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The contribution of data-driven poverty alleviation funds in achieving mid-21st-Century multidimensional poverty alleviation planning

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The first Sustainable Development Goal (SDG) is intended to eradicate multi-dimensional poverty globally. The same multidimensional poverty indices for India and the Middle East/Africa in 2020 indicate that 10–14 years are still required to reach the level of China's poverty eradication. Using machine learning, spatial statistics, and a scenario analysis, we demonstrate how a Monte Carlo simulation of poverty alleviation funds-guided shared socio-economic pathways (PAFs-SSPs) in China reveals the necessity to adopt an integrated poverty alleviation strategy. This approach employs multi-dimensional development indicators to reduce wide regional differences. We developed the data-driven model framework of a PAFs-SSPs to analyze the multifaceted and long-term planning needs of poverty alleviation policies, which can be applied to the formulation of poverty alleviation policies in different developing countries. Our findings point to the importance of implementing multidimensional development policies in China to achieve the first SDG worldwide.

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Introduction

The first of the United Nations (UN) Sustainable Development Goals (SDGs) aims to “end poverty in all its forms everywhere in 2030” (Ravallion, 2013), requiring a coordinated and comprehensive sustainable development in the economy, environment, resources, welfare, and other sectors. The concept of poverty has expanded from a single economic index to a multidimensional poverty index (MPI) (Cuaresma et al., 2018). In recent decades, the UN Millennium Development Goals (MDGs) have lifted more than a billion people out of extreme poverty. However, in many countries, progress in the development and implementation of multifaceted social indicators is still insufficient (Liu and Xu, 2016). While the MDGs focused on developing countries, the SDGs seek to establish future global frameworks, with periodic progress reviews at the national, regional and global levels.

China has lifted more than 700 million people out of poverty, which, according to the international poverty line standard (US \$1.90 per day), equates to a global poverty reduction of over 70% over the past 40 years. This was achieved by implementing a targeted poverty alleviation strategy by using poverty alleviation funds (PAFs). Its success indicates that the accurate monitoring and assessment of the dynamic performance of poverty indices is paramount. It also points to the necessity of understanding the relationship between MPI and PAFs. However, these strategies also require scenario analyses for MPI, as failure to include such analyses will prevent research communities from informing policy and governance debates concerning poverty eradication. To bridge this gap, we considered the following key questions: (1) What was the status of multidimensional poverty (MP) regions globally prior to implementation of the SDGs; (2) What are the future SSP tendencies of regions such as China, the United States, India, and the Middle East/Africa? (3) What is the future tendency of a PAFs-SSPs-influenced MPI in China?

Using a single index to characterize poverty might not measure regional differences, spatial characteristics, or poverty drivers sufficiently accurately (Wagle, 2008). The Oxford Poverty and Human Development Project and the United Nations Development Program jointly propose an MPI (Alkire et al., 2017) to measure poverty by weighting deprivation in health, education, and standards of living. Furthermore, Sharp has developed an extended model to measure poverty by incorporating human, natural, financial, material, social capital, etc. (Sharp, 2003) (Supplementary Table SI). The most obvious challenge in establishing a set of global MPI frameworks lies in its inadequacy in measuring poverty development—hampering efforts to identify poverty regions and design relevant policies.

The most plausible strategy required to achieve the SDGs is a reliable evaluation of national, regional, and global processes to eradicate poverty. Nighttime light satellite imagery (NLS) is an objective and efficient method for monitoring and evaluating regional poverty due to its macro, dynamic, and objective advantages, especially in areas where data are scarce (Jean et al., 2016). Li et al. have used a machine learning method to identify high-poverty counties in China, as well as their key classification features, which were extracted from China’s Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) data in 2010 (Li et al., 2019); while Yu et al. (2017) have used National Polar-orbiting Partnership/Visible Infrared Imaging Radiometer Suite (NPP/VIIRS) data to measure and analyze poverty at the county level. Multisource data fusion combines NLS, Moderate-Resolution Imaging Spectroradiometer (MODIS) data, and statistical data to establish a unified MPI framework to identify and analyze poverty areas—providing a scientific reference for formulating poverty alleviation policies.

Five possible scenarios are proposed for the recently developed SSPs that are considered critical components in the ongoing Intergovernmental Panel on Climate Change (IPCC) assessment of changing global climate (Chen et al., 2020). SSP1 (Green Road) proposes a sustainable pathway (Van Vuuren et al., 2012). SSP2 (Middle of the Road) focuses on development trends following historical patterns (Fricko et al., 2017). SSP3 (A Rocky Road) is oriented toward regionally heterogeneous development (Fujimori et al., 2013). SSP4 (A Road Divided) centers on development that promotes geographical and social inequalities (Calvin et al., 2017). SSP5 (Taking the Highway) suggests a fossil-fueled development scenario (Kriegler et al., 2017). Some recent studies used these SSPs to predict climate change and urban land distribution, poverty, and other factors. Cuaresma presents a methodological framework for assessing absolute poverty changes at the global level according to different scenarios (Cuaresma et al., 2018). Kurniawan attempts to explain the effect of key socioeconomic variables on long-term global sustainability (Kurniawan and Managi, 2018). However, relevant MPI research is still scarce.

