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Satellite and artificial intelligence in mapping multidimensional poverty in Africa

A review study

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ABSTRACT

Context and background

Multidimensional Poverty (MP) considers poverty in multiple dimensions of deprivations such as health, education, energy, the standard of living and access to basic services. MP remains a major challenge in Africa, with a large proportion of the population living in MP. According to United Nations Development Programme (UNDP), Africa has shown the highest Multidimensional Poverty Index (MPI) having over 40% of its population living in MP.

Goal and Objectives:

This paper is a review, aimed at assessing the potential of the integration of satellite and Artificial Intelligence (AI) in mapping MP, with a specific focus on Africa.

Methodology:

Based on the reviews of past studies, the combination of satellite data such as nighttime light, daytime satellite imagery and high-resolution settlement data in combination with techniques such as field surveys, statistical correlation models (transfer learning) and AI (deep learning) has been applied in mapping MP.

Results:

The findings from studies show that the combination of satellite data and AI has the capability of providing more accurate and granular MP maps, compared to the traditional approach. Again, this paper explains the concept of MP with a specific focus on Africa and presents a map depicting the current MPI in African countries. Finally, pitfalls especially in the accuracy, granularity and frequency of MP data were identified. Consequently, the satellite and AI approaches are recommended for more accurate, frequent, cost-effective and granular data, required in mapping poverty and design of interventions that effectively address the needs of the vulnerable populations in Africa.

Keywords

Africa, Artificial Intelligence (AI), Geospatial, Mapping, Multidimensional Poverty Index (MPI), Satellite

1. INTRODUCTION

Among the 17 Sustainable Development Goals (SDGs) officially launched in 2015, poverty eradication topped the list. Included in the Global Indicator Framework for monitoring progress on poverty reduction is the proportion of a country's population living below its national poverty line, which is typically sourced from household income and expenditure surveys. From the perspective of statisticians and other compilers of official poverty statistics, the SDGs' leave no one behind principle which requires data to be disaggregated by geographic location, ethnicity, gender, income class, and other relevant dimensions, presents several challenges. Conventionally, household income and expenditure surveys have sample sizes that are sufficient to provide nationally representative poverty estimates, but not large enough to provide reliable estimates at levels granular enough to meet all disaggregated data requirements of SDG 1. Moreover, the sample sizes are inadequate in providing reliable estimates at levels granular enough to allow development planners efficiently target areas that need immediate poverty intervention (Hofer et al., 2020).

The integration of geospatial techniques and Artificial Intelligence (AI) in mapping multidimensional poverty has the potential to provide more accurate and refined understandings of poverty, and to inform the development of effective poverty reduction strategies (Steele et al., 2017). Geospatial approach in mapping multidimensional poverty involves the use of spatial data and mapping techniques to identify and visualize the spatial distribution of poverty across different dimensions. This approach combines geospatial data, such as satellite imagery and Geographical Information Systems (GIS), with multidimensional poverty measures to produce poverty maps that provide a more accurate and nuanced understanding of poverty. Artificial intelligence (AI) can be applied in mapping multidimensional poverty to improve the accuracy and efficiency of poverty measurement and analysis (Hersh et al., 2021; Sohnesen et al., 2022). AI techniques such as machine learning, computer vision, and natural language processing is now being applied in analysing large amounts of data and to identify patterns and trends in multidimensional poverty.

Several of milestones have been achieved through the integration of satellite data and artificial intelligence in mapping poverty which could facilitate in understanding and addressing poverty. Mobile phone and geospatial data have been combined in the past to provide insight into the spatial distribution of poverty measurements (Steele et al., 2017), allowing for more frequent and granular datasets. Also, open-source satellite imagery features and machine learning has been incorporated to improve poverty mapping accuracy, making it more practical for most applications (Hersh et al., 2021). Convolutional Neural Networks has been applied on high-resolution satellite images of cities in Mozambique and combined their outputs with household level geo-referenced survey data to generate detailed neighborhood-level poverty maps, providing key operational guidance for implementation of the urban social safety net(Sohnesen et al., 2022). Supplementing survey data with satellite data has proven an improved poverty estimate (Klemens et al., 2015).

Satellite imagery can be used to identify features such as housing, infrastructure, and vegetation, which can be used as indicators of poverty. Machine learning algorithms can then be trained to analyze these features and to identify areas that are most likely to be affected by poverty (Jean et al., 2016; Sohnesen et al., 2022). Social media and survey data can provide valuable insights into the experiences of people living in poverty. Natural language processing techniques is applied to analyze these data sources and to identify indicators of poverty and the live experiences of those affected by poverty. GIS can be used to combine and visualize multiple data sources, such as satellite imagery, census data, and survey data, to create a more comprehensive understanding of poverty across different dimensions. Machine learning algorithms can be applied to develop predictive models that can forecast changes in poverty over time (Steele et al., 2017). The study of (Jean et al., 2016) demonstrated an accurate, inexpensive, and scalable method for estimating consumption expenditure and asset wealth from high-resolution satellite imagery using a convolutional neural network, which could transform efforts to track and target poverty in developing countries.

Accuracy is germane in mapping multi-dimensional poverty, considering the limitations in the accuracy of satellite-based poverty maps. The accuracy of satellite-based poverty maps is limited by factors such as the quality of the satellite imagery and the availability of ground truth data (Ayush et al., 2020). An interpretable computational framework to accurately predict poverty has been demonstrated at a local level by applying object detectors to high-resolution satellite images (Ayush et al., 2020). An accuracy of 0.539 Pearson's R^2 was achieved in predicting village-level poverty in Uganda, which indicated a 31% improvement over existing benchmarks. Again, a global poverty map at 30 arcsec resolution using a poverty index calculated by dividing population count by the brightness of satellite observed lighting was produced (Elvidge et al., 2009).

