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Economic well-being assessment: a review of traditional and remote sensing approaches

Longfei Wang[a,b], Tengfei Long[a,b], Wei Jiang[c], Elhadi Adam[d], Chunhui Wen[a,b], Weili Jiao[a,b] and Guojin He[a,b]

[a]Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing, People's Republic of China; [b]University of Chinese Academy of Sciences, Beijing, People's Republic of China; [c]China Institute of Water Resources and Hydropower Research, Beijing, People's Republic of China; [d]School of Geography, Archaeology and Environmental Studies, University of the Witwatersrand, Johannesburg, South Africa

ABSTRACT

This paper reviews the evolution of economic well-being assessment, examining traditional methods based on surveys and statistics alongside the emergent field of satellite remote sensing. Traditional approaches, employing indicators like GDP, HDI, and MPI, offer established methodologies but face limitations in data accessibility, spatial coverage, and capturing dynamic changes. Satellite remote sensing, utilizing nighttime light, daytime imagery, and derived data like NDVI, overcomes these constraints by providing large-scale, timely, and periodic surface information. Furthermore, we analyze methods for large-scale economic well-being assessment using remote sensing, encompassing statistical analysis, machine learning, deep learning, and transfer learning. Finally, we explore future directions, emphasizing the development of more comprehensive indicators, multi-source data fusion integrating subjective well-being, and advancements in deep neural networks to improve accuracy, generalization, and interpretability for robust, large-scale economic well-being assessment and poverty reduction strategies.

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Poverty; subjective well-being; satellite; deep learning; transfer learning

1. Introduction

The eradication of poverty is the first goal of the United Nations' 2030 Agenda for Sustainable Development, which aspires to eliminate all forms of poverty globally by 2030. Poverty is not simply a lack of financial resources but a multifaceted phenomenon encompassing multiple deprivations, including compromised access to healthcare, education, and suitable living conditions (Alkire and Santos 2014). While a few countries, such as China, achieved the remarkable feat of eradicating absolute poverty ahead of schedule in 2021, significant global challenges persist in achieving this universal goal. Existing research suggests that, based on prevailing trends, global poverty eradication will lag behind its target date by 19 years (Liu et al. 2023), underscoring the urgent need for intensified poverty reduction efforts.

CONTACT Tengfei Long longtf@aircas.ac.cn Aerospace Information Research Institute, Chinese Academy of Sciences, 100094, Beijing, People's Republic of China; University of Chinese Academy of Sciences, 100049, Beijing, People's Republic of China; Wei Jiang jiangwei@iwhr.com China Institute of Water Resources and Hydropower Research, Beijing 100038, People's Republic of China

To effectively eradicate poverty, it is crucial to formulate comprehensive poverty alleviation policies and accurately assess its effectiveness. For countries and regions that have been lifted out of poverty, it is also necessary to establish long-term mechanisms, and implementing continuous dynamic monitoring to prevent regression is critical.

Poverty reduction is a multifaceted challenge that requires a comprehensive approach. Different key indicators, such as income, health, education, living standards, economic growth, employment, social inclusion, and environmental sustainability, have been used to monitor poverty reduction(Illien et al. 2022; Poole 2005). However, combining these indicators can provide a more accurate and holistic understanding of poverty and the effectiveness of poverty reduction strategies.

Economic well-being is a crucial indicator of poverty reduction as one of the key indicators of poverty reduction; it reflects individual satisfaction with material living and encompasses various dimensions such as income, wealth, access to essential services, and overall living standards. Therefore, accurate assessment of economic well-being is paramount for formulating effective poverty reduction policies, monitoring the poverty reduction process in a timely manner and ultimately achieving the Sustainable Development Goals (SDGs).

The SDGs are interconnected, forming a complex web of interdependent objectives (Cook and Davíðsdóttir 2021). The pursuit of poverty eradication must be synergistically aligned with the goals for sustained economic growth, fulfillment of social needs, mitigation of climate change, and environment protection. For instance, economic growth can generate employment opportunities and raise income levels (Haider et al. 2023), thereby improving the economic circumstances of the impoverished populations. Social policies can provide essential resources and improve access to healthcare and education. Conversely, climate change and environmental degradation can severely impact the livelihoods of vulnerable populations, exacerbating existing poverty (Kumssa 2025). Consequently, these factors must be carefully considered in the development of comprehensive and impactful poverty reduction strategies.

In recent years, countries have gradually shifted from a single focus on economic levels to the pursuit of broader and more sustainable well-being in the development process, and have actively sought more appropriate evaluation indicators to measure social progress. Stiglitz, Sen, and Fitoussi (2009), for example, advocates for a multidimensional approach to measuring economic progress, encompassing not only GDP but also household disposable income, income distribution, environmental quality, health, and education. This reflects an evolving understanding of development, one that prioritizes holistic human development and improved well-being alongside economic growth. While macroeconomic indicators provide valuable insights into a society's overall economic health, individual subjective well-being, reflecting personal perceptions of quality of life, constitutes another crucial dimension for assessment (Voukelatou et al. 2021). Happiness captures subtle changes in people's perceptions of their quality of life and can be a powerful complement to objective indicators, providing a more humane and people-centered perspective for policy formulation. Incorporating subjective well-being into assessment frameworks can help to identify poverty more accurately, contribute to the comprehensive eradication of poverty and ultimately improve overall societal well-being. This can be achieved through the collection of data on life satisfaction and happiness via surveys and other methods and integrating this data with objective economic indicators to construct a more holistic assessment system.

The spatial and temporal resolution requirements of economic well-being assessment fundamentally shape methodological choices. For instance, national-level poverty monitoring may prioritize broad coverage through satellite-derived proxies like nighttime lights, whereas local policy planning necessitates high-resolution poverty mapping at village or neighborhood scales. The statistical methods used to collect poverty data on a regular basis in national surveys such as the census are limited by space and frequency and can only be representative of rough spatial units. Therefore, when a small range or more frequent survey statistics are needed, other statistical methods should be selected, such as small area estimation and higher resolution remote sensing data. In poverty studies, high-resolution poverty maps are essential for effective policy planning. High resolution poverty maps can improve the accuracy of poverty reduction policy making, and they can direct more policies to the poorest households than traditional survey-based poverty maps (Smythe and Blumenstock 2022).

High resolution remote sensing images can often support related work (Ayush et al. 2021). At the same time, high-resolution poverty maps may have limitations such as insufficient spatial coverage and limited by specific data environments. Therefore, appropriate statistical methods should be selected according to different policy requirements of different policy scenarios.

We conducted a literature search with the keyword 'economic well-being' on the Web of Science, then used Google Scholar and other academic websites to search for keywords, screened the highly relevant literatures that were not in the database, and removed the less relevant literatures such as pure economic models in the subsequent literature reading. As shown in Figure 1, more and more research institutions use a variety of data sources and methods to assess economic conditions. Reviewing these studies allows understanding and learning about the strengths and limitations of various approaches, providing valuable insights into current and emerging research trends that benefit both researchers and policymakers.

Traditional methods based on surveys and statistics, as well as satellite remote sensing assessment methods that have emerged in recent years, are widely used to assess economic well-being, and researchers use a variety of different data sources, including survey data, daytime remote sensing data, nighttime remote sensing data, and other spatial data such as temperature and Normalized Difference Vegetation Index (NDVI). Sorting out and summarizing different research methods, learning the outstanding advantages of each method, and discovering its shortcomings can contribute to the assessment of economic well-being in the future and lay a solid theoretical foundation.

This paper presents an overview of methods for assessing economic well-being, focusing on traditional survey-based and statistical approaches alongside the emergent field of satellite remote sensing-based assessments. It will discuss the respective strengths, limitations, and future trajectories of these methods (Figure 2). Furthermore, this paper will explore the future development of large-scale economic well-being assessment methodologies to provide a robust scientific foundation for the design and implementation of effective poverty reduction policies.

This review makes three key contributions to the field:

1) We systematically analyze and synthesize commonly used indicators of economic well-being derived from both traditional survey data and remote sensing sources. We critically evaluate the strengths and weaknesses of each indicator, providing guidance for selecting appropriate metrics for different research contexts and spatial scales. This synthesis aids in the construction of more robust and contextually relevant economic well-being indices.

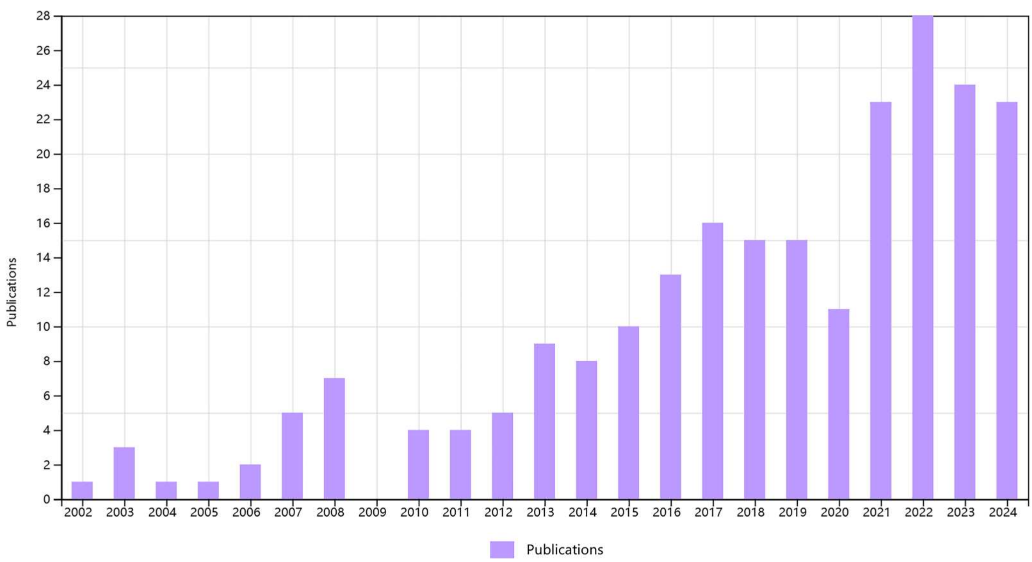

Figure 1. Number of journal articles published per year containing the keyword 'economic well-being' from 2002–2024. This data was acquired from Web of Science (www.webofknowledge.com).