In this article, using multi-source data including NLS, MODIS, and statistical data in China from 2000 to 2017, we provide a comprehensive analysis of MPI by exploring the spatiotemporal properties of poverty and the evolutionary tendency of multiple perspectives. The multiple factors of MPI on a global scale was provided in (Supplementary Table SII), furthermore, the multiple factors of MPI in China was presented in (Supplementary Table SIV). We do this using a hybrid model that combines machine learning and a multidimensional weighted learning framework. Based on the complex relationship between MPI and PAFs provided by government, a novel data-driven simulation model to predict future tendencies of the MPI is developed by replicating various poverty alleviation policies. Monte Carlo simulation is used to obtain the diversified future development path, while the regional MPI from 2005 to 2050 under SSPs was realized using a multidimensional weight from China’s perspective.

Methods

Online MPI learning weight. An approach for weighting of MPI involves entropy weight (He et al., 2016), hierarchical evaluation (Büyükoğkan and Çifçi, 2012), and expert scoring (Gracht, 2012). The entropy weight approach considers only the data distribution characteristics and ignores the potential significance of the data. Monte Carlo simulation can provide the best index weight in the form of human-like scoring (Hegazy et al., 2003), and hence it is used in combination with the entropy weight method to comprehensively evaluate various indices. Taking the 2012 list of national poverty alleviation counties as the target, the weight of different indices can be dynamically adjusted using online learning to obtain maximum accuracy in identifying poverty alleviation counties. The output weight score corresponds to the highest identification accuracy of poverty-stricken counties.

The index can be normalized and the matrix standardized according to the index type:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^n x_{ij}^2}} \quad (1)$$

Calculating the probability matrix

$$p_{ij} = \frac{z_{ij}}{\sqrt{\sum_{i=1}^n z_{ij}^2}} \quad (2)$$

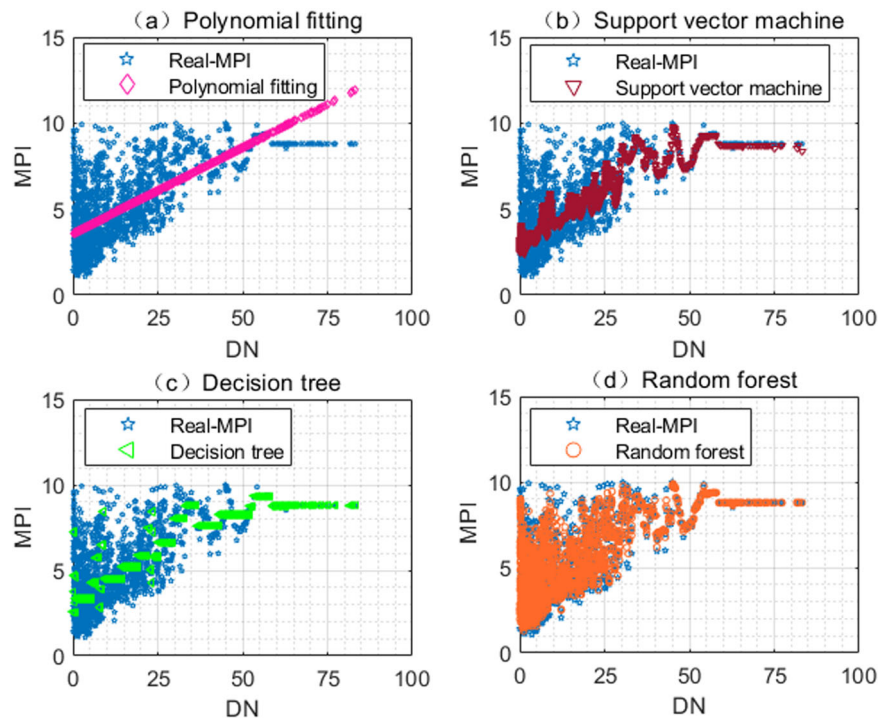


Fig. 1 Predicting MPI with night light satellite imagery. The prediction MPI for the 2017 incomplete dataset, Polynomial RMSE, support vector machine, decision tree, and random forest is 1.57, 1.548, 1.541, 1.42, 1.24, and 0.41, respectively.