Satellite-based poverty maps can be a useful tool for estimating poverty, especially in areas where traditional census data is unavailable or out-of-date. For instance, (Jarry et al., 2021) proposed a new methodology combining grid-cell selection and ensembling to improve poverty prediction. (Elvidge et al., 2009) produced a global poverty map using a poverty index calculated from satellite observed lighting and population count, calibrated using national level poverty data. Furthermore, studies in metropolitan areas of North and South America have showcased the feasibility of estimating household income and socio-economic conditions, by applications of computer vision to satellite imagery (Piaggesi et al., 2019). Satellite-based poverty maps are of great benefit in complementing traditional poverty maps, especially in areas where census data is limited.

Even though the satellite and machine learning approach are of great benefit, there are limitations to its use. Considering the findings of (Hersh et al., 2021), although incorporating open-source satellite data improved poverty mapping, proprietary imagery can be costly and infrequently acquired. Again, in the study involving the convolutional neural networks on high-resolution satellite images to generate neighborhood-level poverty maps in Mozambique (Sohnesen et al., 2022), an interpretable computational framework to predict poverty at a local level using object detectors on high-resolution satellite images, achieving improved accuracy and interpretability in poverty mapping in Uganda (Ayush et al., 2020). A lack of detailed data on poverty was observed to be common in many developing countries especially in Africa. Satellite data alone may not be sufficient for poverty mapping, as such incorporating survey-derived variables may improve model performance (Hersh et al., 2021). While satellite data can be a useful tool for poverty mapping, studies have suggested that it should be used in conjunction with other data sources, considering its limitations.

This paper focuses on review of the milestones achieved in integrating geospatial techniques and artificial intelligence in mapping multidimensional poverty in Africa for the purpose of proffering possible solutions in the challenges of lack of detailed data on poverty common to developing countries. This review will address the key concept of multidimensional poverty and world Bank measures of MP, poverty in Africa, Trends in the applications of satellite data and artificial intelligence in mapping multidimensional poverty. Finally potential areas relevant for future research in the aspect of multidimensional poverty would be identified.

2. POVERTY MEASURES AND CONCEPTS OF MULTIDIMENSIONAL POVERTY

There are several measures and approaches used to measure poverty. Here are some commonly used poverty measures these include: Income Poverty; Multidimensional Poverty (Alkire & Foster, 2011; World Bank, 2020); Human Development Index (HDI), proposed by the United Nations Development Programme (UNDP) (Priambodo, 2021); Capability Approach, Proposed by Amartya Sen (Frediani, 2010); Subjective Poverty (Achdut et al., 2021); Absolute and Relative Poverty (Foster, 1998). These measures vary in their focus, scope, and methodology, and are often used in combination to provide a more comprehensive understanding of poverty. Each measure has its strengths and limitations, and the choice of measure depends on the specific context and objectives of the analysis.

Multidimensional poverty is a concept that considers poverty not only in terms of income or consumption but also in terms of multiple dimensions of deprivation, such as health, education, and living standards (World Bank, 2022). It recognizes that poverty is not only about a lack of income or material resources but also about the inability to access basic services and opportunities that are necessary for a decent standard of living. The multidimensional poverty approach uses a set of indicators that capture different dimensions of poverty, such as health, education, housing, sanitation, and access to basic services. These indicators are combined to create a multidimensional poverty index (MPI) that measures the extent of poverty in a given population (World Bank, 2018). The MPI provides a more comprehensive and nuanced understanding of poverty than income-based measures alone. It enables policymakers to identify the specific dimensions of poverty that need to be addressed and to design targeted interventions that address the root causes of poverty(World Bank, 2022). The concept of multidimensional poverty has gained increasing recognition in recent years, with a growing number of countries adopting MPIs to measure and address poverty. The United Nations Development Programme (UNDP) and the Oxford Poverty and Human Development Initiative (OPHI) are among the organizations that have played a leading role in developing and promoting the use of MPIs(United Nations General Assembly, 2015; World Bank, 2018, 2022).

2.1 Multidimensional Poverty Measure (MPM)

The Multidimensional Poverty Measure (MPM) introduced by the World Bank has gained popularity as an indicator that gauges the proportion of households facing deprivation across three dimensions of well-being: monetary poverty, education, and basic infrastructure services. Its aim is to present a more comprehensive understanding of poverty. Although poverty is commonly associated with a lack of financial resources, focusing solely on income poverty fails to encompass a broader range of well-being indicators. In fact, the World Bank's Poverty and Shared Prosperity report (World Bank, 2022) demonstrates that nearly 39 percent of individuals experiencing multidimensional poverty are not identified as poor based on income poverty alone.

Alkire and Foster proposed a comprehensive approach to measuring multidimensional poverty that goes beyond solely relying on income or consumption-based measures. Their methodology combines multiple indicators or dimensions of poverty, such as education, health, living standards, and social participation, into a single poverty index (Alkire & Foster, 2011). Since its introduction, the Alkire-Foster method has gained widespread recognition and has been applied in various studies and reports to provide a more nuanced understanding of poverty beyond income measures alone (Abeje et al., 2020; Batana, 2013). It has been used to measure multidimensional poverty at the national, regional, and global levels, contributing to policy discussions and interventions aimed at reducing poverty and improving well-being.

