remote sensing

Review

Remote Sensing of Urban Poverty and Gentrification

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Abstract: In the past few decades, most urban areas in the world have been facing the pressure of an increasing population living in poverty. A recent study has shown that up to 80% of the population of some cities in Africa fall under the poverty line. Other studies have shown that poverty is one of the main contributors to residents' poor health and social conflict. Reducing the number of people living in poverty and improving their living conditions have become some of the main tasks for many nations and international organizations. On the other hand, urban gentrification has been taking place in the poor neighborhoods of all major cities in the world. Although gentrification can reduce the poverty rate and increase the GDP and tax revenue of cities and potentially bring opportunities for poor communities, it displaces the original residents of the neighborhoods, negatively impacting their living and access to social services. In order to support the sustainable development of cities and communities and improve residents' welfare, it is essential to identify the location, scale, and dynamics of urban poverty and gentrification, and remote sensing can play a key role in this. This paper reviews, summarizes, and evaluates state-of-the-art approaches for identifying and mapping urban poverty and gentrification with remote sensing, GIS, and machine learning techniques. It also discusses the pros and cons of remote sensing approaches in comparison with traditional approaches. With remote sensing approaches, both spatial and temporal resolutions for the identification of poverty and gentrification have been dramatically increased, while the economic cost is significantly reduced.

Keywords: gentrification; urban poverty; remote sensing; machine learning

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1. Introduction

Poverty reduction is one of the most challenging tasks for both developed and developing countries around the world. Poverty is related to population growth and urban expansion [1]. Moreover, studies have found that poverty is one of the main contributors to health issues and social unrest [2,3]. Some scholars argue that poverty is a natural outcome and will exist forever [4]. On the other hand, the United Nations (UN) is working on improving living conditions for all impoverished populations to eliminate poverty by 2030 [3].

Different countries define poverty using various methods: some use income to represent the current financial status of residents, while others estimate the value of total household assets to determine the poverty level for households [5–10]. Steele et al. summarized opinions on different approaches and concluded that evaluating poverty using a single metric could be incorrect and misleading [11]. For example, the same households could be classified into different social groups using different evaluation methods: income and home assets [11]. Comparing income could represent the financial status of a household for a short time period, while measuring assets could represent long-term wealth [12–15].

Although poverty exists almost everywhere, the formation of poverty is not the same in developed versus developing countries. In developed countries, it is clear that the rich moved to the suburbs while poor neighborhoods emerged in cities during the twentieth century, especially in post-industrialized cities [16]. For example, starting from the middle of the twentieth century, most old and industrialized cities in the United States experienced a significant population loss [1,17,18]. However, within different metropolises, the trend of wealthier populations moving toward outer rings and poorer populations remaining in cities was clear for decades [1,16]. In the twenty-first century, the moving pattern of populations was no longer simply in developed countries [16,19]. Although many wealthy people stayed in the suburbs, some moved towards the city center; though most of the poor population remained in the city, some of them spread out [16]. In the last decade of the twentieth century, some suburbs were big enough and had developed the same problem as old industrialized cities, and these new suburban cities started to experience the same economic collapse and population decrease [16,17].

Rapid urbanization is one of the main contributors to the growth of the urban poor in developing countries [20]. Unlike developed nations, most developing countries have not completed their urbanization process [21,22]. Interestingly, research has shown that Africa has both the highest rates of urbanization and simultaneously poor urban poverty [3,23]. The speed of urbanization is still accelerating as the urban population is estimated to increase to over one billion in Africa, and most of them will become urban poor [3]. Meanwhile, other developing nations (e.g., countries in East Asia, Latin American cities) are facing a similar problem of expanding urban poverty in recent decades [15,24–26].

Some scholars state that poverty can be eliminated, while others argue that poverty will always exist [4,27]. We do not try to go against either theory, but we agree with many scientists that the entire world should work together to reduce poverty [28,28–30]. This paper summarizes and evaluates conventional and novel approaches for delineating urban poverty and gentrification with the latest techniques. It also discusses the problems and limitations of traditional mapping methods and how these issues could be addressed by emerging technologies. As technologies continue emerging and advancing, it is anticipated that the identification and mapping of urban poverty and gentrification will continue to improve. These research outcomes will contribute to poverty reduction and the Sustainable Development Goals (SDGs).

2. Understanding Poverty and Gentrification

2.1. Formation of Poverty and Consequences

Although there are different types of poverty, the causes are similar [31]. Many studies have been conducted to understand the formation of poverty: from a global perspective to the individual level [10]. On the global scale, many scientists believe globalization is the root cause of poverty and that capitalist development is the barrier to developing countries [32,33]. The government should be responsible for poverty at the national level, according to research [34,35]. Moore (2001) [35] argues that poorly designed policies and corrupted governments could lead to a decrease in investment and economic activities. The lack of economic activities will result in the growth of poverty due to the shrinking of the labor market [36]. A study also found that personal experience and characteristics are important to poverty's formation [10]. For example, research has shown that a household is more likely to become chronically poor (fall into long-term poverty) if the home experiences persistent poverty for a few years [37,38].

