoring. The study reported the ability of SAR sensors to provide data regardless of the weather conditions, including penetrating rain showers, fog, clouds and vegetation, as well as their high revisit frequency. In agreement, Dewan et al. (2006) and Rahman and Thakur (2018) noted that SAR data have an enhanced contrast between land and water, which makes them more appropriate for identifying flood extent and monitoring over time.

Table 2 provides some of the SAR data that are available to assess flood. These sensors have been designed with varying spatial resolutions, acquisition modes, bands and swath width Leng et al. (2016). Overall, there are different datasets available for flood monitoring in southern Africa and these datasets were used by few studies in southern Africa (Long et al., 2014; Martinis and Twele, 2010; De Groeve, 2010). For example, Long et al. (2014) used the ENVISAT/ASAR and Radarsat 2 datasets to assess temporal flooding, extend and frequency for the Caprivi region of Namibia from February 2008 to March 2013. The study also used Landsat to assess the performance of the SARs data used. Their findings indicated a good agreement between SAR and Landsat data. However, the study also reported an increase in error associated with an increase in spatial resolution. This might be an indication that studies to be conducted using low spatial resolution SAR data need to do so with caution. Although, some of the radar data are expensive or not freely available for monitoring of floods, the availability of the Sentinel 2, free of charge opens a new dawn for the advanced monitoring of floods in the region.

Table 2
Typical SAR data that can be used for flood monitoring.

Data	Band	Spatial resolution (m)	Swath width (km)	Source link (acquisition cost)
ALOS PALSAR-2	L	1–100	25–490	https://docs.disasterscharter.org/missions/sar/alos-2/(commercialized)
ENVISAT ASAR	C	30; 150	100; 405	https://learningzone.rspsoc.org.uk/index.php/Datasets/ENVISAT-ASAR/Introduction-ASAR (freely available)
ERS AMI SAR 2	C	30	50–500	https://earth.esa.int/eogateway/instruments/sar-ers (commercialized)
RADARSAT-1	C	100	10–500	https://earth.esa.int/eogateway/catalog/radarsat-1-2-full-archive-and-tasking
RADARSAT-2	C	3–50	10–500	https://earth.esa.int/eogateway/catalog/radarsat-1-2-full-archive-and-tasking (commercialized)
Sentinel-1A	C	5–40	250	https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1 (freely accessible)
TerraSAR-X Scan	X	1–50	10–500	https://earth.esa.int/eogateway/missions/terrasar-x-and-tandem-x/sample-data (commercialized)

3.3. Remote sensing products for flood monitoring

There are various remote sensing products that have been prepared and are readily available for flood monitoring. Table 3 provides the details of some of these products which are available for flood monitoring in southern Africa. These include products prepared to monitor climate variables, particularly rainfall and temperature, products to monitor surface water depth/storage, soil moisture and ground water storage, as well as topography. These variables have been reported to influence flood occurrence (Reager and Famiglietti, 2009; Elkhrachy, 2015); hence they have been integrated with other remote sensing and meteorological datasets to monitor floods.

Climate products, particularly rainfall and Land surface temperature (LST) are the most critical input datasets for modelling floods, as rainfall variability contributes to flooding. The most common rainfall products which are widely used are the Tropical Rainfall Measuring Mission (TRMM), the Climate Hazards Group Infra-Red Precipitation (CHIRP) and the CHIRP with Stations observations (CHIRPS), the Tropical Applications of Meteorology using Satellite data and Ground-based observations (TAMSAT), Meteosat-8, the Special Sensor Microwave Imager (SSM/I), the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network; (PERSIANN) (Hsu et al., 1997), Global Precipitation Climatology Project (GPCP) (Adler et al., 2018), and the Geostationary Operational Environmental Satellite (GOES). The CHIRP and CHIRPS satellite-based rainfall products have been regarded as datasets with relatively high temporal and spatial resolutions associated with quasi-global coverage (Dinku et al., 2018). In southern Africa, the TRMM rainfall product is one of the widely used dataset for flood mapping and monitoring. These rainfall products have shown good agreement with field-based rainfall observations (Dinku et al., 2008; Pombo et al., 2015; Toté et al., 2015). This emphasizes their potential in understanding flood occurrence within the region.