The World Bank developed its Multidimensional Poverty Measure (MPM) in 2018, drawing inspiration from other well-known multidimensional measures such as the Multidimensional Poverty Index (MPI) created by the UNDP and Oxford University. Unlike the MPI, the MPM includes the dimension of monetary poverty, which is measured as household income or consumption per capita falling below $2.15 per day based on the International Poverty Line established in 2017 (Jolliffe et al., 2017). By incorporating both monetary and non-monetary deprivations, the MPM highlights to policymakers the significance of addressing various aspects of human welfare beyond income poverty alone. It recognizes that households in rural areas of Sub-Saharan Africa, for instance, may have sufficient income to surpass monetary poverty but still lack access to vital services like healthcare, education, or reliable electricity. Conversely, households that are income poor but have access to basic services may experience better well-being than those deprived in non-monetary dimensions such as healthcare or education. The interaction and overlap of multiple dimensions can intensify poverty and inequality, perpetuating cycles of deprivation.

The Multidimensional Poverty Measure (MPM) encompasses three dimensions of well-being: monetary standard of living, education, and basic infrastructure services. Within these dimensions, six standardized indicators are considered: consumption- or income-based poverty, educational enrolment, educational attainment, access to drinking water, sanitation, and electricity. Each indicator is assigned a value of 0 or 1, with 1 indicating deprivation. To create a single index, the MPM combines the number of deprivations, requiring a decision on the weighting of each indicator. The World Bank's MPM assigns equal weight to dimensions and indicators within each dimension. Individuals are classified as multidimensionally deprived if they are lacking in at least one dimension or a combination of indicators that equals or exceeds one-third of the weight of a full dimension. Since the monetary dimension has only one indicator and there are three equally weighted dimensions, being income poor also indicates poverty in the broader multidimensional context. Selecting the dimensions, indicators, and thresholds for deprivation parameters is crucial. For instance, the educational enrolment indicator considers a child up to grade 8 who is not enrolled in school as deprived. Detailed indicators, weights, and thresholds for the MPM are presented in Table 1. While Table 2 presents the share of population deprived in each indicator, derived from 121 countries, around the world.

Dimension	Parameter	Weight
Monetary	Daily consumption or income is less than US$ 2.15 per person.	1/3
Education	At least one school-age child up to the age of grade 8 is not enrolled in school.	1/6
	No adult in the household (age of grade 9 or above) has completed primary education.	1/6
Access to basic infrastructure	The household lacks access to limited-standard drinking water.	1/9
	The household lacks access to limited-standard sanitation.	1/9
	The household has no access to electricity.	1/9

Table 1. Multidimensional Poverty Measure Indicators, Weights, and Thresholds
Source: (World Bank, 2020)

Region	Monetary (%)	Educational attainment (%)	Educational enrolment (%)	Electricity (%)	Sanitation (%)	Drinking water (%)	Multidimensional poverty, headcount ratio (%)
East Asia & Pacific	3.2	7.6	2.4	2.4	15.3	7.5	4.8
Europe & Central Asia	0.3	0.9	1.6	1.7	7.1	4.5	2.1
Latin America & Caribbean	3.8	9.4	1.6	1.0	16.6	3.0	4.6
Middle East & North Africa	1.2	8.2	2.6	0.3	2.7	1.1	1.8
South Asia	8.1	20.5	19.2	14.6	35.6	5.2	17.3
Sub-Saharan Africa	32.5	35.9	19.5	48.0	65.6	30.5	51.9
Rest of the World	0.7	0.9	0.3	0.0	0.2	0.2	1.4
All regions	8.8	12.7	8.9	12.1	23.1	10.5	14.5

Table 2. Share of population deprived in each indicator, around the world
Source: Source: (World Bank, 2020)

3. SATELLITE DATA AND ARTIFICIAL INTELLIGENCE IN MAPPING MULTIDIMENSIONAL POVERTY

Poverty statistics are typically compiled based on data collected from household surveys. However, sample sizes of these surveys are typically not large enough to provide reliable estimates at more granular levels, and therefore resulting poverty estimates may not be reliable at very granular disaggregation levels. Increasing sample sizes is a way to enhance reliability of survey estimates, but it is often not practical as achieving such increases requires significant additional resources, which are not readily available to NSOs or the organizations that conduct these surveys (Asian Development Bank (ADB), 2020). An alternative method is the use small area estimation (SAE) techniques, in collaboration with development partners like the World Bank, by combining survey results with census and other auxiliary data to produce more granular data.

On the other hand, there have been attempts to integrate beyond traditional types of data such as those coming from surveys and censuses. A good example is the use of satellite imagery for various development indicators, and there are several reasons why its popularity is increasing. For one, advances in satellite-based socioeconomic measurements have led to an influx of high frequency data for both, data-rich and data-poor environments. One of these measurements is night-time light intensity which has been increasingly used following the initial works of (X. Chen & Nordhaus, 2011) and (Henderson et al., 2012). This helped mitigate some of the known data shortcomings, including those of the SAE, if enhancing granularity is the main objective. Night-time light intensity can also be used to estimate values in between surveys and enable nowcasting as well as help illuminate areas that are less covered by surveys and censuses. However, using data on nightlights alone have several drawbacks. The data produced by satellites are top-coded which makes highly developed, urbanized areas hard to differentiate. On the other side of the spectrum, the least developed areas often do not have measurable night-time lights, and this makes it difficult to obtain estimates for proxy measures of socioeconomic development in such areas. Building on these developments, the use of daytime satellite images has started to become an important focus of research. (Xie et al., 2016) showed that poverty mapping using satellite imagery in combination with transfer learning and convolutional neural networks (CNN) can lead to the predictive performance of survey data collected in the field. (Jean et al., 2016) trained a CNN to extract features in high-resolution daytime images using night time images as labels. The extracted features were used to predict asset wealth and consumption expenditure across five African countries.(Jean et al., 2016) were able to provide that such a model is strongly predictive of both average household consumption expenditure and asset wealth as measured at the cluster level for countries where recent survey data is available. On the other hand, (Head et al., 2017) has proven that this method does not generalize in the same way that other measures of development predict access to drinking water and a variety of health and education-related indicators. It is possible to apply this method in other countries and continents given certain limitations. The study presented in this manuscript serves as a proof of concept in implementing the techniques used by (Jean et al., 2016) using only publicly available satellite data that have lower resolution and are readily available tools for data processing, akin to the objective of (Yeh et al., 2020) which used the same kind of satellite imagery to examine spatial distribution of economic well-being in Africa.