The impacts of poverty have been researched in many studies [6,8,30,39–44]. As research has pointed out, regardless of the causes of poverty, it has devasting impacts on people living in it. We briefly summarized the impacts of poverty at different scales and showed that poverty could be harmful to individual families and society. First of all, health problems commonly exist in poor communities. Low-income individuals cannot afford enough nutrition for their bodies, which causes them to suffer health problems [6]. Insufficient nutrition negatively impacts their performance in studying and working, thus making them poorer [44]. Meanwhile, as research has shown, many poor individuals cannot afford expensive health insurance and medical care, especially in developing nations [36]. Even in developed countries such as the United States, scientists argue that health insurance for poor populations was not readily accessible until the early twenty-first century [44]. Secondly, poor people often face more stress than wealthier people [44]. According to research, such stress could lead to various conflicts between family members, such as domestic violence and child abuse [39,40,42]. At the same time, scientists found that poor populations usually lack resources or abilities to solve these conflicts [44]. Moreover, such conflicts bring more stress to the family, resulting in them becoming poorer [8,44]. Because of these huge stresses and uninhabitable living conditions, it is not a surprise to see an increasing number of health crises in low-income neighborhoods, such as during the COVID-19 pandemic [45,46]. These health crises not only impact the poor themselves, but also bring huge uncertainties to the entire society [46]. Lastly, poverty could introduce more criminal activities, either committing crimes or becoming victims [40,44]. It is common to see poor populations live in high crime rate communities, and these regions are often not safe while lacking police patrol. Scientists argue that poor people living there are exchanging their safety with low-cost living [41,47]. All these consequences show the difficulty for people to get out of poverty by themselves since all these outcomes make the poor population poorer.

2.2. Poverty Reduction and Gentrification

Because poverty has various negative consequences for individuals and society, poverty reduction is one of the top priorities for both developing and developed countries [48,49]. Craig and Porter (2003) [50] summarized three main approaches to reduce poverty from empirical research: first, increasing opportunities for the impoverished population; second, enhancing authority's governance by resisting corruption and improving public accountability; and third, providing security infrastructure by improving living conditions and reducing the risk of natural hazards for poor people. In fact, the global population living in extreme poverty (extreme poverty was defined as below 1.9 international dollars per day in 2011 value according to the World Bank) has been reduced dramatically in the past few decades, especially in East and South Asia and Pacific regions [51]. However, research also pointed out that many other areas only experienced minor changes in poverty population reduction [51,52]. Meanwhile, Nolan et al. (2017) [52] found there is a trend of increasing urban poor compared with rural regions. For example, in the United States, the poverty rate for urban areas surpassed the rural poverty rate around 2000. The gap between the two rates has become wider, indicating the shrinkage of rural poverty and the expansion of the urban poor [52].

Gentrification is a term first invented by British scientist Ruth Glass in 1964. However, the meaning and representation of gentrification have changed multiple times in the past. Gentrification was first used to describe the displacement of low-income neighborhoods caused by the expansion of middle-class communities [53]. Others argue that gentrification is the result of uneven city development [54]. Smith (1979) [54] believed this economic gap introduced opportunities for gentrification. A few years later, Hamnett (1991) [55] and Rose (1984) [56] introduced a hybrid theory, which argued that gentrification is a combination of both theories from Glass and Smith. Other scientists also concluded that a significant number of post-industrialized cities were gentrified based on this theory [57].

Gentrification plays an important role in urban poverty reduction as it directly changes poor communities and influences the living conditions of impoverished people [1,58]. Gentrification is a process intended to balance the economic gap in a city [55,56]. As a result, gentrification often takes place in less developed areas of cities [24,59]. Gentrification is different from urban redevelopment [58]. Urban redevelopment is a term to describe large-scale city renewal, such as a new commercial center that will benefit residents in all social classes [60]. On the other hand, Hamnett (1991) [55] argues in his paper that gentrification could lead to a dramatic change in a local neighborhood since it involves a mix or transition for different working classes [1]. Some research states that gentrification is a phenomenon that only occurs in cities in developed countries [55,61]. Other scientists discovered that megacities in the developing world, such as Shanghai, are more active in urban gentrification than traditional industrialized cities in the Western world [21,62]. In fact, recent studies suggest that the Global South is the emerging site and frontier for urban gentrification [21,62]. Research has also found that the most common type of gentrification transition is the middle class replacing the working class (or lower) in both residential and commercial sectors [1]. In recent decades, some researchers have argued that gentrification has no contribution to reducing poverty; however, others disagree and argue that when new problems of poverty in cities and suburbs surface, gentrification is an efficient tool for reducing poverty [16,24,58]. Identifying places facing (or potentially facing) gentrification is the first step in poverty reduction management. Scholars found that most traditional industrialized cities are facing substantial pressure of displacement [63–65]. For example, Washington, D.C. is one of the top cities facing gentrification pressure; about one-third of the population lives in areas that are/will be gentrified in the near future [16]. Orfield (2019) [16] developed an empirical model to group each census tract in the United States into four categories to represent economic health and to identify low-income neighborhoods. The model could be used across different regions to identify possible places for gentrification, while many other studies focus on smaller areas [16].