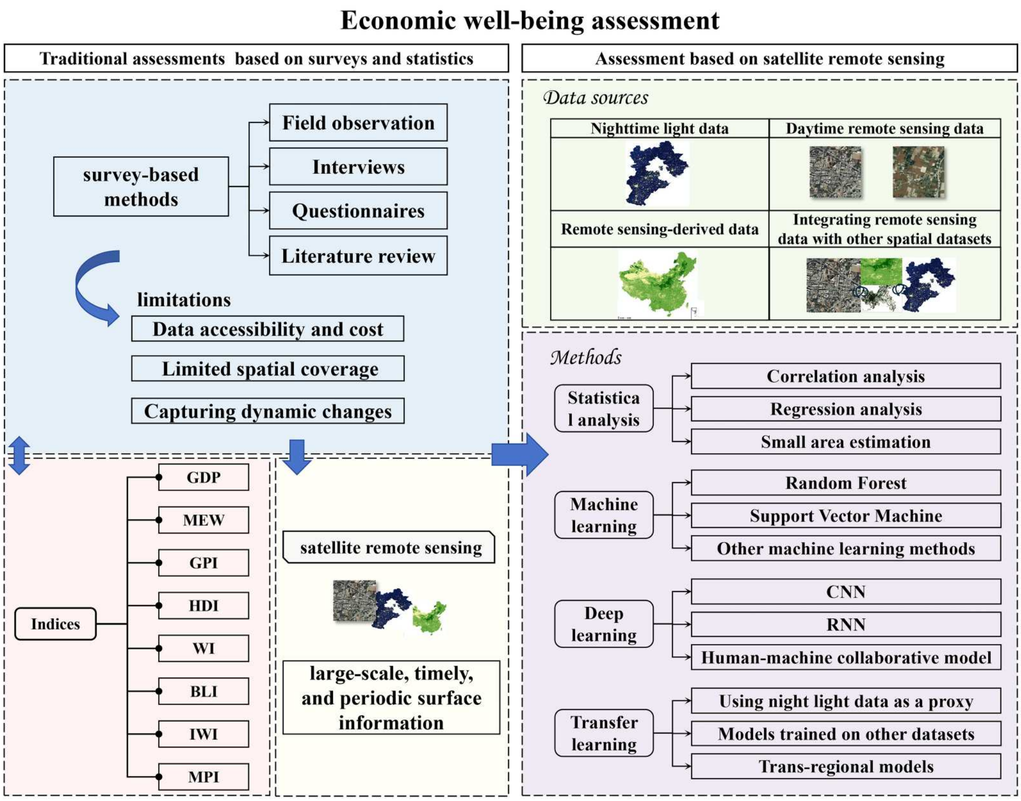

Figure 2. Structure of this paper.

2) We present a novel, structured framework that categorizes economic well-being assessment methods into two primary groups: (a) traditional survey-based approaches and (b) remote sensing-based approaches. Within the remote sensing category, we further delineate methods based on the analytical techniques employed (e.g. statistical regression, machine learning, deep learning). This framework clarifies the evolution and interrelationships between different methodological approaches.
3) We provide a critical evaluation of cutting-edge methods, including machine learning and deep learning techniques, highlighting their advantages and limitations. We identify key challenges and propose concrete directions for future research. A central theme of this future direction is the strategic integration of diverse data sources, including remote sensing data, traditional surveys, and novel sources like textual data from media news analyzed using Large Language Models (LLMs). We emphasize the importance of addressing challenges related to multi-source data fusion, bias mitigation, ethical considerations, and enhancing model interpretability to ensure that these advanced techniques are used responsibly and effectively for policy-making.

2. Traditional assessments of economic well-being based on surveys and statistics

Traditional assessments of economic well-being have predominantly relied on social surveys and statistical data, employing a multi-indicator system to quantify various facets of individuals' economic circumstances. These indicators typically encompass income levels, consumption capacity, asset ownership, and access to social security.

2.1. Indices for measuring economic well-being

1) Comprehensive indices

Gross Domestic Product (GDP), as a core indicator of national economic accounting, initially served as a primary indicator of economic well-being, often considered synonymous with it (C. Xie and Jin 2023). However, evolving societal understanding of well-being has revealed GDP's limitations in fully capturing its multifaceted nature. For example, GDP fails to account for the environmental and resource depletion costs associated with economic growth, overlooks income and wealth distribution inequalities, and neglects qualitative aspects of life. Recognizing these shortcomings, the United Nations Development Programme (UNDP) in 1996 cautioned against using GDP as the sole indicator of economic well-being, identifying five detrimental forms of GDP growth: jobless, unequal, unsustainable, insecure, and voiceless growth. These highlight the importance of considering additional indicators reflecting employment opportunities, income disparities, environmental sustainability, social security, and public participation, respectively.

Several alternative indicators have been proposed to address GDP's limitations. The Measure of Economic Welfare (MEW) (Nordhaus and Tobin 1971) adjusts GDP by subtracting costs associated with environmental pollution and urbanization, while adding factors such as the value of housework and leisure. However, MEW remains incomplete, failing to incorporate welfare gains from advancements in health and education. For instance, it does not account for improved health outcomes resulting from medical and public health advancements, nor does it consider the increase in knowledge brought about by the spread and quality of education.

To further refine the MEW, the American economists Daly and Cobb proposed the Index of Sustainable Economic Welfare (ISEW) in 1989 (Cobb and Daly 1989). The ISEW considers the distribution of income, net capital, and the growth of foreign and domestic capital, depletion of natural resources, environmental damage Subsequently, an organization called Redefining Progress revised the ISEW methodology and published a renamed Genuine Progress Indicator (GPI). Both ISEW and the GPI remain in use, with only minor differences between them, and often considered equivalent (Posner and Costanza 2011). Multi-country analyses suggest an inverse relationship between ISEW and GDP, indicating a widening gap between economic output and genuine well-being (Sánchez, Toledo, and Ordóñez 2020). However, practical application of GPI faces challenges due to data limitations and boundary issues at finer geographical scales, particularly regarding accurate quantification of environmental damage costs.

The Human Development Index (HDI), published annually by the UNDP since 1990, incorporates life expectancy, adult literacy, and logarithmic GDP per capita, reflecting longevity, knowledge, and standard of living, respectively. While more comprehensive and objective than GDP, with readily available data, the HDI neglects the environmental impact of development (Sagar and Najam 1998). In addition, indicators such as literacy rates are heavily influenced by historical factors and do not accurately reflect the true effects of current policies.

In 2004, the DHS Wealth Index (WI) was introduced (Rutstein and Johnson 2004), to measure the relative economic status of households through indicators such as household assets, public services, and consumer goods. Employing principal component analysis to weight these variables, the WI generates a standardized score reflecting overall household economic status, facilitating international comparisons and policy development. However, its applicability and accuracy across diverse cultural contexts remain subject to debate due to potential influences of cultural differences and data collection constraints.

In 2009, the Organization for Economic Co-operation and Development (OECD) proposed the OECD Better Life Index (BLI) (Nardo et al. 2005). The BLI consists of 11 topics, including income, education, and life satisfaction, and collects data mainly in the form of questionnaires and interviews. Its distinctive feature is the ability for individuals to weight topics based on personal values, aiming to capture subjective well-being more comprehensively (Greco et al. 2020). However, the BLI's credibility remains contested due to the potential influence of internal and external factors on individual responses.

In 2012, the UNEP released its first global report on inclusive wealth, using the Inclusive Wealth Index (IWI) to measure sustainable development (UNU-IHDP and UNEP 2012). The IWI considers natural capital (land, minerals, water, and other natural resources), human capital (health, education, etc.), and productive capital (infrastructure, etc.) to provide a more comprehensive measure of human well-being and development. However, data availability challenges hinder its widespread application, particularly at the city level. In addition, IWI neglects some renewable energy sources and environmental impacts, leading to its inadequacy and accuracy (Cheng et al. 2022).

The UNDP and the Oxford Poverty and Human Development Initiative collaborated to develop the Multidimensional Poverty Index (MPI) to quantify high levels of poverty (Alkire and Santos 2014). The MPI reflects the extent to which a person is unable to meet minimum international standards for Millennium Development Goal-related indicators in three dimensions of health, education, and standard of living, and contains ten specific indicators. nuanced (Dotter and Klasen 2017).

Table 1 summarizes these commonly used indicators, highlighting their respective advantages and disadvantages.