There are many sources of nightlight intensity data. However, the best known and publicly published are datasets based on Defense Meteorological Satellite Program Operational Line-Scan System (DMSP-OLS) and Suomi National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite (SNPP-VIIRS) missions. Both were conducted by the National Oceanic and Atmospheric Administration (NOAA). It was decided that images from VIIRS will be used for this study because it offered a substantial number of improvements over Operational Line-Scan System as stated in the work of (Elvidge et al., 2013). A cloud-free average radiance value was used to filter out the effects of fires and other transitory events as well as irrelevant background, while unlit areas were set to zero.

When combined with machine learning, high-resolution satellite imagery has proven broadly useful for a range of sustainability-related tasks, from poverty prediction; (Ayush et al., 2020; Blumenstock et al., 2015; Jean et al., 2016; Sheehan et al., 2019; Yeh et al., 2020) to infrastructure measurement (Cadamuro et al., 2018) to forest and water quality monitoring (Fisher et al., 2018) to the mapping of informal settlements (Mahabir et al., 2018). Compared to coarser (10-30m) publicly-available imagery(Drusch et al., 2012), high-resolution (< 1m) imagery has proven particularly useful for these tasks because it is often able to resolve specific objects or features that are undetectable in coarser imagery. When combined with machine learning, recent work demonstrated an approach for predicting local-level consumption expenditure using object detection on high-resolution daytime satellite imagery (Ayush et al., 2020). showing how this approach can yield interpretable predictions and also outperform previous benchmarks that rely on lower-resolution, publicly-available satellite imagery (Drusch et al., 2012).

3.1 Satellite data in mapping poverty

Since 1999 and 2013 respectively, Landsat 7 and 8 satellite series cover the entire Earth surface with a temporal resolution of 16 days and a spatial resolution of 15 to 30 meters depending on the spectral bands (8 for Landsat 7 and 11 for Landsat 8). Since 2014, Sentinel satellite series generate images with a spatial resolution of 10 meters. It is then possible to get remote-sensing data with a high time-frequency and a good spatial resolution (Jarry et al., 2021). Researchers are turning to volunteer-curated geographic information and open geospatial datasets to study socioeconomic development, social inequalities, and territorial conflicts (Gervasoni et al., 2018; Grippa et al., 2018; Mahabir et al., 2018). One of the more popular geospatial data crowdsourcing platforms is OpenStreetMap (OSM), a global geospatial database containing billions of entries of volunteered geographic information, maintained by a massive community of mappers from around the world all working towards the goal of curating accurate and complete geospatial data. The community of OSM contributors typically consists of individual mappers, university researchers, volunteer communities, and non-profit organizations. Such organizations regularly organize field mapping activities, workshops, and events that promote geospatial data mapping and contribution.

The combined use of coarse and fine spatial resolution remote sensing data is utilized to gain a deeper understanding of human living conditions (Lin et al., 2019). Coarse resolution satellite imagery, which is readily accessible, frequently updated, and often free, offers a broad overview for large-scale decision-making (Lin et al., 2018, 2019). On the other hand, fine spatial resolution remote sensing data, although less common and more costly due to commercialization, play a crucial role in accurately identifying poverty (Duque et al., 2015; Varshney et al., 2015). Despite their scarcity and expense, high spatial resolution data remain a more cost-effective alternative compared to traditional surveying methods (Zhao et al., 2019).

Remote sensing imagery classification, a popular technique in land use/land cover studies, has been integrated with local expert knowledge and ontology to enhance the accuracy of poverty identification using remote sensing images (Kohli et al., 2015). Adjusting thresholds for different study areas is often necessary to ensure meaningful results (Kohli et al., 2015), and post-processing is required due to misclassifications (Lin et al., 2019). Additional data layers from Geographic Information Systems (GIS) have been found to improve the performance of remote sensing-based poverty classification by incorporating local knowledge and supplementary information (Kohli et al., 2013).

For informal settlements, characterized by lower socioeconomic status, poor living conditions, and unfavorable environments, the integration of remote sensing and GIS techniques has proven advantageous in identifying and understanding such communities (Kohli et al., 2016). The vegetation, impervious surface, bare soil method has been successfully applied to classify detailed urban land use using very high-resolution remote sensing data, both in developed and developing countries (Herold et al., 2002, 2003; Kohli et al., 2016; Stoler et al., 2012; Stow et al., 2007; Stow et al., 2010; Weeks et al., 2007). Combining GIS and remote sensing techniques can enhance the temporal and spatial resolution of poverty identification. For instance, the integration of remote sensing data with mobile operator Call Detail Records (CDRs) has shown potential in representing human living conditions, especially in urban areas (Steele et al., 2017). Furthermore, the affordability of GIS and remote sensing-based informal settlement identification makes them invaluable tools in developing nations (Kohli et al., 2016).