The scale of gentrification in developing countries is much smaller than in Western countries since the middle-class population is significantly smaller in developing countries [24]. In developing countries such as India, gentrification usually begins with rapid growth in private housing development and investment; thus, these gentrification projects typically take place in big cities [16]. Gentrification is found in neighborhoods with less social influence, such as urban slums and poor communities [24]. On the other hand, research has shown that there is more resistance in low-income communities for migrating from the existing environment, while educated middle and upper classes are willing to move from existing neighborhoods to higher value regions [66]. As a result, gentrification for middle-class neighborhoods is usually voluntary; however, for low-income neighborhoods, gentrification could be non-voluntary [66].

2.3. Managing Gentrification to Eliminate Damage

While gentrification economically rejuvenates cities, it comes with some drawbacks. Many gentrification projects do not consider the interest of local communities, and displacement could be one of the worst negative outcomes [63,67–69]. Displacement describes the involuntary departure of households from their homes in areas to be gentrified [70]. Displacement increases the cost of living for gentrified neighborhoods while the quality of living does not change or even worsens [63]. Even when gentrified residents remain in the same location or move back after gentrification is completed, they may still feel displaced [71]. Empirical studies acknowledge the negative impacts caused by gentrification, and many discussions focus on ways to reduce displacement [63,67–69,71]. From 1980 to 1990, most papers criticized and argued for ending gentrification to reduce displacement [72–74]. However, researchers argued that most conflicts in gentrification are not for refusing gentrification but for reducing displacement [75,76].

There is no single approach to resolve all the side effects of gentrification [70]. Starting from the 2000s, many scientists began supporting managed gentrification to reduce displacement and believed this was a more effective approach than fighting against gentrification [1,63,71,77]. The strategy of managing gentrification to minimize the side effects of gentrification was later called "acceptable gentrification" [71]. Ghaffari et al. (2018) [71] summarized a few gentrification managing solutions to reduce displacement and concluded that these state-of-the-art approaches are not very different from solutions invented in the 1980s. For example, policies were implemented to increase rent for high-end properties, and the excess could be used to lower rent for low-income families [65,68,72,73,78–80]. Additionally, when tenants are forcefully evicted, policies and some laws (e.g., the United States passed the Fair Housing Act (FHA) in 1968) were implemented to allow tenants priority to purchase their rented house and to provide assistance on relocation [68,70,72,73,75,78,79,81,82]. It is important to reduce the cost of relocation/rehabilitation for displaced households during gentrification. For this reason, the involvement of government agencies and local authorities is essential to balance the interest for both developers and gentrified communities [78,83]. In addition to external support, community involvement is critical to avoid involuntary displacement during the gentrification process. Numerous studies have concluded that increasing community participation in gentrification decision-making will reduce conflicts and displacements [68,74,78,81,84]. Education is important for households so that they can understand their rights, know when their rights are violated, and learn how to influence the decision-making process [81,84]. Due to the lack of access to news and information, the lower social class may receive incorrect information about their gentrification projects without legal assistance from local authorities [74,78]. Legal assistance is important since the government could directly help poor communities in negotiating with gentrifiers [68].

Gentrification is highly localized, and it is very difficult to directly transfer such knowledge to another area [24]. For example, a community could benefit from increased opportunities after gentrification while another could suffer from increased living expenses. Gentrification planning needs to consider the different residents in regions with varying geographical and social environments and local political conditions. Betancur (2014) [24] summarized three rules for successful gentrification projects: Gentrification requires combining knowledge from previous projects and local experiences by private/public and national/international corporations; Every country's economy is different, and thus the gentrification market should not be performed in the same ways as existing experiences; Due to differences in the scale of gentrification, a successful small gentrification project might fail when upscaled to larger projects. If gentrification is not conducted correctly, low-income communities do not disappear, but rather they move to other locations [1]. Forced eviction needs to be replaced by compensated migration with affordable housing and facilities [78,84]. Although gentrification is the result of representing the interests of wealthy parties, it should ensure the benefit of urbanization can reach poorer communities as well [1,71]. All social classes need to be included in urban development [70].

3. Mapping and Monitoring Urban Poor and Gentrification

Since poverty has a devastating impact on humans, it is not a surprise that there have been many studies on mapping and monitoring poverty areas and urban gentrification for the past few decades. The mapping and monitoring of poverty areas and gentrifications have a few significances. First of all, a caption of spatial and temporal variation in poverty region changes could help governments estimate the overall population in poverty [8]. Government support could be better planned according to this information [85]. Secondly, these maps and estimates could help researchers better understand the cause and effect of poverty, and then scientists could provide precise advice to local agencies [58,86]. Without real-world data and validation, scientists cannot evaluate their theories and hypotheses on poverty. Monitoring the gentrification process could help scientists assess the result of poverty reduction efforts [87]. Lastly, the mapping of poverty and gentrification could significantly contribute to the SDGs as poverty reduction is among the most urgent tasks [3]. For these reasons, it is not difficult to see that having detailed maps representing the dynamic changes of poverty areas is essential and fundamental in many urban studies.