Calculating the information entropy of each index^[22], which can be defined by

$$e_{ij} = \frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij} \quad (3)$$

Since it takes much human labor and material resources to collect expert experience, Monte Carlo simulation is used for scoring the different indicators, with the weight described as:

$$W_j = \frac{(1 - e_j) \omega_j}{\sum_{j=1}^m (1 - e_j) \omega_j} \quad (4)$$

The output of MPI in counties can be defined by

$$\text{MPCI} = \sum_{j=1}^m z_{ij} W_j \quad (5)$$

The nonlinear relationship between the average digital number (DN) and MPI by using the machine learning method can be calculated by

$$\vartheta = f(\text{DN}, \text{MPCI}) \quad (6)$$

The missing data from each index can be acquired by using the nonlinear relationship established by Eq. (6):

$$\text{MPI}_{\text{loss}} = f(\text{DN}_{\text{loss}}, \vartheta) \quad (7)$$

The robustness and effectiveness of nonlinear fitting algorithms can be improved by using a combination of machine learning and linear regression methods to select the parameters of the best fitting output (see Supplementary Fig. S6 and Table VI). The classification of counties and cities (poverty-stricken, developing, primary developed, medium developed, and advanced developed) can be obtained using the G* natural fracture method (Chen et al., 2013). Taking the list of poverty-stricken counties published by the Chinese government in 2012 as the learning objectives, the accuracy rate of poverty-stricken counties can be obtained by G* fracture. We repeated steps 1–7 and scored each index by using the Monte Carlo simulation; the output is the index score

corresponding to the maximum accuracy. The parameter for simulation can be divided into four categories according to MPI; each dimension of parameter has its boundary constraints which can eliminate the uncertainty caused by using a random strategy. Moreover, each parameter boundary can be estimated by combining the frequency spectrum and prior knowledge. Considering the unstructured data features from NLS and the demand of identifying poverty alleviation counties, the following machine learning methods in terms of support-vector machines (Amari and Wu, 1999), logistic regression (Yang and Marco, 2018), decision tree based on the Gaussian function (Kocsor and Toth, 2004), neural networks (Hecht-Nielsen, 1989), decision tree ensemble learning (Agrawal et al., 2019), and random forest (Aldersley et al., 2011) are used in this study (Fig. 1).

Relationship between MPI and PAFs. The complex relationship between MPI and PAFs can be defined as

$$\text{MPI}_i = \begin{cases} f_1(\text{PAF}_i) & f_1 \text{ is the poor countries} \\ f_2(\text{PAF}_i) & f_2 \text{ is the non-poor countries} \\ f_3 & f_3 \text{ is the average growth rate} \end{cases} \quad (8)$$

where the relationship of f_1 , f_2 , and f_3 can be learned from historical data by the least square fitting algorithm.

PAFs-SSPs. Based on the data-driven model of the relationship between MPI and PAFs, Monte Carlo simulation can be used for development path planning considering the boundaries of PAFs and growth rates in different provinces. After several simulations, the SSP1–SSP5 pathway can be selected for observing the trade-off between investment and development. The definition of PAFs-SSPs is as follows.

SSP1 is the ‘green road’ of poverty alleviation, and its provincial PAFs coordinate both the inter-provincial differences in poverty and imbalance between development of the economy, resources, environment, and welfare. The distribution of PAFs in

SSP1 can be calculated as

$$P_j^{\text{ssp1}} = \exp(-f_j^{\text{MPI}}) \quad (9)$$

$$\tilde{P}_j^{\text{ssp1}} = \frac{P_j^{\text{ssp1}}}{\sum_{j=1}^H P_j^{\text{ssp1}}} \quad (10)$$

$$\text{PAF}_j^{\text{ssp1}} = T_{\text{PAF}} \tilde{P}_j^{\text{ssp1}} \quad (11)$$

where H is the number of provinces. The smallest MPI regions can be given the most PAFs; conversely, the regions with a large MPI can also obtain the PAFs for collaborating the development of the multidimensional index.

SSP2 is the ‘middle of the road’, only focusing on poverty alleviation of the MPI value. PAFs will be injected in provinces with poverty-stricken counties (PSCs): otherwise, PAFs will not be allocated. The PAF can be supplied for the provinces with the poor counties—those provinces without poor counties can rely on their own development funds to coordinate multidimensional development. The distribution of PAFs can be calculated by using the same SSP1 strategy; the provinces without poverty counties are not involved in the computational process.

SSP3 is a ‘rocky road’: the PAFs will be provided for provinces with many PSCs but those with few PSCs will be eliminated by self-development.

$$P_j^{\text{ssp3}} = \begin{cases} \exp(f_j^{\text{PCN}}) & \text{PCN} > 0 \\ 0 & \text{PCN} = 0 \end{cases} \quad (12)$$

$$B > f_{2\sigma}^{\text{GP}}(P_j^{\text{ssp3}}) \quad (13)$$

$$\tilde{P}_j^{\text{ssp3}} > \frac{P_j^{\text{ssp3}}}{\sum_{j=1}^H P_j^{\text{ssp3}}} \quad (14)$$

$$\text{PAF}_j^{\text{ssp3}} = T_{\text{PAF}} \tilde{P}_j^{\text{ssp3}} \quad (15)$$

where $\tilde{P}_j^{\text{ssp3}}$ and P_j^{ssp3} are the weight and standardization weight of the j -th provinces, while $\text{PAF}_j^{\text{ssp3}}$ denotes the PAFs of the j -th provinces. Those with many impoverished areas can obtain more support, while those with a smaller number of poor counties should rely on self-development. The distribution of the number of poor counties can be described by the Gaussian distribution, and the boundary for relying on their own development to eliminate poverty should satisfy condition (13).