The Earth Observation (EO) satellite missions focusing on land have measured physical properties of the land surface as well as the use of the land in different forms. This includes generic land cover and land use, (Gong et al., 2013) or more thematic maps such as forest cover maps (Hansen et al., 2013), surface water (Pekel et al., 2016), and human settlements and their dynamics (Melchiorri et al., 2018; Pesaresi et al., 2016). Nightlights recorded by satellites can now be used to complement the information provided by global built-up areas and population density used to address societal activities (Ehrlich D. et al., 2018). In recent times, common geospatial data applied in mapping poverty include: Nighttime Luminosity Data, Daytime Satellite Imagery and High-Resolution Settlement (Ehrlich et al., 2018; Tingzon et al., 2019).

3.2 Poverty Identification with Machine Learning

With significant advancements in computer hardware and ongoing research, machine learning, including deep learning techniques like ImageNet, has emerged as a frontier in computer science (Russakovsky et al., 2015). Deep learning enables the extraction of meaningful features from remote sensing data through automatic learning and classification (Jean et al., 2016; Lin et al., 2018). Numerous studies have successfully applied deep learning methods to classify remote sensing images for poverty identification (Zhao et al., 2019). For instance, ImageNet has been used to predict poverty based on nighttime light intensity, leveraging the learned knowledge (Noor et al., 2008). Nighttime light, which correlates with manufacturing, population, and socioeconomic patterns, has emerged as a valuable remote sensing data source for measuring human activities (Chand et al., 2009; Chen et al., 2015, 2017; Ghosh et al., 2013; Shi et al., 2019; Yu et al., 2018; N. Zhao et al., 2017). NTL data is commonly used to represent socioeconomic status (Ma et al., 2014; Shi et al., 2019; Zhou et al., 2015), and its correlation with poverty has led to its adoption in poverty research in developing countries (Elvidge et al., 2009; Noor et al., 2008; Yu et al., 2015).

Transfer learning, which allows the transfer of knowledge learned by convolutional neural networks (CNN) to related problems, proves useful when limited labeled data is available (Kohli et al., 2013). Random Forest Regression (RFR), a popular machine learning method for handling multiple data sources, has been utilized in various applications (Abdel-Rahman et al., 2013; Belgiu & Drăguţ, 2016; Immitzer et al., 2012; Stevens et al., 2015; van Beijma et al., 2014; Yao et al., 2017). For example, a study combined different data sources and employed RFR to develop a machine learning model for estimating regional poverty levels based on NTL data (Zhao et al., 2019). The integration of machine learning, remote sensing, and Geographic Information Systems (GIS) has demonstrated promising potential, surpassing traditional field surveys and standalone remote sensing classification methods in several research endeavors (Lin et al., 2018; Zhang et al., 2020).

Table 3 is a summary of techniques adopted in mapping poverty including the advantages and challenges encountered in their applications as derived from (Lin et al., 2021).

Techniques	Advantage	Limitation and Challenge
Field surveys and investigations; Evaluation of culture and history	Both methodologies and results are easy to understand	Require knowledgeful investigators; high financial cost; labour-intensive and low scalability
Statistical correlation models; Transfer learning	Models are easy to use and replicable; low financial cost	Too many algorithms; results are not reliable
Machine learning imagery classification; Time-series deep learning	Emerging technology and promising results; low financial cost	Require high quality labels and advancing algorithms; lack of research

Table 3: Summary of techniques for mapping poverty
Source: (Lin et al., 2021)

4.0 MAPPING MULTIDIMENSIONAL POVERTY IN AFRICA

Multidimensional poverty remains a major challenge in Africa, with a large proportion of the population living in poverty across multiple dimensions such as health, education, living standards, and access to basic services. According to the United Nations Development Programme's (UNDP) Multidimensional Poverty Index (MPI), which measures poverty across multiple dimensions, Africa has the highest level of multidimensional poverty in the world. In 2021, the MPI estimated that over 480 million people in Africa (around 40% of the population) live in MP. The drivers of multidimensional poverty in Africa are complex and multifaceted, with factors such as conflict, climate change, inequality, and weak governance contributing to the persistence of poverty in many countries. The COVID-19 pandemic has also had a significant impact on poverty in Africa, exacerbating existing vulnerabilities and pushing more people into poverty. Consequently, the need for mapping poverty still remains an issue. While most of the studies focused on African continent is still highly dependent on traditional approach, a number of studies have been seen to have adopted the geospatial and AI methodologies.

Several studies have been conducted involving the application of Geospatial and AI technologies in MP mapping in Africa. The challenges of designing poverty alleviation programs with tightening budgets was addressed by (Bigman & Fofack, 2000). Geographical information systems (GIS) were highlighted for detailed poverty mapping, MP identification, and optimizing service delivery to the poor. Household survey data combined with environmental variables from satellite imagery was used to create poverty maps in Uganda, which reveals that combining household survey data with satellite imagery improves poverty predictions, highlighting the influence of environmental factors (Rogers et al., 2006). Batana, (2013) applies the Alkire and Foster multidimensional poverty measures to estimate poverty among women in 14 Sub-Saharan African countries, revealing significant differences across dimensions. Including additional dimensions alters country rankings, with rural areas experiencing higher poverty rates and lack of schooling being a key contributor. Marx et al. (2014) carried out a systematic review to examine the use of geoinformation analyses in studying malnutrition in Sub-Saharan Africa. The review suggests incorporating crowd-sourced geodata collection and spatial health data infrastructures to deepen understanding of this complex issue. Remote sensing and household surveys was applied to link agro-ecological factors with poverty patterns in Burkina Faso, revealing strong spatial dependency and validating the approach (Imran et al., 2014). Geospatial visualizations of poverty deprivation were created as a contextual baseline for future evaluation by (Victor et al., 2014). The MPI of water poverty is applied to show the impact of water scarcity on African populations (Jemmali, 2017). The findings reveal disparities in water poverty between developed but water-scarce countries and lower-income water-rich countries. This study demonstrates the use of multidimensional poverty measures and geospatial maps to evaluate public health interventions, highlighting the prevalence and determinants of poverty in Mozambique. Geospatial analysis of Nigeria's MP, focusing on Jigawa State reveals a dynamic poverty pattern and highlight the role of physical and natural resources in contributing to the state's high poverty rate (Gambo et al., 2022). Berenger (2019) examines poverty levels and trends in Malawi, Mozambique, Tanzania, and Zimbabwe using various poverty measures. The findings emphasize the importance of considering both breadth and inequality components in multidimensional poverty analysis. Abeje et al. (2020) examines multidimensional poverty in three drought-prone agro-ecological settings in Ethiopia. The Alkire-Foster method and Correlation Sensitive Poverty Index (CSPI) are used to analyze poverty. The study emphasizes the need for contextualized indicators and location-specific approaches in poverty research and policy design. Based on the study of (Jean et al., 2016), involving the application of the transfer learning approach within 5 African countries, Malawi, Tanzania, Nigeria, Uganda, and Rwanda the out-of-sample R2 accuracies obtained are 0.55, 0.57, 0.68, 0.69 and 0.75 respectively. Ayush et al. (2021) proposes a reinforcement learning approach that combines low-resolution imagery with high-resolution imagery to predict poverty in Uganda, achieving improved performance with fewer high-resolution images.