3.1. Traditional Approaches to Mapping Poverty and Gentrification

A quantitative understanding of poverty is needed in order to understand poverty properly [20]. The spatial and temporal distributions of poverty and its severity are critical for poverty management, but collecting such data is extremely difficult in both developing and developed countries [85]. As we summarized the process of poverty formation earlier in this paper, traditional methods to identify poverty mainly rely on field surveys of impoverished populations, their health, and their surrounding environment [58,85]. Such methods heavily depend on the experience of investigators, so results are subjective since experience varies between individuals [58,86]. In addition, survey results could introduce uncertainties when households do not return accurate feedback [88]. It requires a considerable economic cost and human power to survey developing communities [8,89]. Furthermore, poor neighborhoods usually change rapidly, while the temporal gap between surveys could take few years or even decades [85]. Scientists also discovered that large impoverished populations often lack permanent shelters, and they frequently migrate for reasons such as natural disasters or government involvement [71,90]. Therefore, the data from these costly traditional poverty surveys could be useless after a short period of time [8].

Like poverty mapping, the traditional method of distinguishing gentrification areas also relies on using socioeconomic indicators by applying quantitative thresholds criticized by scientists since thresholds are arbitrary [91]. Moreover, using socioeconomic indicators to represent gentrification could result in inaccurate gentrification mapping. For example, the data aggregation process, which reduces temporal/spatial resolutions of the socioeconomic data, could reduce the accuracy of gentrification identification [92–94]. In addition, the spatial distribution of gentrification might not fit in administrative boundaries [95]. For these reasons, these classical gentrification models, which could explain what has happened in the study area, usually do not work when the study area changes [96]. Research pointed out that parameters used to evaluate gentrification across various regions are significantly different [96–98].

3.2. Remote Sensing of Urban Poverty

In order to remedy these limitations in traditional poverty and gentrification mapping approaches, several alternative or complementary technologies have been proposed and implemented: remote sensing, geographic information systems (GIS), and machine learning technologies [99–103]. The following subsections discuss state-of-the-art poverty identification and mapping with remote sensing, GIS, and machine learning.

3.2.1. Mapping and Monitoring Poverty Using Satellite Data and GIS

As we discussed earlier in this paper, no singular metric can be used alone to measure poverty and displacement. For this reason, it is common to see research that spans across multiple disciplines when estimating poverty [85]. A tremendous amount of work has been devoted to evaluating the feasibility of using remote sensing and geographic information system data to represent human living conditions [45,104–116]. Scientists and decision-makers have begun to evaluate poverty operationally using remote sensing techniques based on findings from these studies. Coarse and fine spatial resolution remote sensing imageries are jointly used to better understand human living conditions [103,117]. Coarse-resolution satellite imageries, which are widely available with frequent temporal coverage and often free to use, could be used to capture overall situations and provide information for large-scale decision-making [100,103]. Fine spatial resolution remote sensing data, which are not as common as coarser-resolution imageries due to the commercialization of such types of data, also play an important role in precisely identifying poverty [118,119]. Although high spatial resolution data are scarce and usually expensive, they are still a cheaper alternative compared to the traditional surveying method [85].

Remote sensing imagery classification is one of the most popular techniques in land use/land cover studies [102,120–122]. Studies have combined remote sensing classification with ontology from local experts to improve the accuracy of the identification of poor communities using remote sensing images [88]. Such an approach often involves adjusting thresholds for different study areas in order to produce meaningful results [88,123]. In addition, post-processing is often necessary as a lot of misclassification exists [103]. For example, land price data could be used to remove falsely classified slum areas since some buildings (e.g., historic districts) and poor communities share common physical features [88]. Moreover, topography information (e.g., slope) could be used to remove false classifications of shadows from buildings and terrain [103].

There are some similarities for informal settlements (usually poor communities) across the globe: lower social/economic status, poor living conditions, and bad surrounding environments [20]. Studies have shown that the combination of remote sensing images with auxiliary data layers from a GIS outperformed the remote sensing alone method due to the inclusion of local knowledge and additional information during classification [124,125]. In the past, the vegetation, impervious surface, bare soil (V-I-S) method was successfully integrated into classifying detailed urban land use from very high resolution (VHR) remote sensing data [126,127]. This method was studied mainly in developed countries and in recent years has become more prevalent in developing countries [20,126–131]. The temporal and spatial resolution of poverty identification could be improved by combining GIS and remote sensing techniques. For example, Steele et al. (2017) [11] tried to bring remote sensing data and mobile operator Call Detail Records (CDRs) together to represent human living conditions, as monthly mobile service usage could be used to describe the social business of communities. Experiments found a correlation between low-income populations and fewer phone calls but higher Short Message Service (SMS) traffic [11]. Although this model could not be used in rural regions because the population is less diverse in rural areas than in cities, it is still valuable since many poor communities are located in urban areas [3,23]. Moreover, CDR data can be updated frequently and be available in near-real-time for timely monitoring and analysis [11]. In developing nations, GIS and remote sensing-based informal settlement identification are invaluable thanks to their low economic cost [20].

3.2.2. Poverty Identification with Machine Learning

Although the idea of machine learning is not new, with the continuous research and huge advances in computer hardware, machine learning (e.g., ImageNet) has become one of the frontiers in the field of computer science [132,133]. Thanks to automatic learning and classification, deep learning could be used to extract meaningful features from remote sensing data [100,104].