SSP4 is a ‘road divided’, providing the most PAFs for areas on the verge of poverty alleviation and concentrating investment for provinces with many PSCs. The distribution of PAFs can be calculated by

$$G_{ij}^{\text{ssp4}} = \exp\left(-\left\|f_{ij}^{\text{MPI}} - B^{\text{MPI}}\right\|\right) \quad (16)$$

$$\tilde{P}_j^{\text{ssp4}} = \frac{\sum_{i=1}^{L_i} G_{ij}^{\text{ssp4}}}{\sum_{j=1}^H \sum_{i=1}^{L_i} G_{ij}^{\text{ssp4}}} \quad (17)$$

$$\text{PAF}_j^{\text{ssp4}} = T_{\text{PAF}} \tilde{P}_j^{\text{ssp4}} \quad (18)$$

Note that f_{ij}^{MPI} is the MPI of the i -th poverty counties in the j -th provinces. B^{MPI} is the boundary of ridding poverty. $\tilde{P}_j^{\text{ssp4}}$ is the weight of the j th provinces. L_i is the number of poverty counties. $\text{PAF}_j^{\text{ssp4}}$ is the PAFs of the j -th provinces. This strategy aims to rid poverty following a sequential order, i.e., those on the verge of eliminating poverty firstly get rid of poverty, and then focus on helping areas that are in poverty.

SSP5 is the fossil-fueled development pathway at the price of depleting resources and polluting the environment to achieve rapid poverty alleviation. Given that the weight of various aspects in terms of environment, resources, economy, and welfare differ in poverty counties, the changes of an aspect weight for improving the development of others might lead to a significant difference. Thus, the generation of a random weight is needed for promoting economic development by resource consumption. The other computational process is similar to SSP2.

In terms of Monte Carlo simulation, this study uses three-layer simulation in terms of the total of PAFs, random noise, the alteration of weight in different county aspects at SSP5. The random noise simulation aims to incorporate the uncertainty in data estimation.

Results

Multidimensional poverty data. We collected the MPI of 2369 counties in China from 1998 to 2020 due to the acquisition of the statistical yearbook, NLS, and MODIS data. The MPI involves environmental, resources, economic, and social aspects. From the environmental aspect, the indices in terms of altitude, average slope, vegetation coverage, vegetation normalization index, and biological land quality were selected by using MODIS data for the long-term global observation of the surface, biosphere, and atmosphere. As for the resource’s aspect, we include statistical data concerning per capita land resource ownership, and total output of per capita agriculture, forestry, animal husbandry, and fishery. By using statistical yearbook data, we construct a social measure for the beds for health centers in hospitals and middle school students. The statistical yearbook data was used for analyzing economic index in terms of total GDP (CNY 100 million), GDP per capita (CNY/person), total retail sales of social consumer goods per capita, and the per capita disposable income of rural residents. Moreover, the average night light intensity index for the economic aspect was selected by using DMSP/OLS and NPP/VIIRS.

Taking the list of 592 key poverty alleviation counties published by the National Poverty Alleviation and Development Group in 2012 as a benchmark (data for 574 counties can be collected), the spatiotemporal evolution characteristics of MPI is explored. Compared with the MPI weight based on human experience, a Monte Carlo-driven supervised learning strategy is used for exploring the weights in different indexes (i.e., the list of key poverty alleviation counties provides the label, and the output best weight of maximum identification rate can be obtained by simulating the weights). A form of machine learning method termed ‘the random forest’ is used for the prediction of MPI due to regional statistics data being incomplete. The root mean squared errors of these methods indicate that random forest method has the best performance.

Future tendency of MPI under various SSP pathways. After the UN MDGs expired, we observed a significant difference in the level of poverty between northern and southern hemispheres, particularly in terms of economic poverty, where 81.5% lies in sub-Saharan Africa and Asia. By contrast, Europe and North America have only 12.3% economic poverty. Given that the UN 2030 agenda for SDGs proposes to eliminate all forms of poverty by 2030, poverty eradication is a social issue of concern for such developing countries and regions as China, India, and the Middle East/Africa. Compared with China lifting more than 700 million people out of poverty (the international poverty line standard is US\$1.90 per day), India and the Middle East/Africa are still the typical areas with the largest number of poor people globally. Compared with China, on the one hand, India and the Middle

