Big Earth Data in Support of the Sustainable Development Goals

Big Earth Data Program
Chinese Academy of Sciences

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Big Earth Data in Support of the Sustainable Development Goals

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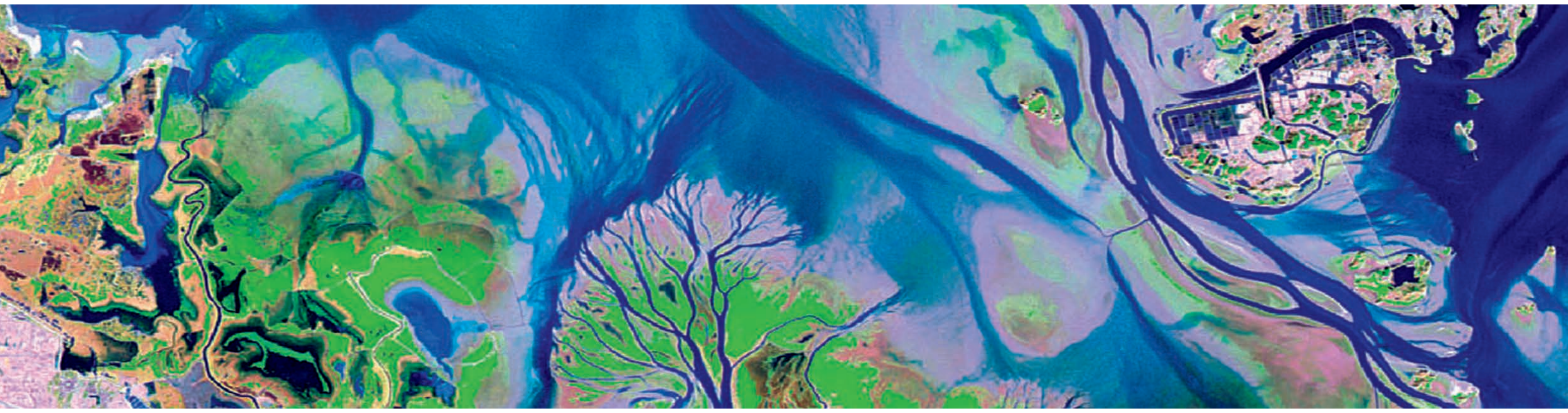


Preface

On the 70th anniversary of the United Nations (UN) in September 2015, heads of state and delegates gathered at the UN headquarters in New York and adopted the 2030 Agenda for Sustainable Development. This comprehensive sustainability framework was built on the basis of the historical experiences of human society and a shared expectation for the future. It presents a blueprint for countries to pursue global sustainable development in the next 15 years. The 17 Sustainable Development Goals (SDGs) incorporate various social, economic, environmental, and developmental targets and indicators, and have been endorsed by all countries with respective national implementation plans.

With the advancement of science, technology, and innovation (STI) accelerating, there is a growing international consensus that STI must play a key role in facilitating the implementation of SDGs. To this end, the UN established the "Technology Facilitation Mechanism" to bring together scientific communities, policy makers, business sectors, and other stakeholders for their collective ideas, knowledge, and wisdom to build societies with harmony between humankind and nature. The Chinese Academy of Sciences (CAS), being a member of the international scientific community, has been mobilizing its research capacities for action.

The SDGs consist of 17 goals, 169 targets, and over 230 indicators. Countries have different and very diverse development contexts. The key to success for one goal is often linked to solving issues associated with other goals. The SDGs thus constitute a vast system that is complicated, diverse, dynamic, and interconnected. This makes effective assessment and monitoring of each and all SDG targets and indicators essential to ensure the achievement of SDGs. Currently, only about 45% of indicators are supported by both methods and data, about 39% have methods but lack data, and some 16% have neither standard methods nor data. The full implementation of the 2030 Agenda for Sustainable Development will be hampered if these problems are not effectively resolved.

CAS addresses these challenges and concentrates on five SDGs, including: SDG 2 (Zero Hunger), SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 14 (Life below Water) and SDG 15 (Life on Land). CAS thus works on the 11 associated indicators of these SDGs, especially the indicators that are relatively weak in data or methods. The case studies presented in this report demonstrate that Big Earth Data and related technologies can provide new analytical tools and data infrastructures for understanding complex and interconnected sustainability issues. The continued effort to develop a Big Earth Data system will provide robust and complementary data services to support and improve SDG indicators. Furthermore, China's effort on Big Earth



Data applications in service of SDGs will likely be of interest to some other developing countries, particularly those lacking technological capabilities.