The deep learning method was successfully adopted in many studies to classify remote sensing images for poverty identification [85,133]. One study used ImageNet to classify and predict nighttime light intensity, and with the knowledge learned, predicted poverty from nighttime light [134]. Nighttime light (NTL) is one of the emerging remote sensing data sources to measure human activities thanks to its correlation with manufacturing, population, and other socioeconomic patterns [25,26,135–140]. Many researchers use NTL data to represent socioeconomic status [139,141,142]. Knowledge learned by CNN could be transferred to related problems through transfer learning [120,125,133]. NTL has been proven to be correlated with poverty and has been adopted in poverty research in developing countries [134,143,144]. Random Forest Regression (RFR) is a popular method in many machine learning applications when multiple types of data sources are presented [145–150]. For example, a study combined different data sources and used the Random Forest Regression (RFR) method to develop a machine learning model to estimate the poverty level at the regional level based on NTL data [85]. The result shows that traditional computer vision methods do not return good results for poverty identification, while the machine learning approach has great potential to be generalized to different regions facing similar challenges [133]. Scientists argue that this outperformance is attributed to the transferred knowledge from other socioeconomic indexes [133]. The transfer learning technique is extremely useful when there are fewer labels [134]. Research has indicated that the combination of machine learning, remote sensing, and GIS has promising potential to outperform many traditional field surveys and standalone remote sensing classification methods [100,151,152].

3.3. Remote Sensing of Urban Gentrification

3.3.1. Quantitative and Qualitative Factors Used in Modeling Gentrification

Understanding the causes of gentrification is important for urban planning and policymaking; however, gentrification definitions and indicators are different in various studies [96]. Most researchers agree that gentrification identification is not an easy task since the causes of gentrification vary [97,153]. For example, slum clearance could lead to a community upgrade to the financial district, and historical communities could be redeveloped for tourism industries. Although it is hard to find an indicator to represent gentrification directly, empirical studies have demonstrated the feasibility of understanding gentrification's spatial distribution through various socioeconomic parameters [96].

The Social Status Index (SSI) is one of the early indexes developed to measure gentrification [154]. It measures the household status change by adopting a simple correlation model to analyze employment and education [153]. Ley (1986) [154] tested 35 factors for four hypotheses to explain the occurrence of gentrification. Unlike using social class, other scientists tried to use physical changes to evaluate gentrification [155]. Helms (2003) [155] believes that gentrification results from investment injection and infrastructure renewal of low-income communities. The Gentrification Index (GI) was invented to represent gentrification by measuring house market activities and building reconstruction [155]. Yonto et al. (2020) [153] evaluated both SSI and GI and concluded that both indexes provide excellent value for identifying gentrification, while both approaches cannot represent the whole picture of gentrification. By combining SSI and GI theories, researchers and local governments built their gentrification model by combining residents' activities and communities' physical variation [96,97]. Bousquet (2017) [97] summarized the displacement risk index to represent gentrification introduced by different cities in the United States. A higher displacement risk indicates the area has a high possibility of experiencing gentrification. The displacement risk index is calculated based on the residents' social and economic status, access to facilities, and communities' development [97].

In addition to the above factors, which could be quantitatively measured, qualitative factors provide a significant contribution to gentrification studies [153]. Research has found that a field survey is the critical approach for qualitative researchers to understand gentrification's specific characteristics [156]. For example, local traditional culture could be harmed when gentrifying historical sites, but such data are not able to be quantitatively measured [24]. Most of these qualitative studies rely on investigators' observations and interviewee responses [157,158]. Unfortunately, it is nearly impossible to conduct such qualitative assessments of gentrification at a large scale due to limited economic and labor resources and security concerns for investigators, especially in underdeveloped regions and regions of unrest. As a result, although qualitative assessment could benefit gentrification studies, most gentrification identification and mapping studies are based on quantitative data resources.

3.3.2. GIS and Gentrification Mapping

Undoubtedly, GIS has become one of the most popular tools across many scientific disciplines. GIS not only visualizes gentrification data onto maps; more importantly, it serves as a tool for scientists to understand gentrification by linking data to demographic and socioeconomic characteristics [140,159–161]. The contribution of GIS to gentrification identification and mapping could be divided into the following aspects. First of all, GIS data helped the validation and improvement of many existing gentrification theories. Secondly, GIS introduced the concept of location, which is essential in gentrification studies. Lastly, using GIS is necessary for measuring the impact of gentrification.

With the development of GIS, the U.S. Census started to produce geo-coded surveys in addition to the traditional atlas in 1990 [162]. Before the release of the 1990 U.S. Decennial Survey, gentrification studies mainly focused on developing concepts and theories. With the release of geo-coded census data, researchers could display, store, and analyze the geospatial census data to represent gentrification [163]. Furthermore, as previous sections pointed out, no single metric could be used alone to describe gentrification. As more GIS data became available, scientists started to incorporate these data sources (e.g., American Community Survey (ACS)) to understand communities' changes [164–166]. Various GIS models were established to identifying gentrification. For instance, Hammel and Wyly (1996) [163] developed a high-accuracy model to identify heavy investment areas. Unlike previous research, which relies on general statistics analysis, new GIS-based models are more accurate because they can count the geographic information [97,167,168].