Table 3
Remote sensing products for flood monitoring.

Remote sensing product	Variable	Spatial resolution (km)		Temporal resolution (days)	Source (acquisition cost)
ASCAT	Soil moisture	12.5		Daily, Monthly, Yearly,	https://navigator.eumetsat.int/product/EO:EUM:DAT:METOP:SOMO25 (Free)
AMSR-E (Aqua)	Soil moisture	25		daily	https://nsidc.org/data/ae_land3/versions/2 (free)
CHIRPS	Rainfall	0.1		Daily, 5-day, dekadal	https://www.chc.ucsb.edu/data (Free)
GOES	Rainfall	0.3		daily	https://www.goes-r.gov/products/baseline-rainfall-rate-qpe.html (Free)
GPCP	Rainfall	0.11		daily	https://www.ncei.noaa.gov/products/climate-data-records/precipitation-gpcp-daily (Free)
GRACE	soil moisture, surface & ground water storage, snow	0.3		monthly	https://earth.esa.int/eogateway/missions (Free)
Global Flood Detection System	Surface water extent	0.09		daily	https://global-flood.emergency.copernicus.eu/technical-information/glofas-gfm/(Free)
GloFAS Flood Forecast	River flow forecasts	1		–	https://global-flood.emergency.copernicus.eu/technical-information/glofas-gfm/(Free)
Meteosat-8	Rainfall	3; 12		15 min	https://www.eumetsat.int/meteosat-third-generation (Free)
MODIS Near Real-Time Global Flood Mapping Project	Flood water maps	0. 250		daily	https://www.un-spider.org/links-and-resources/data-sources/near-real-time-global-modis-flood-mapping-nasa (Free)
MYD11A2 (Aqua)	LST	1		Daily, 8 day	https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MYD11A2 (Free)
Multi-sensor Precipitation Estimate (MPE)	Rainfall	3		15 min	https://www.weather.gov/marfc/multisensor_precipitation (Free)
PERSIANN	Rainfall	25		daily	https://www.ncei.noaa.gov/products/climate-data-records/precipitation-persiann (Free)
SSM/I	Rainfall	2.5, 12.5		daily	https://www.ncei.noaa.gov/products/ssmi-hydrological (Free)
TAMSAT	Rainfall	4		dekadal	https://researchdata.reading.ac.uk/112/(Free)
TRMM	Rainfall	0.5		Hourly, daily, monthly	https://gpm.nasa.gov/missions/trmm (Free)
DEM	Elevation	SRTM	0.09; 0.03	–	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-shuttle-radar-topography-mission-srtm-non (Free)
		Airbus	0.01; 0.04		https://intelligence.airbus.com/imagery/reference-layers/elevation1-4/(commercialized)
		ASTER	0.03		https://asterweb.jpl.nasa.gov/gdem.asp (Free)

In southern Africa, based on literature available, different studies have used different products for assessing areas vulnerable to floods and flood extent (Asante et al., 2007; Bangira et al., 2015; Toté et al., 2015; Awadallah et al., 2011; Awadallah and Awadallah, 2013). For example, the study by Bangira et al. (2015) used the TRMM to identify potential areas to flooding in Cape Town, South Africa. It was found that high flash flood potential areas were associated with high rainfall, antecedent precipitation and TWI. TRMM 3B42 produced better accuracy of rainfall intensity. ASCAT soil moisture had a reasonable positive association with ground-based measurements ($R^2 = 0.58$). In a different study, Toté et al. (2015) evaluated the potential of satellite rainfall products for drought and flood monitoring over time in Mozambique. The study found that satellite products overestimated low and underestimated high dekadal rainfall. In a different study, Awadallah et al., (2011) used the TRMM product to understand flood frequency in Angola where the study area was characterized by limited ground-based measurements. Their findings indicated that TRMM performed well producing robust rainfall estimates for large areas. The study by Asante et al. (2007) explored the application of the TRMM rainfall product to flood monitoring, in Limpopo basin, South Africa. The study reported that satellite-derived precipitation allows for the identification of extreme rainfall and flood events, both in terms of relative intensity and spatial extent.