The research on Big Earth Data for SDGs is an important contribution of China towards the 2030 Agenda for Sustainable Development. It is a new platform for Chinese scientists and international scientific communities to work together. I would like to thank the research team led by Prof. GUO Huadong for their efforts towards implementing SDGs, and I expect them to bring new and more exciting results in coming years.

BAI Chunli
President, Chinese Academy of Sciences

Foreword

There are four major challenges in the implementation of the 2030 Agenda for Sustainable Development, including: (1) missing data and the evolution of SDG indicators, (2) complementary and non-complementary interconnections between different Sustainable Development Goals (SDGs), (3) complicated and varied problems in quantifying and monitoring indicators within different national and local contexts, and (4) difficulties in modeling indicators to monitor SDGs. Particularly, the main challenge in monitoring progress relates to the lack of data available for the development of indicators, and this lack of data has been identified for more than half of indicators.

In order to achieve the SDGs and effectively assess their progress with the full strength of science, technology, and innovation (STI), the United Nations (UN) has established the “Technology Facilitation Mechanism” (TFM). The TFM consists of three components: Interagency Task Team on STI for the SDGs (IATT) with a 10-Member Group to support TFM, a collaborative Multi-stakeholder Forum on STI for SDGs (STI Forum), and an online platform as a gateway for information on existing STI initiatives, mechanisms, and programs. Presently, a pressing priority of TFM is to make breakthroughs towards Tier II indicators (methods established but with poor data) and Tier III indicators (methods under development with either poor data or no data).

As an important aspect of technological innovation today, big data is bringing new tools and methodologies to scientific research. Based on Earth science, information science, and space science, Big Earth Data derives and integrates data from spatial Earth observations as well as terrestrial, oceanic, atmospheric, and human activity data from other sources. Big Earth Data is therefore characterized in terms of massive quantity, multiple sources, heterogeneous structure, and high complexity. Big Earth Data can also be non-stationary, unstructured, multi-temporal, and multi-dimensional. Effective use of Big Earth Data has offered a new key to generating knowledge about planet Earth, playing a major role in promoting sustainable development.

To this end, the Chinese Academy of Sciences (CAS) has launched research on Big Earth Data for the implementation of the 2030 Agenda for Sustainable Development. SDGs, especially the goals closely related to Earth’s surface, the environment, and natural resources, have the characteristics of being large-scale with cyclical changes. The macroscopic and dynamic monitoring capabilities of Big Earth Data thus fit well as an important means for assessment of progress on sustainable development.

The main objectives of the research on Big Earth Data for SDGs include converting Big Earth Data into SDG-related information, providing decision support for SDG implementation, constructing a Big Earth Data integration system for SDG indicators, and investigating the inter-linkages among different components of the Earth system. We have preliminarily sorted out 11 indicators from five SDGs as a priority. These indicators constitute 6% of Tier II indicators and 8% of Tier III indicators. The five SDGs include: SDG 2 (Zero Hunger), SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 14 (Life below Water), and SDG 15 (Life on Land).

Big Earth Data supports SDG indicators in three major ways. (1) Big Earth Data is used to fill in missing data and provide new sources of data for evaluation. (2) New methodologies are created to evaluate SDGs on the basis of Big Earth Data technologies and models. (3) The research provides practice cases of Big Earth Data for SDGs, and aids in monitoring

the progress of SDG indicators. It relies on novel methods for multi-source data acquisition, cloud data analysis, and artificial intelligence technologies to study cases at different scales. These methods also aid in developing global and regional SDG indicator assessment systems based on Big Earth Data for global and national appraisal and reporting.

The report *Big Earth Data in Support of the Sustainable Development Goals* presents 12 case studies of Big Earth Data on the development of SDG indicators and sustainability assessments in the above-mentioned five SDGs. These cases provide in-depth, systematic research and evaluation results on the selected SDGs and indicators by means of data, method models, and decision support. The case studies with focus varying from constructing databases, building index systems, and evaluating indicator progress. Each case study first clearly lists the corresponding SDG targets and indicators it addresses, and then proceeds with the research methods, data, analysis results, and the prospects for future research. It can be seen that Big Earth Data as a new scientific methodology has started demonstrating its great value and potential for application in monitoring and evaluating SDGs. The report concludes with a summary of the major progress in Big Earth Data for SDGs and future research priorities.