In addition to supporting the improvement of model accuracy, GIS helps to evaluate the gentrification model in different regions. As a phenomenon that happened worldwide, GIS provides gentrification studies with a comparable system and datasets for evaluating gentrification in different regions [97,168]. Scientists were able to test if their model works in other cities or compare models developed from different areas. The latest research found out that many gentrification models do not work when migrating to other towns [96,168]. In addition, by comparing various models, scientists found that gentrification models use many different factors. For example, four gentrification models were compared, and only two factors were used in all four models among 18 variables in total [96]. In addition, the agreement of gentrification identification is shallow when adopting these methods in a new city [96,97].

Most models use economic and demographic changes, which explain why gentrification occurs, to identify gentrification. It is worth noting that gentrification also has some direct impacts on the city. Gentrification changes not only the demographic information but also the physical appearance of the town. Some research pointed out that GIS data could be used to quantify these impacts from gentrification. For example, by using census and ACS data, scientists found that the gentrification project could impact local social media activities [169]. Another study found that gentrification is correlated with local public transportation investment [167]. By using these indicators, scientists can conduct post-gentrification studies and gentrification early identification.

3.3.3. Modeling Gentrification Using Deep Learning and Time-Series Remote Sensing

The old-fashioned visual inspection approach was replaced by computer vision in remote sensing research to provide a fast and accurate alternative for image interpretation [170]. Traditional computer vision algorithms have already achieved massive success in time-series image classifications. Research has found that Support Vector Machines (SVMs) and Random Forests (RFs) are two traditional machine learning algorithms with the best performance in remote sensing time-series classification [171]. However, although these algorithms use time-series inputs, the temporal sequence was not considered [172]. Other studies were developed to extract features from temporal sequences and then refeed these results back into algorithms [173–175]. Another study tried to apply a hybrid approach (Nearest Neighbor algorithm) in time-series data to measure spatial and temporal similarities [176]. These attempts have improved the result by adding temporal features; however, this requires enormous computing power and processing time [146,177].

With recent advancements in computer vision and machine learning, deep learning-based remote sensing studies increased exponentially [87,172]. Scientists have proven the feasibility of using deep learning in remote sensing studies. For instance, Xiao et al. (2019) [178] proposed a deep learning model to understand the temporal variation in sea surface temperature. Ienco et al. (2017) [179] explored the feasibility of using deep learning in land cover classification. Iino et al. proposed a deep learning approach to study the urban changes in developing countries [180]. Other studies were conducted to compare the accuracy from CNN and Random Forest methods in urban change classification [172,181]. In most comparison studies, deep learning always results in higher classification accuracy [87,180]. Furthermore, researchers found that deep learning algorithms could benefit from the fine textures in remote sensing imageries [171,182]. Other studies confirmed this finding by investigating deep learning classification using sub-meter spatial resolution satellite data [183,184].

In urban research, a study pointed out that gentrification could be identified from deep learning approaches [185]. Another study explored the feasibility of applying deep learning algorithms on Google Street View (GSV) to detect gentrification [95]. Scientists expanded this idea to remote sensing images (true-color composition) to distinguish different building types [99]. Both studies' classification algorithms use Siamese Convolutional Neural Network (SCNN) [95,99], which is suitable for training images taken at various times and angles. Both studies, which are based on CNN with inputting temporal variables, imply RNN is not ideal in gentrification identification. Although Srivastava (2020) [99] used satellite images in his deep learning algorithm, it only consumes true-color composition, which is the same as the composition of GSV. Unfortunately, the study did not utilize the strength of satellite imagery: spectral signatures.

Theoretically, the spectral pattern for gentrification is significantly different from other features. Since the physical appearance of buildings often experiences massive upgrades during gentrification, meaningful temporal patterns could be obtained from satellite time-series data using deep learning [186]. Gentrification could be identified using deep learning to find temporal anomalies in remote sensing time-series data [187]. However, as this paper discussed earlier, most time-series machine learning algorithms used in gentrification studies only considered demographic and economic indicators, and there are many limitations in these models [96,153,188]. Only a few studies utilize true-color-composition remote sensing images with deep learning algorithms to identify gentrification [95,99]. Clearly, there is a research gap in utilizing time-series satellite spectral data for gentrification identification [87,182,189,190].

Although there is a shortage of using deep learning and remote sensing time-series data in gentrification research, it is easy to see the benefits that come along. In the era of rapid global urban developments, remote sensing time-series data, which provide continuous observation from space, could be crucial for gentrification studies [87,180,191]. Existing gentrification models use many different indicators, while these traditional models often result in low accuracy [91,187]. For instance, recent research found that many existing gentrification models yield misleading results when migrating to other towns [96,168,185]. Deep learning works better when requiring complex models [87]. Deep learning could help extract all hidden features and find common patterns for gentrification across spatial regions on the contract. For example, a study compared four gentrification models and found only two factors were used in all four models among 18 variables [96]. Unlike socioeconomic indicators, remote sensing data could be valuable for gentrification since both are continuous in space and not divided by administrative boundaries [95].