The observations of Terrestrial Water Storage Anomaly (TWSA) mission from Gravity Recovery and Climate Experiment (GRACE) mission is also one of the products that is available to assess soil moisture, surface water storage, ground water storage and the potential of flood occurrence (Reager et al., 2014; Reager and Famiglietti, 2009). The mission provides data at global scale which can be used to assess floods at regional coverage such as southern Africa. However, the study by Reager and Famiglietti (2009) has indicated some of the limitations associated with the use of GRACE data. These include, its coarse spatial resolution, which limits its application in small river basins, its approach of using aggregated values which include snow, soil moisture, and groundwater for each pixel, as well as its 2–3 months lag delay. In southern Africa, the GRACE dataset has not yet been explored for flood monitoring; nevertheless, the mission has been successfully used to assess flood potential in other parts of Africa, including east Africa from which the southern African region can adopt.

In addition, DEMs are one of the commonly used ancillary spatial data, for modelling topographic variables which are used as variables in assessing flood, vulnerable areas or flood impacts. The most used DEMs are also presented in Table 3. DEM are used to derive the topographical variability of an area. Flood occurrence is highly influenced by the topography of the area, where low-lying areas experience more flooding compared to other areas (Zambrano et al., 2018; Masoudian and Theobald, 2011). Some of the variables which can be derived from DEMs are elevation, slope, drainage network and total wetness index. These variables influence the flow and accumulation of flood water hence plays an important role in understanding flood occurrence. Remote sensing-based DEMS are derived from Lidar remote sensing data. In addition, topographic maps and field-based elevation data can also be used to derive continuous DEM to model variables such as river morphology/drainage basin characteristics, slope and soil moisture (Karlsson and Arnberg, 2011). In this regard, DEMs and topographic maps have been used with remotely sensed data and products, as well as with meteorological data to assess flood occurrence or to model flooding (*e.g.,* by Karlsson and Arnberg, 2011; Twumasi et al., 2017; Kabanda and Palamuleni, 2013). For example, Karlsson and Arnberg (2011) assessed the quality of the SRTM and HYDRO1K, for modeling flood inundation for the Lower Limpopo basin in Mozambique. Findings indicated that although both DEMs performed well at a local scale, their use should be applied with caution due to their data inadequacies which can result in over- and under-estimation.

Previous studies have also reported the potential of integrating low, medium, remote sensing products and DEMs in assessing floods, and vulnerability mapping (Twumasi et al., 2017; Zimba et al., 2018). Twumasi et al. (2017) assessed flood vulnerability in Limpopo basin, of South Africa. The study used an integration of Landsat, MODIS, DEM, questionnaire surveys and remotely sensed rainfall products. Their findings indicated the potential of using different datasets to understand vulnerability to flooding. In another study, Zimba et al. (2018) used Landsat 8 and MODIS to map and monitor the occurrence of flood in the Zambezi River basin. Awadallah and Awadallah (2013) used the Global flood detection system (GFDS), the TRMM, Landsat and Earth Observing-1 in mapping the extent and frequency of flood in Cuvelai Basin, located in southern Angola and northern Namibia. Their findings indicated that Landsat and Earth Observing-1 Mission (EO-1) satellite images produced very similar results in mapping flood extent. On the other hand, GFDS values for wetland areas were always underestimated, by about 25 km^2, compared to satellite-based estimates.