However, a call for validation of the outputs over the African continent still remains a bone of contention. Using remotely sensed data to illustrate the nature of poverty in Africa based on the night light emission as a poverty indicator, Figure 1 shows the Niger River Delta between Lagos (Nigeria) in the West and Doula (Cameroon) in the East. Highlighting the statement of Ehrlich et al., (2018) based on this figure "Both major cities exhibit the expected features of large well-lit metropolitan areas. The secondary cities and rural areas are represented by yellow reddish colours representing diffuse settlement infrastructure with little or no public illumination. There is however a number of blue dots, which map the oil extraction sites in the delta. They can be seen as an allegory of inequality. The oil revenues generated by the oil extraction a largely disconnected from the local population.

From the current global MP database (World Bank, 2022), the information for Africa were extracted and presented on Table 4 and mapped in Figure 2. The database has revealed that MP data in Africa are limited and outdated. For instance, from the global MP database, the 2019 data is the latest data in Africa, which is found in only 3 countries in Africa (Malawi, Uganda and Zimbabwe). While Congo in Central Africa has its latest MP data in 2011. Also, some countries in Africa such as Tanzania, Eritrea, Central African Republic, Algeria and Libya were completely missing on the global MP databased.

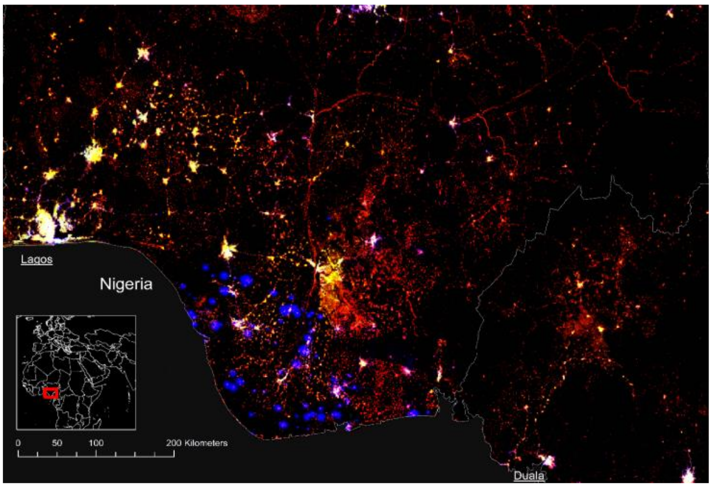

Fig. 1. Typical example of night time light illustrating the well-lit oil extraction sites in the midst of highly populated settlements deprived of nightlights.
Source: (Ehrlich et al., 2018)