Beyond the aforementioned established indicators, various governmental bodies and research organizations have developed more nuanced indicator systems tailored to specific contexts, aiming for a more holistic representation of societal progress and well-being. For instance, the New Zealand government's 2019 'well-being budget' guided by the Living Standards Framework (LSF), exemplifies this approach. The LSF considers four capital assets – natural, human, social, and financial/physical – underpinning twelve domains of well-being, including environmental quality, health, housing, income and consumption, social connections, and subjective well-being. This framework provides a multidimensional perspective on national development and individual well-being, offering a compelling model for integrating well-being into national policy and budgetary processes.

2) Individual indicators and specific methodologies

Complementing comprehensive indicator systems, researchers have explored a range of individual indicators and assessment methodologies.

Table 1. Economic well-being measurement indicators and their advantages and disadvantages.

Index	content	advantage	disadvantage
GDP	Production value within a region.	Core economic indicator; widely available.	Ignores distribution, environment, non-market factors.
MEW	GDP adjusted for environment, urbanization, housework, leisure.	Broader than GDP; includes non-market & environmental costs.	Incomplete; lacks data.
ISEW/GPI	Consumption, inequality, assets, environmental & resource costs.	Reflects distribution, environment, and resource depletion.	Data-intensive; geographically limited.
HDI	Life expectancy, education, GNI per capita.	Comprehensive; objective; readily available; multi-dimensional.	Ignores environment; influenced by history; life expectancy limitations.
WI	Household assets, services (PCA based).	Integrated household status; easy to measure; comparable internationally.	Data limitations; cultural variations in asset ownership.
BLI	Subjective life satisfaction (survey-based).	Captures subjective well-being; individual weights; comprehensive for individuals.	Subjective biases; credibility concerns.
IWI	Human, produced, and natural capital.	Includes natural capital; broader view of development.	Data limitations; incomplete environmental factors.
MPI	Health, education, living standards (10 indicators).	Combines poverty incidence & intensity; multi-dimensional; guides interventions.	Data limitations; may lack quality information.

The Grameen Foundation's Progress out of Poverty Index (PPI), a country-specific metric based on ten closed-ended questions employing a ten-point scoring system, predicts the likelihood of households living below the poverty line (Desiere, Vellema, and D'Haese 2015). Its simplicity facilitates rapid poverty assessment. Cook and Davíðsdóttir (2021) advocate for considering the interconnections between economic activity and human well-being, employing a suite of indicators – GDP, Environmentally Adjusted Net Gross Domestic Product (EDP), MEW, Genuine Savings (GS) (also known as Adjusted Net Savings), GPI, and IWI – to provide a more complete picture of economic well-being. Moro-Egido, Navarro, and Sánchez (2022) explored the influencing factors of subjective well-being over time based on the German Socio-Economic Panel (GSOEP) data, which includes self-reported life satisfaction scores on a 0–10 scale, alongside information on economic, family, and social goals. Ali and Khan (2023) leveraged data from the Chinese General Social Survey (CGSS) and utilized binary logistic regression to assess the influence of human capital and social interaction on individual economic returns. Saridakis et al. (2021) developed a four-point family happiness index and investigated family economic status and spending power through questionnaires, using an ordered logit model to explore the determinants of economic well-being.

These diverse studies underscore the complexity of economic well-being and the multifaceted approaches required for its assessment. The selection of appropriate indicators and methodologies should be guided by specific research objectives and data availability.

In summary, the landscape of economic well-being assessment exhibits increasing diversity, encompassing single indicators and comprehensive systems, objective and subjective measures, and traditional and emerging methodologies. Future research should prioritize the judicious selection of indicators and methods, aligned with specific research questions and data constraints, to ensure accurate assessments of economic well-being and inform the development of effective poverty reduction strategies.

2.2. Economic well-being assessment based on social survey data

Traditional economic well-being assessments primarily utilize social survey methods, including questionnaires, field observations, interviews, and literature reviews.

1) **Field observation:** Researchers directly observe and document individuals' living environments, infrastructure, and housing conditions to visualize living standards. While providing real-world insights, this method is susceptible to chance factors, labor-intensive, difficult to scale, and challenging to quantify.
2) **Interviews:** Through in-person or telephone interviews, researchers gather data on income, expenditure, consumption habits, and life satisfaction. While yielding richer information than field observations, interviews are resource-intensive and prone to interviewer bias. When the interview method is applied to the assessment of economic welfare, an additional disadvantage may be introduced, namely that respondents may underestimate or exaggerate their assets and wealth in order to seek benefits or obtain more policy support. While online interviews offer increased efficiency (Zhang et al. 2017), face-to-face interviews remain a reliable and predominantly utilized mode in certain studies (De Leeuw, Hox, and Dillman 2012).
3) **Questionnaires:** Self-administered questionnaires, either paper-based or online, collect data on economic status and quality of life. This method offers scalability and efficiency in data collection and analysis, but requires respondent literacy and is susceptible to biases introduced by questionnaire design and wording.
4) **Literature review:** Researchers compile existing statistics and research findings from government reports, statistical yearbooks, and academic publications. This method offers broad scope and readily analyzable data.

These social survey methods generate valuable data for poverty measurement and economic well-being assessment. For example, Alkire et al. (2023) the Moderate Multidimensional Poverty Index (MMPI) using household survey data from Bangladesh, Guatemala, Iraq, Serbia, Tanzania, and Thailand, while Li et al. (2019) multidimensional poverty in China using various national and provincial statistical sources.

2.3. Limitations of traditional assessment methods

Despite their established methodologies, survey-based assessments face limitations:

(1) **Data accessibility and cost:** Nationally representative surveys are expensive and infrequent in many developing countries, hindering access to timely and reliable data (Yeh et al. 2020). The estimated cost of achieving sufficient sample sizes in low-income countries can be prohibitive (Espey et al. 2015).
(2) **Limited spatial coverage:** Traditional surveys struggle to reach remote or conflict-ridden areas, leading to data gaps. Even in data-rich areas, the spatial resolution may be insufficient for localized assessments.
(3) **Capturing dynamic changes:** Infrequent surveys struggle to capture short-term fluctuations in economic well-being, while traditional indicators like income and consumption may lag behind real-time living standards.

3. Economic well-being assessment based on satellite remote sensing

When conducting large-scale assessments of economic well-being, traditional survey data can present problems such as limited data, time lags (Tiago et al. 2017), and spatial coverage that is difficult to support large-scale assessments. Countries where data on key indicators of economic development are less readily available tend to experience these limitations even more acutely. Satellite remote sensing, on the other hand, offers a powerful alternative, overcoming limitations of traditional survey data by providing large-scale, timely, and periodic surface information. This technology supports economic well-being assessments at local, regional, and global scales.

3.1. Principles of assessing economic well-being using remote sensing data

The fundamental premise of using remote sensing data for economic well-being assessment is that human activities and their associated economic outcomes leave detectable and measurable signatures on the Earth's surface. These signatures, captured by various remote sensing sensors, provide indirect but valuable information about socio-economic conditions. This approach leverages the interconnectedness between human activity, the built environment, and natural resources.

Several key principles underpin this approach:

1) Economic activity and radiance: Higher levels of economic activity often correlate with increased energy consumption, resulting in detectable artificial light emissions, particularly at night.
2) Development and land surface characteristics: Economic development leads to transformations in land cover and land use, creating distinct spectral, spatial, and textural patterns observable in daytime imagery. These patterns reflect the presence of urban areas, infrastructure, and agricultural activities.
3) Well-being and environmental indicators: Environmental conditions, measurable through remote sensing, can be both a consequence of and an influence on economic well-being. Factors

like vegetation health and surface temperature can reflect agricultural productivity, access to green spaces, and the impact of urbanization.

4) Wealth and built environment attributes: The characteristics of the built environment, such as building density, road networks, and even building materials (observable with high-resolution imagery), can provide insights into the relative wealth and living standards of an area.

3.2. Data sources and their relation to economic well-being principles

This section details the specific types of remote sensing data utilized for economic well-being assessment and how they embody the principles outlined above.

3.2.1. Nighttime light data

Nighttime light (NTL) data, acquired from platforms such as satellites and the International Space Station, captures the radiance of artificial light sources and serves as a robust proxy for the intensity and spatial distribution of human activity (Li et al. 2022). Its strong correlation with socio-economic indicators renders it invaluable for diverse applications, including assessing economic prosperity, monitoring urban expansion, and estimating population density (Bennett and Smith 2017; Cao et al. 2014; Chen et al. 2022; Elvidge et al. 2009; Ghosh et al. 2013; Liu, Pei, and Jia 2017; Ma et al. 2014; Mellander et al. 2015; Samha, Yuxiao, and Wenbin 2024; Zhang et al. 2022; Zhang and Seto 2011). The utility of NTL data is particularly pronounced in data-scarce regions, such as those found across the African continent (Yeh et al. 2020), where it offers critical insights into socio-economic development. As shown in Figure 3, the spatial distribution of NTL strongly correlates with regional economic development patterns. Commonly employed NTL datasets encompass DMSP-OLS, VIIRS-DNB, ISS, LuoJia1-01, SDGSAT-1, and commercial satellite products. Each data source is characterized by distinct spatial and temporal resolutions and capabilities (Table 2). While NTL data provide valuable insights into economic dynamics, their utility is constrained by inherent technical limitations. For instance, in rural areas where economies rely heavily on farming, NTL struggles to capture meaningful signals because it mainly detects electrified activities like streetlights or buildings (Andersson, Hall, and Archila 2019). This means it often misses low-light activities common in rural livelihoods, such as small-scale farming or informal markets