It is essential to understand that deep learning is not the perfect answer, and there are mainly two issues for deep learning in gentrification. First of all, the lack of training samples is probably the most significant and complicated issue [172,192]. Unlike GSV data, which receive help on sample labeling from millions of internet users [95,99], remote sensing labeling is not only labor-intensive but also requires knowledgeable users for quality labeling [99,172,182]. Meanwhile, manual labeling of gentrification's temporal pattern is nearly impossible since some other urban structures have similar spectral patterns. In addition, the model developed by deep learning can only represent the numerical correlation while it could miss the entire explanation for the real cause of gentrification. Contradictorily, past studies have proposed too many models for reasoning gentrification while the numerical correlations are weak [96,153].

3.3.4. Limitations of Current Gentrification Mapping

In past decades, gentrification was one of the hottest topics in urban studies. Dozens of models were developed, and a vast amount of research was conducted to understand gentrification. It is easy to conclude from previous research that the current understanding of gentrification is more thoughtful and systematic than in the past. On the other hand, the latest research on gentrification has a few limitations. This section will discuss the cause of these limitations in empirical gentrification research.

GIS data are critical to every geospatial study, and the study of gentrification is not an exception. Assessing gentrification data is not easy due to the substantial economic and labor costs [58,85]. Empirical gentrification research mainly uses other indicators to represent the distribution of gentrification thanks to the correlation between them. These data, such as census and ACS data, have a few issues. First of all, not all data are GIS-ready. For example, building permit/inspection and building assessment reports could be released in a report format, and it often takes considerable time and effort to collect and process these data [153,193]. Different organizations or government agencies could release their data in various formats, bringing difficulty to geospatial analysis [193]. Secondly, the spatial resolution of census and ACS data is coarse due to data aggregation for protecting privacy [94]. It is rare to see these data have a finer resolution than the census tract level, while some micro gentrifications could not be identified [92,93]. In addition, temporal gaps exist in census and ACS datasets, and such gaps could be several years or decades. Gentrification might happen during the temporal gap. Census data could not detect or complete the missing demographic change in a timely manner [153]. Lastly, the accuracies of some data sources are questionable. For example, ACS data only represent 5% of the total population, so the data could be inaccurate [153].

Existing gentrification research often focuses on a small study area. These gentrification models, which could explain what has happened in the study area, usually do not work when the study area changes [96]. Research pointed out that parameters used to evaluate gentrification across various regions are significantly different [96–98]. Meanwhile, it is not rare to see gentrification projects in small cities and megacities worldwide [16]. It is important to include other data (e.g., remote sensing) in gentrification studies to measure gentrification across regions quantitatively.

Many scientists have noticed that the interest in using deep learning for remote sensing applications is rising rapidly [172,178,181,191]. However, the real-world applications of using deep learning in analyzing time-series remote sensing patterns are still scarce [182]. Only a few studies tested deep learning for remote sensing time-series classification [87,172,182]. Deep learning algorithms often occur in complicated classification models, especially when classification can not be accomplished with linear models [87]. In addition, Zhu et al. (2017) [87] discovered that when a temporal phenomenon is not fully understood or cannot be generalized using existing models, deep learning could be used to achieve some meaningful results.

Although deep learning sounds promising in remote sensing research and could yield great results, there are some limitations for deep learning in remote sensing. The limited training sample is one of the critical concerns for many researchers [172,192]. When there are no sufficient training samples or the quality of feature labels is low, the model will perform poorly in learning and generalizing features [87]. Meanwhile, remote sensing imagery interpretation is not as easy as true-color-composited images, not to mention the difficulty of understanding patterns from non-optical satellites [99]. For this reason, the feature labeling task requires remote sensing knowledge and is thus not suitable for crowdsourcing labeling [99,185]. The major advantages and limitations of gentrification mapping techniques for different generations discussed in this paper are summarized in Table 1.

Table 1. Summarizing and comparing the strengths and weaknesses of generational technologies and methodologies for mapping urban poor and gentrification.

Technology	Methodology	Advantage	Limitation and Challenge
Obsolete	Field surveys and investigations [85]; evaluation of culture and history [24,157]	Both methodologies and results are easy to understand [24,157,158]	Require knowledgeful investigators [58,85]; high financial cost; labor-intensive and low scalability [8,151]
Conventional	Statistical correlation models [11,58,88,91,96,97,153–155,160]; transfer learning [134–138,140–143,161,162]	Models are easy to use and replicable [97,167,168]; low financial cost [85]	Too many algorithms [96–98]; results are not reliable [96,153]
Novel	Machine learning imagery classification [95,99,120–122,181,184,185]; time-series deep learning [87,183,190,191]	Emerging technology and promising results [95,185]; low financial cost [85]	Require high quality labels [172,192] and advancing algorithms [99]; lack of research [182]

4. Conclusions and Discussion

Cities around the world are in different stages of economic development. In developed countries, some urbanized cities face population decline and aging infrastructure while others need to solve issues of a rising aging population [16]. Urbanization is more complicated for cities in developing countries due to the dramatically increasing impoverished population. As urban studies have pointed out, 20% to 80% of new urbanization in developing countries is occupied by low-income communities [23].