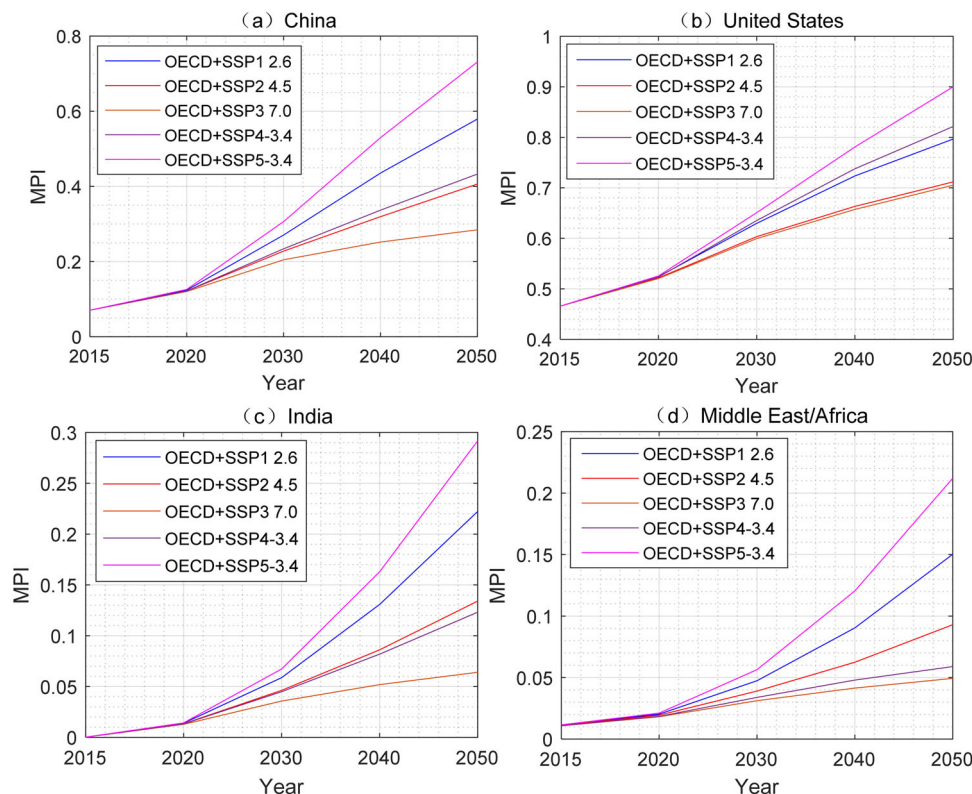


Fig. 2 Future MPI tendency for 2015–2050 under the five SSP scenarios. **a** China; **b** United States; **c** India; **d** the Middle East/Africa, including Algeria, Bahrain, Djibouti, Egypt, Ethiopia, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Malta, Morocco, Oman, Palestine, Qatar, Saudi Arabia, Sudan, Syria, Tunisia, United Arab Emirates, Yemen, Ethiopia, Sudan, and Western Sahara, etc.

Table 1 Rate of change in MPI under different SSPs.

Country/region	SSP1 2.6	SSP2 4.5	SSP3 7.0	SSP4 3.4	SSP5 3.4
China	0.16(0.013)	0.097(0.008)	0.053(0.025)	0.12(0.01)	0.202(0.022)
United States	0.107(0.009)	0.063(0.017)	0.0579(0.015)	0.115(0.003)	0.123(0.006)
India	0.08(0.042)	0.025(0.017)	0.0048(0.0015)	0.044(0.023)	0.0814(0.054)
The Middle East/Africa	0.05(0.024)	0.016(0.008)	0.0014(0.0011)	0.015(0.005)	0.057(0.039)

East/Africa can predict when the United Nations SDGs can be achieved; on the other hand, we can analyze the gap and future evolution between China and a typical developed country (United States) after poverty eradication. Thus, the MPI of four typical areas (China, United States, India, and the Middle East/Africa) under an SSPs pathway where the baseline year is 2015 is displayed in Fig. 2. The change rate of MPIs under different SSPs is presented in Table 1. The MPI growth rate of China is higher than that of developing countries and the United States, which indicates that China and the United States' MPI could be the same in the future (Supplementary Table SIII). The rapid growth rate of China's MPI demonstrates the effectiveness of targeted poverty alleviation policies. The main regions of extremely poor people across the world are India, China, and the Middle East/Africa. In contrast with China's eradication of extreme poverty in 2020, the time still needed to eliminate poverty in India and the Middle East/Africa is at least 10–14 years. Thus, there is a significant negative impact on how the SDGs' objectives may be realized. Given that China's poverty alleviation rate dropped significantly from 88% in 1981 to 0.6% in 2019 and all extreme poverty was eradicated in 2020, we have much to learn from

China's poverty alleviation experience to achieve the SDG goals in 2030—especially for the poorer regions of sub-Saharan Africa and Asia (Fig. 3).