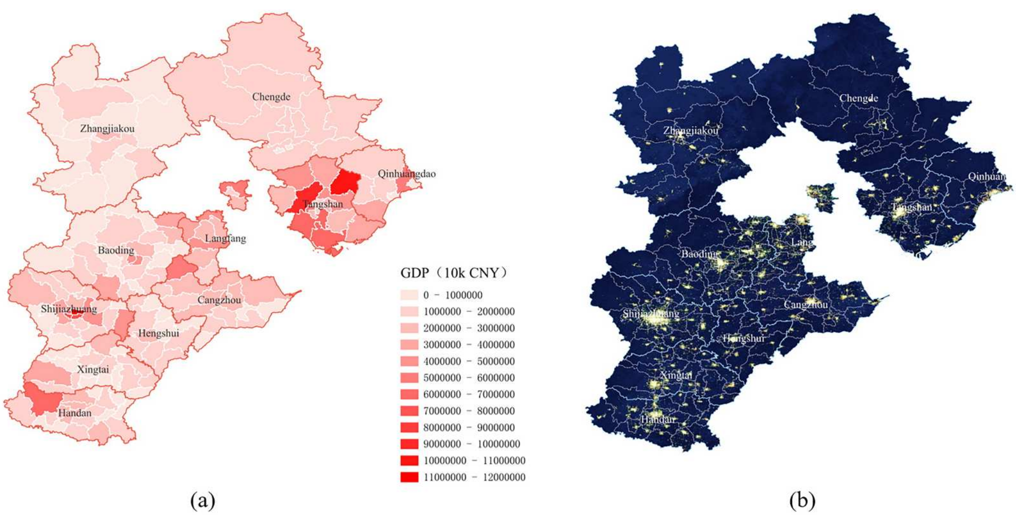

Figure 3. The distribution of nighttime lighting in Hebei Province is highly consistent with the distribution of GDP at the county and district levels. (a) Distribution of GDP at county and district level in Hebei Province, data from China County Statistical Yearbook; (b) Nighttime lighting data in Hebei Province from SDGSAT-1 satellite.

Table 2. Comparison of commonly employed nighttime light (NTL) data sources.

Dataset	Platform/ Sensor	Temporal Coverage	Spatial Resolution	Key Features	Source URL	Access Type
DMSP-OLS	DMSP/OLS	1992–2013	~2.7 km	Longest continuous record; useful for long-term trend analysis.	https://www.ngdc.noaa.gov/eog/dmsp.html	Open
VIIRS-DNB	Suomi NPP/ VIIRS	2012-Present	~750 m	Improved spatial and radiometric resolution; detects fainter lights.	https://www.ngdc.noaa.gov/eog/viirs/download_ut_mos.html	Open
LuoJia1-01	LJ1-01 Satellite	2022-Present	130 m	Dedicated NTL satellite; high spatial resolution and broad spectral range.	http://59.175.109.173:8888/ (registration required)	Open
ISS	Astronauts' camera	2003-Present	5–200 m	High spatial resolution potential; offers unique perspectives and targeted observations.	https://eol.jsc.nasa.gov/	Open
SDGSAT-1	SDGSAT-1/GIU	2021-Present	10 m / 40m	High sensitivity; RGB data; suitable for fine-scale and developing region analysis.	https://www.sdgsat.ac.cn/	Open
BlackSky	BlackSky Constellation	2020-Present	<1 m	Very high spatial resolution; frequent revisit rates; targeted tasking capabilities.	https://blacksky.com/	Commercial

(Gibson et al. 2021). To improve accuracy, combining NTL with daytime satellite data and local survey data can help paint a clearer picture of economic conditions in both cities and countryside areas.

3.2.2. Daytime remote sensing data

Daytime remote sensing data provide higher spatial and spectral resolution, capturing detailed surface information like land cover, vegetation, water bodies, and building density. This data can be correlated with economic well-being by reflecting land use, ecological quality, and infrastructure development. Analysis of building characteristics, road networks, and green spaces provides further insights into living conditions and accessibility. High-resolution imagery is particularly valuable for identifying and assessing poverty in areas like slums (Netzband and Rahman 2009), by analyzing building characteristics (Okuda, Kawasaki, and Yamashita 2023; Sapena, Ruiz, and Taubenböck 2020), road network characteristics (Kohli, Sliuzas, and Stein 2016), and the availability of green spaces (Melon et al. 2024; Tang, Liu, and Matteson 2022) and public spaces (Li et al. 2023; Wurm et al. 2019). Figure 4 illustrates road extraction from high-resolution imagery.

Commonly utilized diurnal remote sensing data sources include the Landsat series, the Sentinel series, and various high-resolution satellite platforms. The Landsat series, jointly developed by the National Aeronautics and Space Administration (NASA) and the United States Geological Survey (USGS), provides a multi-decadal record of surface observations dating back to 1972, offering crucial support for analyzing surface dynamics and long-term trends. The Sentinel series, developed by the European Space Agency (ESA) and operational since 2014, boasts enhanced spatial and temporal resolution, enabling the acquisition of finer-grained surface information and providing a more precise dataset for economic well-being assessments. Furthermore, high-resolution satellite imagery (e.g. WorldView, GeoEye, QuickBird, Gaofen series), with spatial resolutions at the meter or even sub-meter scale, facilitates highly refined spatial analyses for economic well-being assessments. These data permit the extraction of detailed surface features, such as building typology, roofing materials, and road widths, offering a more nuanced representation of regional development and quality of life. High-resolution satellite data are particularly indispensable for investigations requiring fine-grained spatial information, including slum identification and urban expansion analysis. For instance, the WorldView-3 satellite can acquire imagery with a resolution

Figure 4. Road extraction supported by DeepGlobe Road dataset (Demir et al. 2018). (a) DigitalGlobe high-resolution satellite data; (b) Road extraction based on daytime remote sensing imagery.

of 0.31 meters, enabling clear identification of building types, roofing materials, and other pertinent features (Juergens and Meyer-Heß 2021; Warth et al. 2020).

3.2.3. Remote sensing-derived data

Remote sensing-derived data, calculated from remote sensing imagery using algorithms and models, provide insights into surface characteristics and phenomena. These include indicators like NDVI, which reflects vegetation growth, agricultural production, and ecological quality, and land surface temperature (LST), derived from thermal infrared data. These indicators can be correlated with economic well-being by reflecting agricultural productivity, environmental quality, and the impact of climate change. For example, NDVI has been used to analyze the impact of ecological restoration on economic development (Fan, Bai, and Zhao 2022; Hu and Xia 2019; Li, Shi, and Wu 2021) while temperature data inform studies on the economic impacts of climate change (Dell, Jones, and Olken 2012; Kotz et al. 2021; Meierrieks and Stadelmann 2024; Newell, Prest, and Sexton 2021; Shukla et al. 2022).

Remote sensing-derived data are indicators based on remote sensing images, calculated through certain algorithms and models, that reflect surface characteristics or phenomena. Using remote sensing-derived data, the impact of ecological conditions, climate change and other factors on economic well-being can be analyzed, providing more dimensional data support for economic well-being assessment.

Normalized Difference Vegetation Index (NDVI): NDVI is an indicator of vegetation growth and cover, but it can also reflect factors such as agricultural production, ecological quality, etc., which in turn affects economic well-being. For example, in agriculture, NDVI can be used to monitor crop growth, estimate crop yields, and assess agricultural droughts, all of which are closely related to farmers' incomes and food security, and thus affect economic well-being. Li, Shi, and

Wu (2021) combined NDVI and night light data to analyze the impact of ecological restoration on economic development in China, and found that with the increase of NDVI, the value of night light showed a trend of first rising and then decreasing, which suggests that while ecological restoration can promote economic development, we need to consider the potential negative impacts on economic growth, and need to formulate appropriate policies according to the local conditions. Fan, Bai, and Zhao (2022) combined annual per capita GDP and NDVI data to determine the response of ecological health to rapid economic development in 14 consecutive multi-year poverty-stricken regions in China, and then assessed the impacts of policies on ecological health. Hu and Xia (2019) analyzed the changes in vegetation cover in the Pearl River Delta from 2000 to 2016, using medium resolution imaging spectroradiometer NDVI data combined with climate data, GDP and population data, and found that there is a positive correlation between NDVI and economic growth in the Pearl River Delta region, indicating that rapid economic development and improvement of vegetation cover in a region can be achieved simultaneously through good policies, which is a reference for the sustainable development of the region.

Temperature: Temperature is an important indicator of climate change and can be obtained from thermal infrared remote sensing data. Temperature changes, especially extreme heat events, can negatively affect agricultural production, human health, labor productivity, etc., thereby reducing economic well-being. According to the United Nations Intergovernmental Panel on Climate Change (IPCC) report, the global average surface temperature is expected to be 1.09°C higher during 2011–2020 compared to the period 1850–1900 (Shukla et al. 2022), and global warming is projected to have a negative impact on human life. Existing research on the relationship between warming and the economy at the local level is limited and inconclusive, but several studies have shown statistically significant marginal effects of warming on poorer areas with weak political and economic systems (Dell, Jones, and Olken 2012; Kotz et al. 2021; Meierrieks and Stadelmann 2024; Newell, Prest, and Sexton 2021).