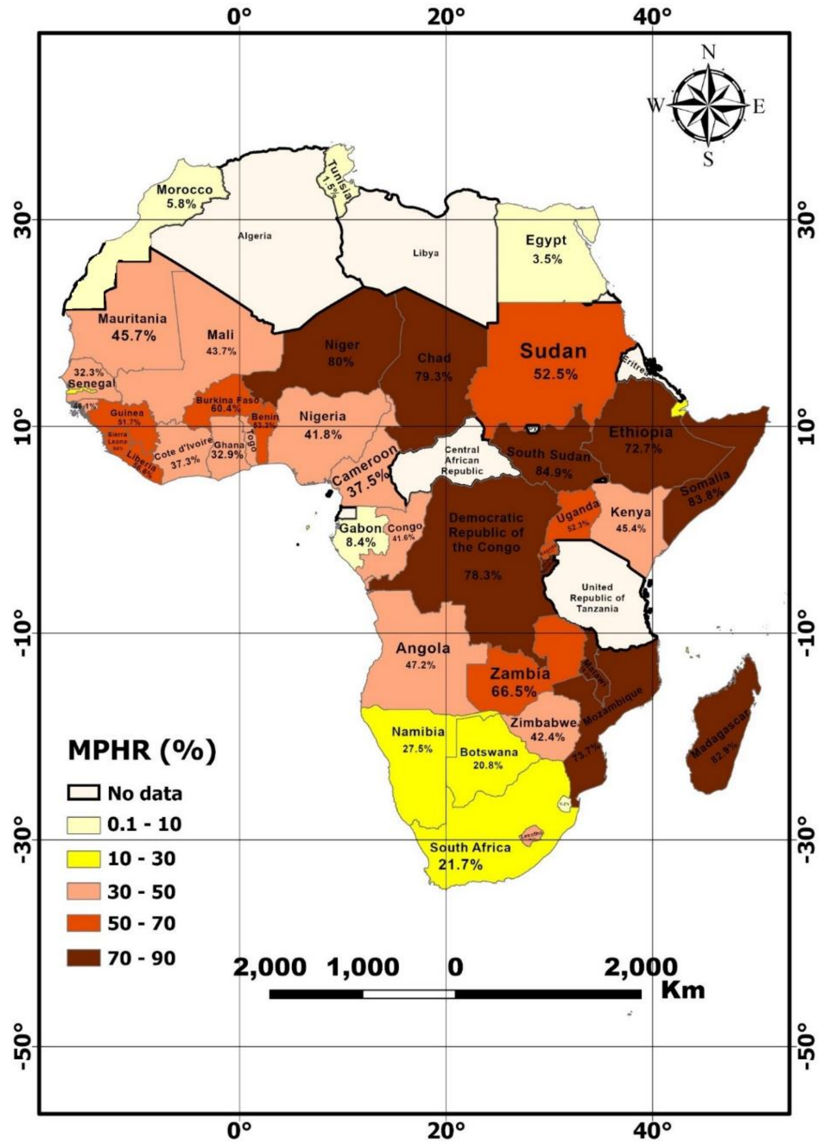

Fig. 2. Multidimensional poverty headcount ratio in Africa
Source: (World Bank, 2022)

Table 4. Individuals in households deprived in each indicator, African, (for 2009 and later; with 2017 ICP). Source: (World Bank, 2022)

	Deprivation rate (share of population)							
Country NAME	**Survey Year**	**Monetary (%)**	**Educational attainment (%)**	**Educational enrollment (%)**	**Electricity (%)**	**Sanitation (%)**	**Drinking water (%)**	**Multidimensional poverty headcount ratio (%)**
Angola	2018	31.1	29.8	27.4	52.6	53.6	32.1	47.2
Benin	2018	19.9	50.2	31.5	54.3	80.0	22.1	53.3
Botswana	2015	15.0	8.2	4.2	35.5	52.0	3.7	20.8
Burkina Faso	2018	30.5	56.4	50.9	47.2	69.6	19.7	60.4
Burundi	2013	65.1	66.3	18.9	91.8	94.3	20.6	85.2
Cape Verde	2015	4.6	11.7	2.7	9.9	30.2	11.1	7.6
Cameroon	2014	25.7	24.4	15.9	1.2	38.9	23.2	37.5
Chad	2018	30.9	69.0	34.9	90.0	87.0	34.8	79.3
Comoros	2014	18.6	15.3	7.3	28.5	67.2	6.4	26.3
DR Congo	2012	69.7	22.5	8.0	83.0	80.0	47.9	78.3
Congo	2011	35.4	13.4	2.3	29.9	47.3	23.4	41.6
Cote d'Ivoire	2018	11.4	48.6	30.4	18.1	64.4	20.7	37.3
Djibouti	2017	19.1	30.1	18.0	34.2	45.4	7.1	29.3
Egypt	2017	2.5	10.6	4.2	0.5	3.2	0.8	3.5
Ethiopia	2015	27.0	66.7	31.2	64.1	95.9	42.7	72.7
Gabon	2017	2.5	11.3	7.9	8.6	68.2	11.5	8.4
Gambia	2015	13.4	29.9	6.1	8.0	58.2	8.2	18.3
Ghana	2016	25.3	15.1	9.0	19.5	79.9	40.8	32.9
Guinea	2018	13.8	61.3	25.0	56.4	71.1	21.0	51.7
Guinea-Bissau	2018	21.7	41.0	30.1	42.1	63.0	21.6	46.1
Kenya	2015	29.4	22.5	6.1	56.9	69.0	32.2	45.4
Lesotho	2017	32.4	18.1	4.8	58.7	55.1	13.7	40.7
Liberia	2016	27.6	30.5	54.1	79.7	61.8	25.7	56.6
Madagascar	2012	80.7	49.0	34.7	13.0	76.9	59.9	82.9
Malawi	2019	70.1	54.3	3.7	88.8	75.1	11.4	78.3
Mali	2018	14.8	66.6	28.2	23.9	51.9	23.8	43.7
Mauritania	2014	6.5	54.3	8.3	54.1	49.3	38.6	45.7
Mauritius	2017	0.1	7.2	0.2	0.2	-	-	0.4
Morocco	2013	1.4	12.7	6.8	2.4	12.9	8.7	5.8
Mozambique	2014	64.6	54.9	33.3	14.6	71.3	41.1	73.7
Namibia	2015	15.6	11.3	6.1	53.8	68.3	9.2	27.5
Niger	2018	50.6	79.7	28.0	78.7	85.2	37.5	80.0
Nigeria	2018	30.9	17.6	20.3	39.4	44.9	27.5	41.8
Rwanda	2016	52.0	36.9	4.3	64.0	28.1	24.5	57.4
Sao Tome and Principe	2017	15.6	19.5	4.3	31.2	62.0	8.2	24.9
Senegal	2018	9.3	42.0	31.9	26.6	37.4	15.2	32.3

Seychelles	2018	0.5	0.4	-	0.0	0.2	5.5	0.9
Sierra Leone	2018	26.0	28.7	18.7	68.7	87.2	33.8	54.0
Somalia	2017	70.7	59.2	56.3	50.6	39.4	11.8	83.8
South Africa	2014	20.5	2.3	2.3	4.1	35.2	10.4	21.7
South Sudan	2016	67.3	39.3	62.2	-	88.1	13.9	84.9
Sudan	2014	15.3	40.2	22.7	48.5	92.9	44.9	52.5
Swaziland	2018	0.2	0.0	-	0.0	0.1	0.1	0.2
Togo	2018	28.1	32.7	14.0	47.4	83.7	25.3	46.4
Tunisia	2015	0.1	20.2	2.1	0.2	6.5	2.1	1.5
Uganda	2019	42.2	31.4	11.8	41.3	71.1	23.7	52.3
Zambia	2015	61.4	24.4	30.4	69.2	60.0	34.4	66.5
Zimbabwe	2019	39.8	0.9	6.0	38.0	38.3	19.3	42.4