Future tendency and spatial distribution of MPI in China. As an important developing country of Asia, China accounts for nearly one-fifth of the world's population for eliminating absolute poverty, with its poverty rate (World Bank standard) decreasing from 66.3% in 1990 to 0.5% in 2016. Considering China's successful implementation of targeted poverty alleviation (Zhou et al., 2018) and fulfillment of the first UN SDG, the definition and standard of poverty in China after 2020 would benefit from being expanded to a multidimensional perspective. Thus, we developed a poverty evaluation index in terms of resources, environment, welfare, and economy using multisource data (including that from remote sensing imaging and statistical yearbooks) to identify deep MPA and spatiotemporal evolution characteristics with the help of the wide application of remote sensing technology (Sambah and Miura, 2016). We took the list of China's 592 key poverty alleviation counties published by the

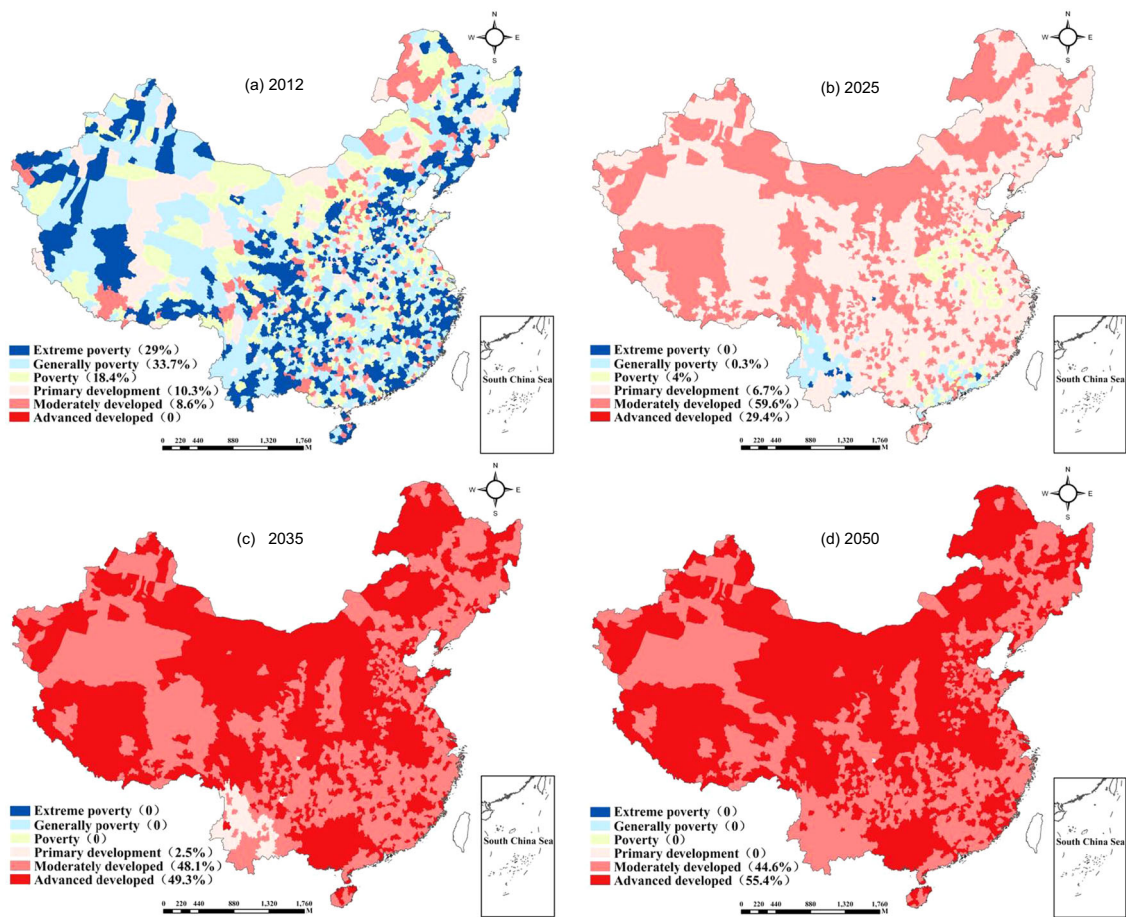


Fig. 3 Spatial distribution of MPI in SSP1 scenarios. This image shows the spatial evolution property of SSP1 pathways in 2012, 2025, 2035, and 2050, respectively. The gradation was determined using G^* fracture, and the boundary of the advanced developed county is above the maximum level of MPI in 2012.

National Poverty Alleviation and Development group in 2012. Due to the incomplete nature of indices from yearbook data, we selected 574 of the key poverty alleviation counties for analysis. The MPI rankings of 2369 counties in China were divided into six categories using the G^* fracture method: extreme-poverty, generally poverty, poverty, primary developed, medium developed, and advanced developed. The MPI generally poverty is mainly in Henan-Shandong in 2025, and the MPI poverty is mainly in Guangdong-Hainan, Yunan-Guangxi in 2025. The primary developed is mainly in Yunan in 2035. Spatial distribution of MPI in SSP2–SSP5 scenarios were also provided in Supplementary Fig. 7.