3.2.4. Integrating remote sensing data with other spatial datasets

To achieve a more holistic assessment of economic well-being, remote sensing data can be integrated with other geospatial datasets (e.g. point of interest (POI) data, census data, house price data, mobile signal data) to construct a multi-source data fusion model, leveraging the complementary strengths of each data source to enhance the accuracy and reliability of the assessment.

1) Integrating nighttime light data with other datasets

Nighttime light and population data: Integrating nighttime light data with population density data allows for the assessment of economic activity intensity and population distribution patterns. For instance, Elvidge et al. (2009) generated a global poverty map by combining nighttime light data with population data to construct a poverty index.

Nighttime light and economic data: Nighttime light data can be combined with GDP data to analyze regional economic development levels (Benedek and Ivan 2018; Zhao et al. 2017) and the relationship between urbanization and electricity infrastructure development (Zhu, Li, and Ru 2022). Kim (2022) exemplified this by using nighttime light data to estimate North Korea's regional economy.

Nighttime light and POI data: Combining nighttime light data with POI data enables assessment of the spatial distribution of commercial activities and public service facilities (Figure 5). For example, Shi et al. (2020) integrated nighttime light and POI data to create a poverty distribution map with a 500-meter spatial resolution, while Chen et al. (2022) used this combination to assess digital economy development.

Beyond utilizing raw nighttime light intensity values, integrating other spatial datasets allows for the extraction of more nuanced luminous features, particularly in areas with limited nighttime light emissions. Wang and Li (2024), for example, combined nighttime light data with the World

Settlement Footprint (WSF) dataset to extract multi-dimensional luminous features for assessing asset wealth in light-deficient regions, such as many unelectrified areas in Africa.

2) Combination of daytime remote sensing data and other datasets

Daytime remote sensing and land use/cover data: Daytime remote sensing data can be combined with land use/cover data to analyze urban sprawl (Wang et al. 2012) and socio-economic drivers of land use change (Seto and Kaufmann 2003). For example, Nurwanda, Zain, and Rustiadi (2016) analyzed land cover change and landscape fragmentation, using regression analysis to identify drivers of land use change.

Daytime remote sensing and census data: Daytime remote sensing data can be combined with census data to assess the level of socio-economic development of an area (Chao et al. 2021; Li and Weng 2007). For example, Salas et al. (2021) combined Landsat-7 imagery with census data to assess the vulnerability of communities.

Daytime remote sensing and urban attribute data: It is possible to link building features extracted from daytime remote sensing data to urban attributes and population distribution (Chao et al. 2021). For example, Engstrom, Hersh, and Newhouse (2022) found that features extracted from high-resolution satellite imagery can explain changes in poverty headcount rates and average incomes in Sri Lankan villages.

3) Combination of remote sensing-derived data and other data

NDVI and economic data: NDVI can be combined with GDP per capita data to assess the response of ecological health to economic development (Fan, Bai, and Zhao 2022). For example, Li, Shi, and Wu (2021) combined NDVI with night-time lighting data to analyze the impact of ecological restoration on economic development in China.

Temperature and economic data: Temperature data can be combined with economic data to analyze the impact of climate change on economic development (Kotz et al. 2021). For example,

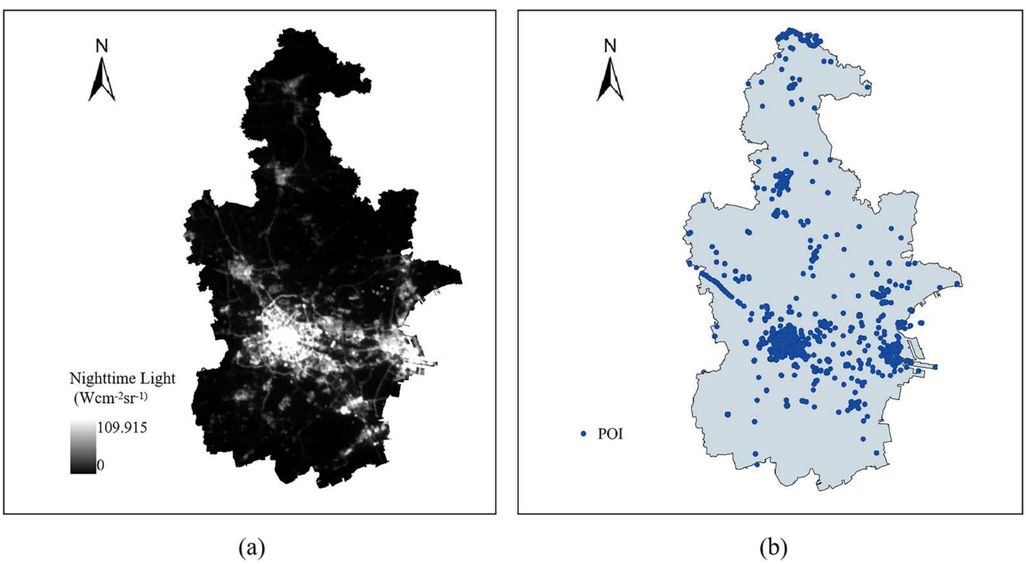

Figure 5. Nighttime light image and POI distribution image of Tianjin, China, based on VIIRS satellite data and OpenStreetMap (OSM) POI data. (a) Nighttime Light data for Tianjin; (b) POI distribution in Tianjin.

Shah and Tallam (2023) predicted poverty in Ethiopia using a transfer learning model trained on temperature data.

Remote sensing derived data and population census data: Remote sensing derived data can be combined with population census data to assess the relationship between the state of the ecological environment and the level of socio-economic development (Hu and Xia 2019; Tang, Liu, and Matteson 2022).

4) Combination of remote sensing data and Mobile signal data

Mobile signal data and mobile call detailed record (CDR) data can provide information on population movements and activities, and when combined with remote sensing data, can more comprehensively and dynamically depict economic well-being. For example, Pokhriyal and Jacques (2017) combined CDR, census data, and environmental variables to predict MPI poverty values for Senegal. Steele et al. (2017) combined CDR, remote sensing data and traditional survey data to construct a poverty prediction map for Bangladesh.

5) Multi-source data fusion

Multi-source data fusion can comprehensively utilize the advantages of various data sources, overcome the limitations of a single data source, and provide more comprehensive and reliable economic well-being information. For example, Yu et al. (2023) expanded the time series of night light data with higher spatial resolution by learning the SDGSAT-1 night light image with limited temporal resolution and integrating NPP-VIIRS and Sentinel-2 images. Poverty assessments at the county level were conducted based on the expanded data and statistical yearbooks. Li et al. (2023) constructed MPI by combining night light data, POI data, census data and housing prices, and took the Pearl River Delta region as the research area to comprehensively measure the degree of poverty. Wang et al. (2023) mapped the urban poverty space at a fine scale by using multiple sources of big data, such as social perception and remote sensing data, with the urban core area of Zhengzhou as the study area. Chao et al. (2024) built a multi-dimensional correlation system by comprehensively using remote sensing images, minimum living security data of urban residents, community data, point of interest (POI), street view images, building contours and community population data to measure urban relative poverty at the community level in Wuhan.

3.3. Methods for large-scale economic well-being assessment based on remote sensing images

At present, large-scale economic well-being assessment methods based on remote sensing images include statistical analysis, machine learning, deep learning, and transfer learning.

3.3.1. Methods based on statistical analysis

Methods based on statistical analysis mainly use the statistical relationship between remote sensing data and economic well-being indicators, such as correlation analysis, regression analysis, etc., to establish a prediction model between remote sensing data and economic well-being indicators. Correlation quantifies the strength and direction of association between two variables in a symmetrical manner, without distinguishing independent/dependent variables. Regression establishes an asymmetrical predictive model to estimate causal effects, requiring explicit specification of predictors and outcomes (Le Cessie, Groenwold, and Dekkers 2021). Correlation often serves as a preliminary step for variable screening before regression modeling, but correlation analysis itself cannot prove causality between variables and can only be used in scenarios such as exploratory data analysis, while regression analysis can establish predictive models and quantify causality. On this basis, small area estimation (SAE) is based on regression modeling, adding random effects into the regression model, and using data fusion to carry out statistical analysis of small sample areas. This class focuses on the use of statistical theory to build models, which are usually relatively simple and less dependent on data.

Correlation analysis: Correlation analysis is used to study whether there is a linear relationship between two variables, as well as the strength and direction of the relationship. In the assessment of economic well-being, correlation analysis can be used to study the relationship between remote sensing data and economic well-being indicators, such as the correlation between night light data and GDP, and the correlation between NDVI and agricultural output value. Benedek and Ivan (2018) analyzed the relationship between GDP and night light with statistical correlation, and the results proved that there is a strong linear correlation between the two, which means that night light is an excellent proxy for measuring economic development. Hu and Xia (2019) analyzed the changes of vegetation coverage in the Pearl River Delta region from 2000 to 2016. They combined climate data, GDP, and population data with NDVI data of medium resolution imaging spectral radiometer and found that there was a positive correlation between NDVI and economic growth in the Pearl River Delta region. It shows that through good policies, the rapid economic development, and the improvement of vegetation coverage in a region can be realized at the same time, which brings reference for the sustainable development of the region.

Pérez-Sindín, Chen, and Prishchepov (2021) used rural Colombia as an example to explore whether night light data are representative of all levels of economic activity at the local level and in rural areas in middle – and low-income countries. Finds that night light data are a good proxy for economic activity in rural areas of Colombia, but considers that there is no guarantee that the same conclusions will be reached in all regions. Li, Shi, and Wu (2021) combined NDVI and night remote sensing data to analyze the impact of ecological restoration on economic development in China, and found that with the increase of NDVI nationwide, night light value showed a trend of first increasing and then decreasing, and appropriate policies should be formulated according to local conditions.