5. POTENTIAL PITFALLS IN MAPPING MULTIDIMENSIONAL POVERTY IN AFRICA

The gaps identified from review of studies in mapping multidimensional poverty using geospatial techniques and artificial intelligence (AI) in Africa, including:

1. Lack of high-quality, spatially disaggregated data: Mapping multidimensional poverty using geospatial techniques and AI requires high-quality data that are spatially disaggregated. However, in many African countries, data are often limited, outdated, or not disaggregated at the local level, making it challenging to accurately map poverty across different dimensions.
2. Limited understanding of the social and cultural context: Poverty is not only an economic phenomenon, but also a social and cultural one. To accurately map multidimensional poverty, it is important to understand the social and cultural context in which poverty occurs. However, there is limited research on how social and cultural factors influence poverty in different regions of Africa.
3. Ethical and legal considerations: The use of geospatial techniques and AI raises ethical and legal concerns related to privacy, data ownership, and informed consent. More research is needed to understand how to ensure that the use of these techniques is ethical, transparent, and inclusive.
4. Limited focus on vulnerable populations: Mapping multidimensional poverty using geospatial techniques and AI should prioritize the needs of vulnerable populations such as women, children, and ethnic minorities. However, there is limited research on how to effectively capture the experiences of these populations and to design interventions that are inclusive and equitable.
5. Limited consideration of the intersectionality of poverty: Poverty is not experienced in isolation, but rather intersects with other social identities and experiences such as gender, race, and disability. Mapping multidimensional poverty using geospatial techniques and AI should consider the intersectionality of poverty, but there is limited research on how to effectively do so.

6. CONCLUSIONS

Geospatial mapping of poverty can be used to identify areas and populations that are most affected by poverty, and to target resources and interventions where they are most needed. Poverty maps can be used to identify areas with high levels of multidimensional poverty and to prioritize the allocation of resources and development projects to these areas. Geospatial mapping can also be used to identify the spatial patterns of poverty, such as the spatial concentration of poverty in certain regions, urban-rural disparities in poverty, and the links between poverty and environmental factors such as land use and climate change. Furthermore, geospatial mapping can provide a valuable tool for monitoring and evaluating poverty reduction programs and policies. By tracking changes in poverty over time, geospatial mapping can help to assess the impact of poverty reduction programs and to identify areas where further interventions may be needed. Application of satellite data can provide a cost-effective and automatic way to estimate and monitor poverty rates at high spatial resolution, especially in countries with limited capacity to support traditional methods of data collection.

Application of AI in mapping MP can be seen is in the analysis of satellite imagery. Satellite imagery can be used to identify features such as housing, infrastructure, and vegetation, which can be used as indicators of poverty. Machine learning algorithms can be trained to analyze these features and to identify areas that are most likely to be affected by poverty. Natural language processing techniques can also be used to analyze text data, such as survey responses or social media posts, to identify indicators of poverty and to better understand the lived experiences of those affected by poverty. By analyzing these data sources, AI can provide a more refined understanding of poverty and its drivers. Another application of AI in mapping MP is in the development of predictive models that can forecast changes in poverty over time. By analyzing historical data and identifying patterns and trends, these models can provide insights into the future trajectory of poverty and can inform the development of poverty reduction strategies.

The integration of geospatial techniques and AI in mapping MP in Africa has the potential to provide more accurate and timely information for policymakers and development practitioners, and to inform the development of effective poverty reduction strategies. However, it is important to ensure that these techniques are developed and used in an ethical and transparent manner, and that they do not perpetuate or exacerbate existing inequalities. There is also need for more research that addresses gaps in mapping MP using geospatial techniques and AI in Africa, in order to provide more accurate and detailed understandings of poverty and to design interventions that effectively address the needs of the most vulnerable populations.

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11. KEY TERMS AND DEFINITIONS

Income Poverty: focuses on assessing poverty based on income levels. It typically involves establishing a poverty line or threshold, below which individuals or households are considered poor (Alkire & Foster, 2011)

Multidimensional Poverty (MP): Unlike income poverty, this measure takes into account multiple dimensions of well-being and deprivation. It considers various aspects such as education, health, housing, access to clean water, sanitation, and other social and economic factors (World Bank, 2020)

Human Development Index (HDI): Developed by (UNDP), the HDI measures poverty by considering factors such as life expectancy, education, and income per capita. It provides a broader assessment of development beyond income measures alone (Priambodo, 2021)

Artificial Intelligence (AI): is the intelligence of machines or software as opposes to the intelligence of humans. It is aapplied in analysing large amounts of data and to identify patterns and trends in multidimensional poverty.

Multidimensional Poverty Index (MPI): created by the UNDP and Oxford University, measures poverty across multiple dimensions. This approach uses a set of indicators that capture different dimensions of poverty, such as health, education, housing, sanitation, and access to basic services. These indicators are combined to create a multidimensional poverty index (MPI) that measures the extent of poverty in a given population (World Bank, 2018).

Multidimensional Poverty Measure (MPM): an indicator that gauges the proportion of households facing deprivation across three dimensions of well-being: monetary poverty, education, and basic infrastructure services. Unlike the MPI, the MPM includes the dimension of monetary poverty.