In *The Sustainable Development Goals Report 2019*, UN Secretary-General António Guterres said in his foreword that "progress is being made in some critical areas", and that from these advances, "we know what works", including "better use of data; and harnessing science, technology and innovation with a greater focus on digital transformation." Liu Zhenmin, Under-Secretary-General of the UN Department of Economic and Social Affairs, also pointed out in the report that "Most countries do not regularly collect data for more than half of the global indicators", and "Increased investment is urgently needed to ensure that adequate data are available to inform decision-making on all aspects of the 2030 Agenda." These messages underline the importance and urgency of data for SDGs, for which Big Earth Data is deemed to make a unique contribution.

The TFM is an important driver for achieving SDGs, fully concurring with China's concept of and strategy for STI for sustainable development. Big Earth Data as an innovative technology has great potential to this end. Research on SDGs will continue and a report will be published on *Big Earth Data in Support of the Sustainable Development Goals* every year. For this perspective, we warmly welcome cooperation from all research partners, both in China and around the world.

On the occasion of this report's publication, I would like to express my heartfelt thanks for the guidance and advice received from CAS, the Ministry of Foreign Affairs of China, the Ministry of Science and Technology of China, and other related departments. My sincere gratitude goes to all contributors engaged in this research, whose hard work has made this report possible.

GUO Huadong
CAS Academician
Research Team Leader, Big Earth Data for SDGs

Executive Summary

In 2015, the United Nations (UN) Sustainable Development Summit adopted the 2030 Agenda for Sustainable Development to promote sustainable development in three dimensions — economic, social, and environmental— in a balanced and integrated manner, which represents a milestone in our progress towards international development cooperation. However, the implementation of the agenda faces several challenges from a scientific perspective, including data deficiency, imperfect methods, interconnected and mutually constrained targets, diverse localization issues, and other problems restricting the pace of progress. As an important part of big data, Big Earth Data provides the capability to integrate data from multiple sources and helps to produce more relevant, frequent, and accurate information about complex processes that can support decision making and policy formulation. These traits hold potential for important contributions towards the agenda and support various aspects of the Sustainable Development Goals (SDGs). *Big Earth Data in Support of the Sustainable Development Goals (2019)* strongly supports and is committed to facilitating the implementation of SDGs. It will focus on research to fill in knowledge gaps and develop technologies, methodologies, data products, and open, accessible cloud-based data analysis environments for selected SDGs, including SDG 2 (Zero Hunger), SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 14 (Life below Water), and SDG 15 (Life on Land).

For SDG 2, this report targets indicator about proportion of agricultural area under productive and sustainable agriculture (SDG 2.4.1), and evaluates the indicator in China by adopting multiple sources of data and employing remote sensing information extraction models, statistical models, and ecological models. Evaluation of the environmental impacts of food production in China indicates that environmental impacts per unit of production has decreased since 2000, showing that China's cropping systems are becoming more sustainable. Meanwhile, land use change driven by urbanization challenged this trend. By monitoring the progress of this indicator, this report proposes that further interactions between land use change and farm management are critical to improving the sustainability of global food production systems for SDG 2.

For SDG 6, this report focuses on water quality (SDG 6.3.2) highlighting the potential of Big Earth Data to support SDG 6 by developing data products and technical methods. In this case, multiple sources of data such as Internet data, and statistics were applied. The integration of spatiotemporal data and model simulations helped produce an overall analysis of surface water environments in China. The results show that the surface water quality of China in 2017 is slightly improved compared with that of 2016, and the surface water quality in China's western region was superior compared to the eastern region.

For SDG 11, this report focuses on five indicators, including public transport (SDG 11.2.1), urbanization (SDG 11.3.1), cultural and natural heritage (SDG 11.4.1), $PM_{2.5}$ (SDG 11.6.2) and public spaces (SDG 11.7.1). This report utilizes Big Earth Data in place of the traditional statistical data and increases the spatiotemporal resolution of SDG indicator evaluation. This report also develops and employs the Big Earth Data methods for assessing China's domestic practices aimed at achieving SDG 11. A global 10-meter spatial resolution impervious surface product with an overall accuracy greater than 86% generated by fusion of optical and synthetic aperture radar (SAR) data provides important data support and resolves data deficiency for the monitoring and evaluation of SDG 11.3.1. Utilizing Big Earth Data, this report has also produced datasets like public transport information, $PM_{2.5}$ products, and proportion of public spaces in built-up urban areas. These products provide support for comprehensive evaluation of sustainable development in Chinese cities. By evaluating SDG 11 indicators and monitoring related processes for SDG 11.4.1, this report has improved the SDG indicator system, making the recommendation to “increase capital investment per unit area to preserve and protect world cultural and natural heritage”.