Using the Monte Carlo method with 10^7 simulation times, economic dimension weight (0.467 ± 0.033) > social welfare dimension weight (0.385 ± 0.014) > resource dimension weight (0.131 ± 0.02) > environment dimension weight (0.017 ± 0.003) when the identification accuracy of poverty alleviation counties is more than 80%. The identification accuracy of poverty-stricken counties in different provinces and regions of China is presented in Supplementary Fig. S1. Furthermore, a unique model is designed for every region by using the relationship between PAFs and MPI for explaining the region's poverty alleviation policy. The poverty alleviation policy models from different regions can use different model parameters, reflecting their respective regional property. Taking Anhui province as an example, the complex relationship of each model is presented in (Supplementary Fig. S2). Using these PAFs and MPI models, we built development scenarios for five poor counties, which covers a wide range of uncertainties caused by varying the model parameters in

Monte Carlo experiments. Considering the investment of poverty alleviation funds at various times, in different regions, and of different amounts, we conducted 1,000,000 simulations for the future scenario simulation. The spatial patterns of our MPI evolution property in China vary substantially across scenarios in 2025 and 2050 (see Fig. 2). Our proposed model is the first to reveal the future spatial changes of MPI at the county level. The differences can be affected by the amount, timescale, and direction of PAFs provided by government. The proposed model was able to capture the spatially explicit divergence between scenarios because it updates the change rate of MPI with PAFs at every time step (i.e., one year). These changes reflect how this region can be affected by PAFs, which allowed spatial patterns under different scenarios to evolve. For all SSP scenarios, a banded poverty zone involving Yunnan-Guangxi-Guizhou, Chongqing, and Henan deserves special attention in 2050. Scenarios SSP1, SSP4, and SSP5 yield a smaller number of less developed counties in 2050, while SSP2 and SSP3 have the slowest speed of poverty alleviation. The SSP2 and SSP3 scenarios rely too heavily on their own ability to become rich, which carries the risk that the area could return to poverty quickly.

Future investment in PAFs and the distribution of MPI.

Although China's poverty population decreased by 770 million during 1978–2020, when we consider the balance of MPI and the future goal of realizing developed counties, our model can reveal the impact of different SSP paths on China's future. Using diverse

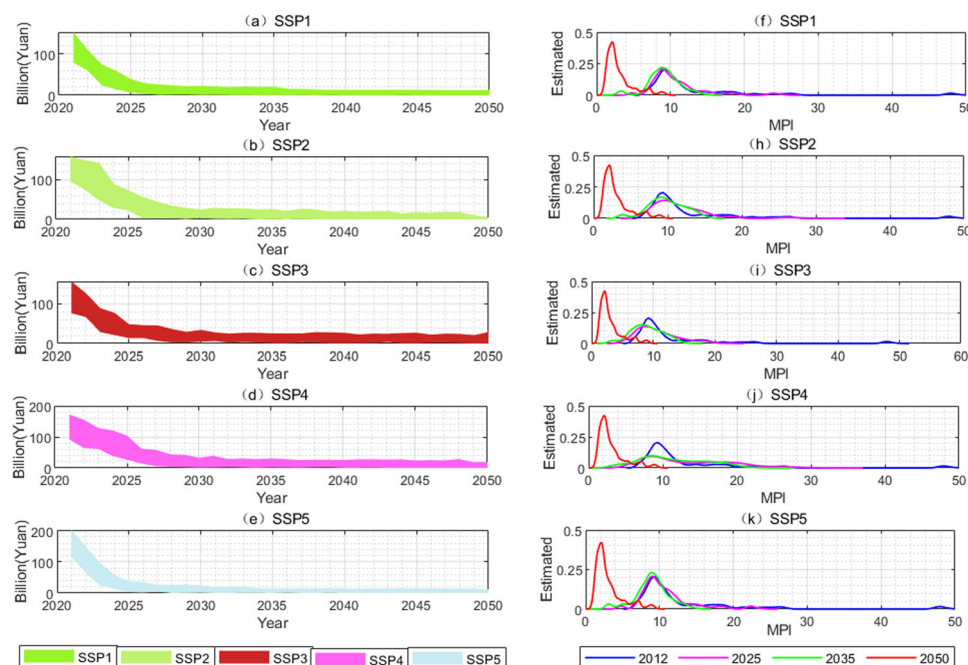


Fig. 4 Future tendency of MPI in China for different development scenarios. **a–e** Uncertainty of investments in poverty alleviation funds in different SSP scenarios; **f–k** The KS density estimate of MPI distribution in different SSP scenarios. The SSP1 path achieves a trade-off between development level and regional differences, making it more likely China would fulfill the SDGs. SSP2 could lead to an aggravation of regional differences. SSP3 would cause minimum regional differences but requires the largest PAF investments. SSP4 can achieve the maximum development level but the regional differences are much greater than those of SSP1, SSP3, and SSP5. SSP5 requires the minimum PAFs but damages the relationship with MPIs.