Zhu, Li, and Ru (2022) examined the relationship between urbanization and electrification by analyzing night light data in Tanzania. They defined the land electrification rate (LER) to measure the degree of electrification and found a negative correlation between LER and the rate of urban expansion, indicating that the construction of power infrastructure lags behind the urbanization process. Kim (2022) used night light data to estimate the regional economy of North Korea, which has few public statistical data, and revealed that the spatial distribution of low-income counties in the country shifted from areas near the border of South Korea to areas near the border of China under the influence of sanctions, and pointed out that there was significant county-level economic inequality in North Korea. Chen et al. (2023) used the strong correlation between night light data and social and economic indicators such as urbanization, GDP and population to study the dynamic change and spatial pattern of economic development differences between eastern and western China.

Regression analysis: Regression analysis is used to study the relationship between one or more independent variables and a dependent variable, and to build a predictive model. In the assessment of economic well-being, regression analysis can be used to establish a forecasting model between remote sensing data and economic well-being indicators, such as using NTL data to predict GDP, using building characteristics to predict resident income, etc. In recent years, some studies have used high-resolution satellite images to extract contextual features and correlate them with urban attributes and population distribution through regression analysis. Zhao et al. (2017) used regression analysis to study the correlation between the corrected VIIRS night light data and regional GDP in southern China, and found that the two presented a quadratic polynomial relationship, and the fitting of county GDP was better than that of city GDP. The study shows that the night light data can effectively reflect the level of regional economic development; Li and Weng (2007) integrated remote sensing data and census data into the GIS framework, evaluated the quality of life in Indianapolis, USA, by constructing the urban quality of life index, and predicted the quality of life by using the regression model. Faisal, Shaker, and Habbani (2016) used multi-temporal Landsat TM satellite images to extract urban built-up areas and conducted regression analysis between socio-economic parameters and built-up areas. Goldblatt, Heilmann, and Vaizman (2020) only relied on medium-resolution satellite images and simple regression models to predict economic activity and consumption measures, and achieved good results in small areas. Chao et al. (2021) evaluated the ability to use context features extracted from multi-scale satellite images to map spatial patterns of urban attributes and population distribution, and the results showed that context features can map urban attributes well, with out-of-sample R^2 values as high as 0.93. Engstrom, Hersh, and Newhouse (2022) showed a strong correlation between features extracted from high-resolution satellite images and economic well-being. For 1291 villages in Sri Lanka, a simple linear model can explain about 60% of the change in poverty rate and average income. It was significantly higher than the interpretability of models built using night lights (15%).

Small area estimation (SAE): SAE is a method of statistical inference for sub-regional and local level with insufficient sample sizes, which produces reliable estimates at fine spatial administrative levels (Pratesi 2016). The commonly used models include Fay-Herriot model and Nested-error Regression model, which are essentially regression models with random effects. Small area estimation (SAE) has become instrumental in addressing data scarcity challenges for localized economic assessments. Schmid et al. (2017) demonstrated the viability of integrating mobile network metadata with national surveys to estimate subnational literacy rates in Senegal. Their Fay-Herriot model utilized tower-level communication patterns as auxiliary variables, revealing gender-specific literacy disparities across 431 communes. This work established mobile data as a cost-effective alternative to traditional censuses, particularly for monitoring Sustainable Development Goals in low-income regions. Masaki et al. (2022) advanced multisource SAE frameworks by systematically comparing household-level Empirical Best Predictor (EBP) and area-level Fay-Herriot models for poverty mapping in Tanzania and Sri Lanka. Incorporating geospatial covariates like nighttime light intensity and building density improved precision by 15-30%, with EBP models achieving efficiency gains comparable to fivefold sample size increases. Their findings underscore the importance of high-resolution satellite data in resolving temporal inconsistencies between infrequent censuses and annual poverty metrics. De Nicolò, Fabrizi, and Gardini (2024) addressed methodological gaps through a Bayesian Extended Beta model for upazila-level poverty estimation in Bangladesh. By introducing censoring mechanisms for extreme proportions and regularization priors, their approach effectively handled clustered survey data and spatial autocorrelation while propagating prediction uncertainty. The model's compatibility with complex sampling designs enhances its utility for governments requiring granular yet statistically robust economic indicators.

3.3.2. Methods based on machine learning

Different from methods based on statistical analysis, machine learning-based methods focus on using algorithms to learn patterns from data, usually with more complex models and a higher degree of dependence on data. Machine learning methods use computer algorithms to automatically learn patterns in data and make predictions or classifications. In economic well-being assessment, the non-linear relationship between remote sensing data and economic well-being indicators can be effectively established, and features can be automatically extracted, thus improving prediction accuracy and efficiency.

Random Forest: Ensemble learning refers to a machine learning paradigm that trains multiple base learners and combines their predictions to improve prediction accuracy and performance (Mienye and Sun 2022). As an ensemble learning method, random forest improves prediction accuracy by building multiple decision trees and combining their prediction results. Its powerful predictive power and interpretability make it one of the most widely used machine learning methods in areas such as economic well-being assessment and poverty identification. Several studies have shown that random forest model can effectively use night light data, daytime remote sensing data and remote sensing derived data to predict poverty levels. For example, Zheng et al.

(2024) combined multi-source data to construct a 10 km resolution poverty level prediction model. Yin, Qiu, and Zhang (2020) found that the model combining NTL and geographical features was more accurate in identifying poverty than the model using only NTL features. Singha et al. (2020) used the random forest model to model the livelihood vulnerability of riverine islands affected by erosion and flood along the Ganges River in India, and the results showed that the method could effectively identify areas of high vulnerability. Arribas-Bel, Patino, and Duque (2017) used land cover, spectrum, structure and texture features extracted from Google Earth images to evaluate the potential of random forest method for predicting living environment deprivation at the level of small statistical areas, and proved the effectiveness of random forest method. Random forest models have also been applied to predict the incidence of malnutrition and poverty. (Browne et al. 2021), the Multidimensional Poverty Index (MPI) (Wang et al. 2021), the Integrated Poverty Index (IPI) (Xu, Mo, and Zhu 2021), Community poverty (Tang, Liu, and Matteson 2022), multidimensional poverty indicators at village level (Marcinko et al. 2022), and so on.

Support Vector Machine: A support vector machine is a supervised learning algorithm for classification and regression analysis that divides data into different categories by finding an optimal hyperplane. Support vector machines have advantages in dealing with high-dimensional data and nonlinear relationships, so they are also used in areas such as economic well-being assessment and poverty identification. Li et al. (2019) used support vector machine and other methods to identify high-poverty counties using only DMSP/OLS NTL images and achieved good performance. The study by Singha et al. (2020) demonstrated that the support vector machine model showed the highest accuracy in predicting livelihood vulnerability. Additionally, Support vector machines have been used to predict MPI (Wang et al. 2021) and poverty status (Yin, Qiu, and Zhang 2020).

Other machine learning methods: In addition to Random Forests and Support Vector Machines, other machine learning methods, such as Gradient Boosting Machine, Adaptive Boosting (AdaBoost), Extreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM) have also been applied to the assessment of economic well-being. For example, Xu, Mo, and Zhu (2021) used the XGBoost model to construct an integrated poverty index (IPI) model for the Dian-Gui-Qian rocky desertification contiguous special hardship area and achieved the best prediction results. Zheng et al. (2024) used a variety of machine learning models, including random forest (RF), support vector machine (SVM), adaptive boosting (AdaBoost),extreme gradient boosting (XGBoost) and light gradient boosting machine (LightGBM) to model the county-level Multidimensional Poverty Index (MPI), and showed that the Random Forest model has the highest accuracy. Arribas-Bel, Patino, and Duque (2017) in addition to exploring classical methods (such as Ordinary Least Squares (OLS) regression and spatial lag models), also explored the potential of gradient boosting regressors and random forests to improve prediction performance and accuracy.

3.3.3. Methods based on deep learning

Deep learning is an important branch of machine learning, which uses multi-layer neural networks to learn complex features in data and can process more complex remote sensing data, such as high-resolution images and multi-spectral images. In recent years, deep learning has made remarkable achievements in image recognition, object detection, semantic segmentation, and other fields, providing new ideas and methods for the research of economic well-being and poverty based on remote sensing images. The commonly used deep learning models include Convolutional neural network (CNN), Recurrent Neural Networks (RNN), human-machine collaboration model and so on.