Poverty is a longstanding side effect of urban development [2,3,114]. According to research, poverty is related to population growth, and it is one of the main contributors to issues with health and social conflict [2,15]. This paper reviewed major factors that cause poverty and why people cannot get out of poverty, especially in cities. As a result, poverty reduction is one of the most critical challenges in the Sustainable Development Goals (SDGs) [3]. Poverty reduction is the primary goal of both developed and developing nations. For these reasons, it is crucial to have accurate and up-to-date information on poverty [3].

Traditional poverty mapping is not only labor-intensive but also poses a tremendous financial burden [58,151]. Studies have summarized traditional poverty mapping approaches in various regions around the world. However, the accuracy of conventional poverty mapping is questionable since errors could occur during data collection by local officials, not to mention the definition of an informal settlement could be different between agencies [5,6]. Sometimes politicians may influence the poverty mapping result for reasons such as requesting more national/international aid [41,88]. In addition, due to differences in technology and economy, there is a huge gap in data collection between developed and developing countries [133]. Remote sensing and GIS, which are recently developed tools, have the potential to provide meaningful data at global coverage [88,118,135,136]. Satellite-based data on vegetation conditions, nighttime light, weather conditions, and road maps could be used to represent human welfare [110,111,134,138]. Research suggested that adding more GIS variables to poverty mappings, such as water and utility accessibility, could increase accuracy (Kohli et al. 2015). Moreover, machine learning technology could help to improve the accuracy of poverty mapping, though it requires the input of local knowledge [139,141,142].

When the term gentrification was first invented, it was used to describe upper classes displacing low-income neighborhoods [53]. Later, gentrification was used to represent the phenomenon of uneven economic development within cities. Gentrification is different from urban redevelopment, which is large-scale and has a broader impact on the general public [60]. Gentrification involves the change of use for buildings and the transition of different social classes [24,86]. In the past half-century, many criticisms have been formed against gentrification [63,67–69]. Research has suggested that inappropriate gentrification could harm society and the local economy, especially when the expectations of local neighborhoods are unsatisfied [3,194]. Previously, it was not rare to see displacement during gentrification projects [1,19,76]. However, many scholars still believe that gentrification is a tool that could benefit cities when used correctly [1,71]. Research has shown that the impact of gentrification on poverty reduction, especially for chronic poverty, is significant [71]. Gentrification could reduce local crime and improve physical appearance [1]. In addition, some scholars state that gentrification is essential for city reconstruction after violent political movements [63,195]. Gentrification could contribute to environmental sustainability and help reduce natural disasters in cities [103]. In past decades, both public and private sectors have invested significant amounts of capital in order to gentrify underdeveloped areas [24].

In the past, scientists have suggested that people should not accept gentrification at all [71]. Conflicts between lower-income communities and wealthy neighborhoods were very common before introducing political negotiation during gentrification [21,71]. Nowadays, the majority of scientists argue that we should not be against gentrification when the interests of local communities can be fulfilled and there are no other bad impacts [1,18,71]. Various solutions were offered for solving the side impacts of gentrification [1,18,58,65,71,72,76,196]. In recent decades, the amount of violent gentrification has dramatically reduced and has been replaced by peaceful negotiations [71]. Acceptable gentrification is the result of combining community involvement in the gentrification decision-making process, educational assistance from local agencies, and political support from governments [70,78,197,198]. Acceptable gentrification plays one of the most important roles in poverty reduction as it provides both economic benefits and benefits to poor communities.

This paper also summarized the state-of-the-art gentrification identification and monitoring approaches. As many studies point out, existing socioeconomic indicator-based models provided firm explanations for gentrification while lacking supporting quantitative model results. This study finds that major gentrification studies utilized GIS technology; however, after reviewing the results and findings, we discovered most of these conclusions are not generalizable and adaptable to border regions. We could rarely find literature on gentrification studies using remote sensing technologies. Fortunately, given the recent advancement in computer vision and machine learning, remote sensing technology was injected with powerful fuels encouraging more disciplines to use remote sensing in their research. This paper thus summarized these few emerging studies that utilize time-series remote sensing classification methods in gentrification identification. Although there is limited research available, this paper tried its best to summarize the potential advantages and limitations of adopting deep learning and remote sensing time-series classification for gentrification studies. With remote sensing approaches, both spatial and temporal resolutions for the identification of poverty and gentrification have been dramatically increased, while the economic cost has been significantly reduced. This paper also discovered that there is a research gap in predicting and mapping potential gentrification sites. Urban planning could be greatly benefited if potential gentrification locations could be identified in advance. Specifically, city planners could focus on designing these regions to help poverty and contribute to the sustainable development of cities. As more and more research is devoted to poverty mapping and gentrification identification, we believe mapping potential gentrification locations is not only achievable but also will happen in the near future.

However, we suggested that two difficulties need to be addressed in monitoring gentrification using remote sensing and deep learning in future research: increasing the training samples by linking the gentrification database with satellite time-series data and distinguishing the process of gentrification from other urban objects in satellite imageries. With the continuing advancement of computer technology, there is an increasing trend of using machine learning and remote sensing techniques in social science research. The authors believe these challenging issues will be resolved in the coming years. There is vast potential in using deep learning and time-series satellite images for gentrification studies.

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