investment strategies by PAF to achieve developed county level by 2050 could lead to uncertainty. The evolution of investment PAFs is decreasing from 2020 to 2050 (see Fig. 4a). SSP1, SSP4, and SSP5 can reach the developed county goal in 2025, and SSP1 yields the minimum difference in regional balance. SSP2 has the best overall development level although regional differences will be intensified. The ksdensity estimate of the MPI distribution in different SSP scenarios is also presented in Fig. 4b. The ratio of poverty alleviation fund to MPI growth rate is used for evaluating the effectiveness of various SSP pathways. SSP1 is higher than SSP2, SSP3, and SSP4 by ratios of 0.0314, 0.2, and 0.029, respectively, and SSP1 is lower than SSP5 by a ratio of 0.024 because it damages the interests of resources and the environment. Therefore, the SSP1 path is more suitable for China to take to achieve the SDGs.

Discussion

In this paper, we present the long-term scenario prediction for future MPI at both county and country scale. The MPI predictions on a country scale are based on the latest SSP scenarios, while the simulated predictions for Chinese counties indicate the future tendency under PAFs-SSPs. This enhances the usefulness of the scientific approach for formulating poverty alleviation policies. In addition, the proposed modeling framework can be extended to such other developing countries as India (Wim et al., 2011), Tajikistan (Jha et al., 2010), and Peru (Flachsbarth et al., 2018).

Great progress has been made in poverty reduction globally. The proportion of the world's extremely poor population is decreasing, from 35.85% in 1990 to 9.2% in 2017. Affected by COVID-19, the proportion of the world's extremely poor population had a reverse growth from 9.2% in 2017 to 9.1–9.4%, and the number of extremely poor people has reached 115 million. The pandemic has brought great challenges to global poverty

reduction. At present, 95% of the world's poor regions lie in East Asia and the Pacific, South Asia, and sub-Saharan Africa (based on the international poverty line at US \$1.90 per day). To mitigate these challenges, poverty alleviation policies should place more emphasis on multidimensional coordinated development rather than a single indicator.

With respect to MPI in China, the mean MPI scores are gradually increasing, and their distribution changes from a “peak” in 2012 to “wide flat” in 2017, which indicates that the depth of poverty is gradually being reduced and the economic development of counties is steadily improving. The MPI variance between China's counties were displayed in Supplementary Table SV and Supplementary Fig. S3, which is slowly increasing, which indicates the poverty gap between counties is gradually reducing and the comprehensive development level of counties is steadily improving. Furthermore, the MPI poverty boundary is decreasing gradually with the number of national poverty alleviation counties (Supplementary Fig. S4a–c). With the increase of PAFs, the number of poverty-stricken counties has also decreased rapidly (see Supplementary Fig. S4d). The success of the targeted poverty alleviation strategy adopted in China demonstrates the importance of poverty reduction programs guided by PAFs in other developing counties. Great changes have taken place in the structure of poverty, and the MPI properties are shown in Supplementary Fig. S5. After the implementation of the targeted poverty alleviation strategy in 2012, the situation in China has improved, but it is difficult to completely reverse the current inter-provincial poverty situation in the short term. Yunnan, Guangxi, Sichuan, Gansu, Qinghai, Ningxia, Liaoning, Jilin, and other concentrated contiguous poverty-stricken areas are widely distributed. The connection of poverty zones is the key area to target to improve China's collaborative approach to poverty reduction.

With China's realization of its absolute poverty reduction goal in 2020, the formulation of a novel MPI standard has become

necessary. The contiguous MPAs are an important obstacle. Using data-driven scenario simulations to predict future tendencies will enable accurate multidimensional poverty alleviation through a feedback and correction mechanism. At the same time, the effective evaluation of the PAFs along with monitoring regional poverty alleviation policies is also necessary.

There are limitations in our future tendency prediction for MPI due to lack of available data. First, we analyzed the MPI at a national level using just two factors (the economy and environment) due to the absence of other fields of data. Second, poverty generally occurs in remote villages, we provide the index of MPI at a county and country scale in this study due to the lack of related village information. With the continuous development of information technology and increasing data access via the Internet, we aim to solve this limitation in our future work by complementing point-of-interest data to obtain relevant community-level data for various scenarios.

Data availability

The China Statistical Yearbook is available at <https://data.cnki.net/YearData/Analysis>. OECD GDP and population data is used for this study. The environmental dataset CMIP6 emissions is provided at <https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=50>. The MODIS dataset is available from <https://modis.gsfc.nasa.gov/data/>. The NLS data in terms of DMSP/OLS and NPP/VIIRS from 2000 to 2017 can be found at <https://www.ngdc.noaa.gov/eog/download.html>. Historical GDP and population statistics are available from <https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=30>. Codes and materials used to produce this work are available upon request.

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Competing interests

The authors declare no competing interests.

Ethical approval

Ethical assessment is not required prior to conducting the research reported in this paper, as the present study does not have experiments on human subjects and animals, and does not contain any sensitive and private information.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

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