Convolutional neural network (CNN): CNN is a feed-forward neural network and it has achieved significant results in the fields of image recognition, target detection, etc. CNN is able to automatically learn spatial features such as edges, textures, shapes, etc. in an image and use them for classification or regression tasks. In economic well-being and poverty studies, CNNs are used to extract features related to economic well-being, such as slums or poor neighborhoods, from remotely sensed images and build predictive models. For example, Wurm et al. (2019) and Lu et al. (2024) used CNNs to identify slums in Mumbai, India, and Ajami et al. (2019) used CNNs to identify poverty in the slums of Bangalore, India. In addition, CNNs have also been used to predict indicators related to economic well-being, such as household wealth, income levels, etc. For example, Huang, Hsiang, and Gonzalez-Navarro (2021) used CNNs to assess the effectiveness of an anti-poverty program in rural Kenya, and inferred changes in household wealth from changes in housing quality. CNNs can also be used to quantify environmental characteristics related to economic well-being, such as urban greening and agricultural production. For example, Tang, Liu, and Matteson (2022) used a publicly available, medium-resolution NDVI index and a convolutional neural network (CNN) to predict poverty in poor neighborhoods that are highly dependent on agriculture, and showed that the NDVI was effective in detecting changes in consumption over time, which is critical for understanding the relationship between agricultural production and economic well-being. Naidoo et al. (2022) evaluated the performance of multiple machine learning methods, including deep learning methods, in estimating maize crop structural parameters (leaf area index (LAI), stem height (HT), stem diameter (DIA) and stem density (SD)) in the Maize Triangle region of South Africa. These parameters are closely related to maize yield and can reflect the state of agricultural production, which in turn affects economic well-being.

Recurrent Neural Networks (RNN): RNN is a kind of neural network capable of processing sequence data, which has achieved remarkable results in natural language processing, speech recognition and other fields. RNNS are able to learn time dependencies in data, such as predicting fluctuations in stock prices, recognizing actions in videos, and so on. In studies of economic well-being and poverty, RNNS can analyze temporal changes in remote sensing images and predict dynamic trends in economic well-being indicators. For example, Tang et al. (2024) comprehensively used NTL, NDVI and other data to extract a model based on ConvLSTM (CNN + LSTM) for poverty assessment and generated a high-precision poverty map of Nigeria with a resolution of 10 km. Pettersson et al. (2023) used multi-temporal images and recursive convolutional neural networks to infer material asset wealth at the community level, and their model performs better in generalization than the most advanced models available, explains 72% of the wealth variation across countries and 75% of the wealth variation across time, and creates a spatial–temporal physical asset data map covering the entire African continent from 1990 to 2019. Zhang et al. (2021) combined the climate and vegetation index extracted from satellites with the maize yield data from field investigations, established a prediction model using long short-term memory network (LSTM), and proved that the LSTM model could represent the cumulative effect of environmental factors on yield. Better results than LightGBM and LASSO.

Other deep learning models: In addition to CNNS and RNNS, other deep learning models have also been applied to economic well-being and poverty research, such as residual neural networks (ResNet), Inception networks, DenseNet, and others. These network architectures show excellent performance in image recognition tasks and can be applied to economic well-being assessment through transfer learning. For example, Tan et al. (2020) proposed a multi-task learning model combining deep residual neural networks (ResNet) and feature pyramid networks to estimate poverty levels using multi-source data such as night light data, Landsat 8 images, and spectral index data. Yeh et al. (2020) used a variant of the ResNet architecture to predict the asset wealth of about 20,000 villages in Africa. Agyemang et al. (2023) separately trained three CNN models using transfer learning methods: ResNet50, InceptionV3 and DenseNet121, and used them to predict long-term poverty in Pakistan's rural Sindh province in a single set. Pettersson et al. (2023) used the CNN-LSTM model combined with multi-temporal imagery to infer material asset wealth at the community level, and their model performed better in generalization than the most advanced models available.

Human-machine collaborative deep learning model: The training of deep learning models requires a large amount of annotation data, and manual annotation is time-consuming and laborious. Human-machine collaboration can effectively solve this problem, combining manual annotation with machine automatic annotation to improve the efficiency and quality of annotation. For example, Ahn et al. (2023) proposed a human-machine collaborative deep neural network model, which first trained a basic model with a small amount of sample data, then used the model to make predictions on a large number of unlabeled satellite images, and ranked the images according to the prediction results. Human experts then annotate the top-ranked images and use the annotated data to further optimize the model. The study used human–computer collaboration to predict North Korea's economic development without any ground data, using publicly available satellite imagery and lightweight subjective ranking annotations. In poverty mapping studies, such collaboration proves critical for mitigating human cognitive biases while preserving domain knowledge. For example, Sarmadi et al. (2024) systematically compared Tanzanian village wealth assessments by domain experts and CNN models, revealing that human evaluators exhibited central tendency bias, whereas the machine learning approach achieved 50% accuracy using Sentinel-2 imagery – 23 percentage points higher than direct human evaluations.

3.3.4. Methods based on transfer learning

Transfer learning is a machine learning technique that uses a model trained on one task to improve the performance of another related task, thereby reducing the amount of training data required for the target task and improving the model's generalization ability. In economic well-being assessment, transfer learning methods can apply existing economic well-being assessment models to new regions or new data sources, for example, applying models trained in developed countries to developing countries, thereby overcoming the problem of data scarcity, and improving the applicability and prediction accuracy of models.

Using night light data as a proxy: Because of the strong correlation between night light data and economic activity, some studies have used night light data as a proxy indicator of economic development, training deep learning models on daytime images to predict the level of night light intensity and thus indirectly predict economic well-being. Xie et al. (2016) proposed a transfer learning approach (Figure 6) that uses nighttime light intensity as a proxy for economic activity and trains a fully convolutional CNN model to predict nighttime light from daytime images while learning features useful for poverty prediction. The model simultaneously predicts nighttime light levels and extracts spatially explicit features relevant to poverty mapping, and achieves 71.58% validation accuracy within 223,500 iterations, demonstrating efficient convergence without spatial cropping. Based on this, Ni et al. (2021) conducted experiments using four different deep learning models to verify the feasibility and effectiveness of the method of predicting poverty through deep learning using night data as a proxy. Liu et al. (2021) used nighttime light remote sensing data as a proxy for socio-economic indicators, constructed a label for night light intensity levels in daytime satellite images, and trained the attention-enhanced VGG-16 network as a feature extractor to estimate county-level GDP in China using both day and night remote sensing data. NTL labels focus on effective regions through transfer learning constraints and reduce overfitting of irrelevant ground objects (such as farmland textures), which improves model generalization ability. This method achieved an R^2 of 0.71 for county-level GDP estimation, a 0.04 improvement in R^2 compared to the model without NTL guidance, without significantly increasing model complexity.

Models trained on other datasets: Some studies use deep learning models trained on other datasets, such as the ImageNet dataset, to extract features from remote sensing images and then apply these features to economic well-being assessments. For instance, Castro and Álvarez (2022) first leveraged a pre-trained model to extract features from daytime images for fitting new CNNs, then classified nighttime light intensity and extracted features adopted in the regression process, thereby demonstrating the validity of socio-economic indicators in Brazil. Daoud et al. (2023) trained a deep learning model using 40% of India's census data to extract features from Landsat satellite imagery, subsequently applying transfer learning to construct a predictive model for developmental variables in the National Family Health Survey (NFHS) through transfer learning.

Trans-regional models: Some studies apply models trained in one region to another, such as models trained in developed countries to developing countries, to overcome data scarcity. Sarmadi et al. (2023) used low-resolution satellite imagery and transfer learning methods to predict poverty in Tanzania, showing that high-precision economic forecasting can be achieved using lower-resolution satellite imagery. Shah and Tallam (2023) used a transfer learning model trained on temperature data to extract features from satellite images and successfully predict poverty in Ethiopia. Agyemang et al. (2023) trained three CNN models, ResNet50, InceptionV3 and DenseNet121, using geocentric household survey data (including poverty scores) and publicly available data (including day and night satellite images and accessibility data) of 1.67 million anonymous households in Sindh province, Pakistan. Using them to predict long-term poverty over a 1 square kilometer area in rural Sindh province of Pakistan in a single set, the results show that the integrated model provides the most reliable spatial predictions for both arid and non-arid regions.

The higher the similarity between two regions, the better the model will work (Leye Wang et al. 2019). Conversely, while trans-regional models enable cost-effective large-scale analysis, their accuracy can decline when applied to regions with distinct environmental or economic conditions (Chi et al. 2022). For instance, models trained in agricultural economies may fail to capture industrial or service-driven wealth patterns visible in urbanized areas. Variations in data availability – such as limited mobile network coverage in remote regions or seasonal satellite obstructions (e.g. cloud cover) – further reduce prediction reliability. Head et al. (2017) based on economic assessments of wealth in small areas of sub-Saharan Africa, concludes by comparison that while satellite imagery and machine learning may provide a powerful paradigm for estimating wealth in small areas of sub-Saharan Africa, the same methods do not easily generalize to other geographic Settings or other human development indicators. Solutions like stratified transfer learning and Bayesian uncertainty quantification may partially mitigate these issues (Yeh et al. 2020), and we must still validate outputs against localized datasets to ensure contextually relevant results.

Transfer learning can effectively utilize the existing data and models, reduce the cost of data acquisition, improve the ability of model generalization, and provide an effective solution for the assessment of economic well-being in data-scarce areas.