3.4. *Trends in flood monitoring using remote sensing*

Considerable studies have been conducted in southern Africa in monitoring floods since the emergency of remote sensing as a data source for earth observation and monitoring. Although a wide range of remote sensing data and products are available, limited research has implemented their ability in monitoring floods in the region. Considering the pre-2006 period, it was noted that limited scientific publications were available, which used remote sensing to monitor flood occurrence, map their extent or identify their effects in southern Africa (Asante et al., 2007). This is problematic, as the changes or shift of flooding, affected or vulnerable areas might vary over space.

Overall, flood monitoring in southern Africa lagged and these studies were identified post 2005 period. Although this was the case, there has been an increasing trend in the use of remote sensing to map flood extent, determine impacts or assess vulnerable areas to flooding in the region. The majority of these studies (Asante et al., 2007; Grodek et al., 2020; De Groeve, 2010; Heritage et al., 2019; Kabanda and Palamuleni, 2013; Twumasi et al., 2017; Zimba et al., 2018; Cai et al., 2017; Martinis and Twele, 2010; Long et al., 2014; Kienberger, 2014; Karlsson and Arnberg, 2011) focused on mapping and monitoring flood extent, using a combination of remotely sensed data, remotely-sensed products, meteorological data and DEMs. Some of these studies also focused more on widely known international or national basins, such as the Okavango, Limpopo, and the Caprivi, as well as few coastal areas. Although this provides useful insights and contributes to the understanding of flooding in the region, it leaves a gap on some of the local areas which might be vulnerable to flooding. Flooding also occurs inland, including informal settlements and low-lying areas, with devastating impacts. The occurrence of floods in these areas need to be recognized.

4. Future directions in flood monitoring using remote sensing

The trends in the use of remote sensing for flood monitoring was explored, from the emergence of remote sensing to present. The studies included those which focused on mapping flood extent, assessing the effects of flooding, and vulnerability to flooding in southern Africa using remote sensing. It was found that many studies conducted in southern Africa mainly focused on mapping flood extent (Asante et al., 2007; Grodek et al., 2020; De Groeve, 2010; Heritage et al., 2019; Kabanda and Palamuleni, 2013; Twumasi et al., 2017; Zimba et al., 2018; Cai et al., 2017; Martinis and Twele, 2010). Overall, the application of remote sensing to map flood extent, impact and vulnerability of areas has been limited in southern Africa. Few studies which were conducted, relied primarily on open datasets, such as Landsat, DEM and MODIS, as well as remotely sensed products particularly the TRMM rainfall (Zimba et al., 2018; Twumasi et al. (2017). In this regard, high spatial resolution datasets, such as the Worldview missions and IKONOS presents an opportunity to monitor flood occurrence, impacts or vulnerability, at sub-basin scale. This has been the approach from other areas beyond southern Africa, such as in west Africa, east Africa and beyond the African continent.

During the last decade or so, advances in satellite remote sensing increased. This led to the availability of new generation sensors, such as the Sentinel missions, which provide radar and multispectral data, the Worldview missions (1–4), with advanced spatial, spectral and temporal characteristics and the Landsat 8 with improved spatial and spectral characteristics, compared to its predecessors (Shastry et al., 2023). These developments offer a new dawn for the remote sensing of floods in southern Africa, as their performances have been proved effective beyond the southern Africa (Shastry et al., 2023). For example, the 10 m spatial resolution of Sentinel 2, its 295 km swath width, and its 5–10 days revisit frequency allow for the frequency and continuous monitoring of flood occurrence, over large geographical areas (Konapala et al., 2021; Tavus et al., 2020). Similarly, Landsat 8, at 30 m spatial resolution, with 185 km swath width allows for continuous monitoring from its predecessors, which enable the identification of historical flooded areas, common areas affected by floods, as well as the opportunity to identify new or emerging areas, which are vulnerable to floods. The integration of these datasets is also an opportunity, which allows for a better and detailed understanding of flooding in southern Africa (Kyriou et al., 2015).