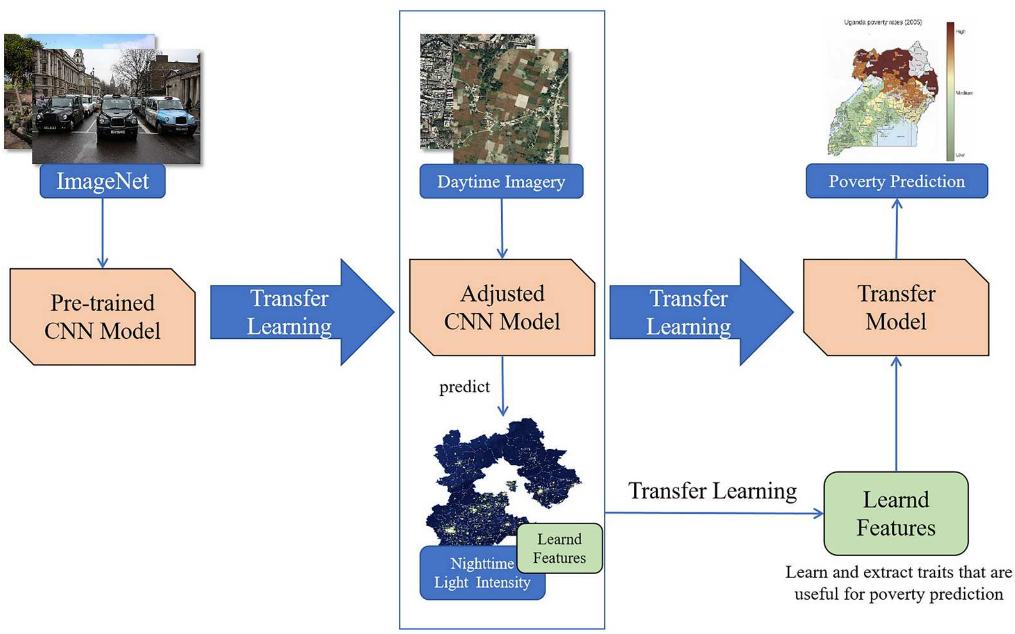

Figure 6. A transfer learning approach using nighttime lighting data as a proxy.

4. Discussions and conclusions

This review has illuminated the significant evolution in economic well-being assessment, charting the progression from traditional survey-based methods to the burgeoning field of satellite remote sensing. While traditional approaches, employing established indicators like GDP, HDI, and MPI, offer valuable historical context and in-depth socio-economic insights, their inherent limitations in data accessibility, cost, spatial granularity, and temporal resolution become particularly salient when seeking comprehensive and dynamic understandings of well-being, especially in data-scarce regions. Conversely, satellite remote sensing emerges as a powerful and increasingly accessible tool, capable of providing large-scale, timely, and spatially detailed data. This capability allows for the observation of economic activity intensity, land use patterns, ecological conditions, and infrastructure development – factors strongly correlated with economic well-being and often inaccessible through conventional means. The application of various analytical methods, ranging from statistical analysis to advanced machine learning techniques like deep learning and transfer learning, further expands the potential of remote sensing in this domain.

However, while remote sensing offers transformative potential, current evaluation models are not without their challenges. Insufficient accuracy and generalization across diverse contexts, difficulties in accurately modeling complex nonlinear relationships between remotely sensed data and economic realities, and a lack of model interpretability remain significant hurdles. The subsequent discussion delves into key areas for future research aimed at overcoming these limitations and further refining large-scale economic well-being assessment methodologies.

4.1. Future directions of economic well-being assessment

Building upon the identified strengths and limitations of both traditional and remote sensing approaches, this section elaborates on critical development trends in large-scale economic well-being evaluation. These trends center on refining measurement indicators, strategically integrating diverse data sources, and harnessing the evolving power of deep neural networks.

1) A crucial area for future research is the development and refinement of economic well-being measurement indicators. While a multitude of indicators currently exist, their suitability and comprehensiveness vary depending on the research context and geographical focus. The continued refinement and optimization of these indicators are crucial for accurate and meaningful assessments (Cook and Davíðsdóttir 2021). A significant future direction lies in embracing the concept of multidimensional poverty more robustly. This necessitates moving beyond purely income-based measures to incorporate critical dimensions such as health, education, access to essential services, and environmental quality. Developing context-specific indicator systems that are sensitive to the unique socio-economic and environmental characteristics of different regions and populations is paramount. This may involve adapting existing indicators or creating novel ones that better capture the nuances of well-being in specific locales. Furthermore, researchers need to critically evaluate the trade-offs between indicator complexity and data availability, ensuring that chosen indicators are not only conceptually sound but also practically measurable with available data sources.
2) Another critical research direction is the strategic fusion of traditional survey data with multi-source remote sensing data. Previous studies have shown that the prediction accuracy of welfare level is mainly driven by three core variables: the size of training data, the way of defining welfare indicators, and the choice of specific learning models (Hall et al. 2023). The future of economic well-being assessment lies not in choosing between traditional surveys and remote sensing, but rather in their synergistic integration. While remote sensing excels at providing objective, spatially explicit, and temporally frequent data, traditional surveys offer valuable insights into individual subjective experiences, nuanced socio-economic dynamics, and information on

factors not readily observable from space. Currently, many studies have used SAE, transfer learning and other methods to assess economic well-being through multivariate data fusion, but most of them primarily rely on remote sensing data or its combination with aggregate statistical data, often neglecting the richness of individual-level subjective well-being. In addition, there are many studies (Aguilar et al. 2021; Shapiro, Sudhof, and Wilson 2022) that try to use news information to assess economic activity, which can obtain economically significant information at a low cost. Future research should prioritize developing robust methodologies for data fusion, seamlessly integrating subjective data (e.g. life satisfaction, perceived poverty) from surveys with objective data from remote sensing (e.g. nightlights, NDVI, built-up area) and other spatial data sources (e.g. POIs). This integration can lead to a more holistic and nuanced understanding of economic well-being, capturing both objective realities and individual perceptions. Furthermore, advanced techniques like spatial downscaling, temporal interpolation, and data assimilation are essential for bridging the spatial and temporal gaps between different data sources, enabling more accurate and comprehensive assessments.

3) Further research is needed to advance the application of deep learning in this domain. Deep learning methodologies offer significant promise for extracting complex patterns and making accurate predictions from remote sensing data. However, several challenges need to be addressed to fully realize their potential. The issue of data scarcity and potential unreliability of ground truth data remains a significant bottleneck for training robust and generalizable deep learning models (Burke et al. 2021). Future research should focus on strengthening the active learning capabilities of deep neural networks, enabling AI to intelligently select the most informative samples for manual annotation, thereby reducing reliance on large, fully labeled datasets and improving training efficiency. Recently, large language models (LLMs) have incited substantial interest across both academic and industrial domains (Chang et al. 2024). LLM can perform text classification and sentiment analysis. Yang and Menczer (2023) found that LLM can generate trustworthiness ratings for a wide range of news media, and that these ratings have a moderate correlation with ratings by human experts. This means that in the future, LLMs can contribute to the improvement of training efficiency. Furthermore, enhancing the transferability and generalization ability of these models is crucial for their application across diverse geographical contexts and data sources. Exploring more effective transfer learning strategies and incorporating domain knowledge into model design can significantly improve model performance in new or data-limited regions. Finally, addressing the 'black box' nature of deep learning models is paramount. Anthropic researchers recently published a groundbreaking paper on interpretability (Templeton et al. 2024). The core content is about how to extract interpretable features from large language models (Claude 3 Sonnet as the research object). The research team used Sparse Autoencoders (SAEs) to break down the activation of the model in order to obtain a more understandable representation of the features. They implemented Dictionary Learning on Claude 3 Sonnet, extracting millions of features from one of the best models in the world and achieving a big breakthrough and allowing us to see the potential for LLMs to improve the interpretability of deep learning models. Future efforts should focus on developing and implementing model visualization and interpretation tools (Roscher et al. 2020) to enhance the transparency and interpretability of model predictions, fostering trust, and facilitating the translation of insights into actionable policies.

4.2. Conclusions

These advancements in indicator development, data integration, and deep learning methodologies pave the way for more accurate and insightful assessments of economic well-being. This review underscores the remarkable progress in economic well-being assessment, highlighting the increasingly vital role of satellite remote sensing alongside established survey-based approaches. Remote sensing demonstrably overcomes traditional limitations by providing large-scale, frequent, and spatially detailed data, unlocking novel perspectives on well-being that were previously unobservable. Beyond simply quantifying economic activity, remote sensing data facilitates a deeper appreciation for the intricate interconnections between environmental conditions, infrastructure development, and human well-being. Machine learning and deep learning techniques have further amplified these capabilities. These technologies collectively improve prediction accuracy while enhancing scalability, enables decision-makers to efficiently derive practical solutions across extensive geographical areas. By streamlining analysis processes, such tools empower policymakers to translate complex data into timely, large-scale interventions.

Looking forward, significant opportunities lie in refining remote sensing-derived indicators to capture the multifaceted nature of poverty and prosperity. The strategic integration of these indicators with traditional socioeconomic data, coupled with continued advancements in machine learning and artificial intelligence, promises to unlock more granular and dynamic assessments. Crucially, future efforts should prioritize: (1) refining and validating robust, contextually relevant remote sensing-derived indicators that capture the diverse dimensions of economic well-being; (2) developing robust and ethically sound methods for multi-source data fusion, integrating traditional surveys, remote sensing observations, and textual data from sources like media news; (3) improving the transferability and, crucially, the interpretability of deep learning models to foster trust and facilitate policy uptake; and (4) the combined power of remote sensing and LLM-processed textual information to capture both objective conditions and subjective perceptions.

In conclusion, by strategically prioritizing these research directions and fostering interdisciplinary collaboration, we can effectively harness the unique capabilities of remote sensing, advanced analytics, and novel data sources to move beyond traditional measures of economic well-being. This integrated approach will empower policymakers to design and implement more effective, targeted, and sustainable strategies for poverty reduction, inequality mitigation, and the achievement of global development goals.

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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