Unmanned Aerial Vehicles (UAVs) which are also referred to as drones are becoming an important data source for monitoring floods. The ability of these systems to provide data at close ranges at low altitude enable the extent and impacts of a flood to be determined (Perks et al., 2016; Iqbal et al., 2023). According to the report released by the World Food Programme (WFP) in 2019, the use of drones in Mozambique has provided more and efficient information about the extent of flood and vulnerable areas than never before, for food relief programs (World Food Programme, 2019). This is a clear indication for the need to shift research towards their application before, during and after a flood event. In addition, the use of UAVs has proved useful in some of southern African countries, particularly in monitoring wildlife, for conservation purposes (Mulero-Pázmány et al., 2014; Nkala, 2014). For example, drones are used in the Kruger National Park of South Africa to fight against rhino poaching (Mulero-Pázmány et al., 2014) and in Namibia (Nkala, 2014). In this regard, the applications of drones can be extended to flood monitoring, including assessing vulnerability, flood extent and impacts in the region. Thos becomes relevant especially at basin scales which are usually affected by floods. This makes the continuous monitoring possible as the monitoring focused on a specific area.

Cloudy computing is another future prospect for continuous flood monitoring, including mapping the extent of the water and the impact of the flood, by assessing physical damages. Google Earth engine is an advanced cloudy computing platform, which allows for continuous monitoring using remote sensing and advanced algorithms (Mutanga & Kumar (2019; Zhao et al., 2021). So far, the platform is showing potential in land use land cover mapping (Zhao et al., 2021; Becker et al., 2021; Feizizadeh et al., 2023), water bodies mapping (Yang et al., 2020), vegetation mapping (Del Valle and Jiang, 2022), land degradation (da Silva et al., 2022), just to mention a few. All these can facilitate detailed understanding of flood occurrence in the region. In addition, beyond the southern African region, this approach has reported valuable insight in understand flooded areas and the use of advanced emerging and freely available sensors such as the Sentinels and Landsat (Mehmood et al., 2021). Similarly, its cloud-based approach allows the use of multi-temporal images over space and time, in a more effective and efficient manner than before. This serves well for flood monitoring, extent mapping and trends within a specific area.

5. Conclusion

The use of remote sensing presents an opportunity for flood monitoring. However, in southern Africa, which is mostly hard hit by floods and their devastating impacts, the use of remote sensing remains rare, since its emergence. Detailed information regarding flood risk in southern Africa is largely unknown and undocumented. This is evident from a lack of research publications which have used remote sensing for flood monitoring in the region. Nevertheless, there are few studies which have attempted to monitor floods, within the region. These studies, with specific focus on small areas, such as basins or catchments, which are nationally recognized. This has placed less importance in other areas which are affected by floods, such as coastal areas, areas located in vulnerable areas such as low-lying areas and informal settlements. Previous studies also mainly used the freely available MODIS, Landsat, DEM and TRMM remote sensing datasets, to map the extent of flooding, frequency, and identify areas vulnerable to flooding and identify areas vulnerable to flooding. These studies highlighted the potential of these freely available datasets for the continuous monitoring of floods, as well as to identifying emerging vulnerable areas. This remains critical, especially in light of global climate change and impacts on the occurrence of extreme events, such as floods. These studies lack the ability to identify environmental and anthropogenic factors facilitating flooding. It is critical to identify flood prone areas, over the region at various scales, over time. This is also critical to implement hydrological measures, which might reduce flooding and associated impacts. In this regard, the emergency of freely accessible medium resolution datasets, drones and advanced cloudy computing provide an opportunity to continuously monitor flood occurrences in southern Africa.

CRediT authorship contribution statement

Cletah Shoko: Conceptualization, Resources, Writing – original draft. **Timothy Dube:** Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Co-author, T Dube is an editor for the 23rd Waternet symposium.

Data availability

No data was used for the research described in the article.

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