For SDG 14, this report focuses on marine pollution (SDG 14.1) and marine ecosystem health management (SDG 14.2). Based on field data on nutrient composition, chlorophyll-a concentration, phytoplankton biomass, and chemical indexes like dissolved oxygen observed in the coastal waters of China, and the bulletin of the national marine monitoring departments, an integrated eutrophication assessment model and an experimental evaluation model for marine ecosystems were developed. Based on the framework of “Pressure-State-Response”, an integrated eutrophication assessment model was developed which was implemented at different scales of estuaries and bays along Chinese coastal lines to assess their level of eutrophication. The results provide scientific support and decision making for the management of discharged offshore nutrient pollutants and coastal eutrophication.Furthermore, experimental evaluation of the ecosystem health of Jiaozhou Bay was carried out, and a simulation system will be developed to predict possible responses of coastal ecosystems to the changes in marine pollution. By further promoting the operational application of related technologies, it is expected to provide decision-making support for offshore environmental protection and management. The system can also effectively promote the realization of the SDG 14 target.

For SDG 15, this report takes proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas (SDG 15.1.2), and Red List Index (SDG 15.5.1) as research objects. The report presents three cases evaluated and monitored at national, and local scales. Biodiversity monitoring platforms were constructed to collect data for assessing the management effectiveness of Qianjiangyuan National Park. Our results show that cross-border cooperation is required to improve the effectiveness of park management. By evaluating the habitat fragmentation of the giant panda, it was found that panda habitats during the period from 1976 to 2013 became smaller and more fragmented. The report proposes to comprehensively consider the number of protected species and the protection of habitat environments. Based on the evaluation of the Red List Index, it was found that the Red List Index of higher plants and terrestrial mammals in China was on the rise from 2004 to 2017, while the Red List Index of birds was on the decline.

This report cites 12 typical cases centered on 11 SDG indicators of five selected SDGs and conducts in-depth research and appraisal of relevant SDG targets and indicators. It covers the perspectives of data, methods, models, and decision support, and provides a systematic of understanding challenges and potential solutions. In addition, it demonstrates the great value and potential of Big Earth Data in monitoring SDG indicators, and provides important support for decision-making and relevant research concerning SDGs.

List of Cases on Big Earth Data for SDGs

Indicator	Name of case	Area/Country	Data products	Method and model	Decision support
SDG 2.4.1	Assessing progress towards sustainable cropping systems: The case of China	China		Methodologies for assessing land productivity, irrigation water consumption, and excess fertilizer application by integrating multisource data and multidisciplinary models	Reveal the progress of sustainable use of cropland in China and the driving forces, and propose suggestions on promoting sustainability of crop production systems
SDG 6.3.2	Analysis of surface water quality in China	China	The proportion of good ambient water quality at provincial levels in China in 2016 and 2017		
SDG 11.2.1	Proportion of the population with easy access to public transportation in China	China	China's regional public transport information data	A simple indicator accounting method is proposed to provide experience and reference for other countries to evaluate and compare the same indicators	Provide data support for comprehensive evaluation of sustainable urban development at the national scale in China
SDG 11.3.1	Monitoring and assessing urbanization progress in China	China	Global 10-meter resolution high-precision spatial distribution information for urban impervious surfaces in 2015 (the base year for SDGs)	A method is proposed for rapidly extracting the information for global urban impervious surfaces using multi-source, ascending/descending orbits, multi-temporal SAR and optical data combined with texture and phenological characteristics. China's localized practices are evaluated for SDG 11	Decision support is provided for comprehensive evaluation of sustainable urban development at the national scale in China
SDG 11.4.1	Preliminary study and suggestions for modifying indicator SDG 11.4.1	China	Statistical data of "total per capita expenditure" and "expenditure per unit area" of national scenic spots in eastern, central and western China; 25-year time series datasets on the Huangshan World Heritage Site Remote Sensing Ecological Index (RSEI)	A method concerning "increasing the capital investment per unit area to preserve and protect world cultural and natural heritage" is proposed	
SDG 11.6.2	Monitoring and analyzing fine particulate matter ($PM_{2.5}$) in China	China	China's 2010-2018 annual average $PM_{2.5}$ products		

Indicator	Name of case	Area/Country	Data products	Method and model	Decision support
SDG 11.7.1	Proportion of urban open public space in China	China	Area indicator evaluation datasets for urban built-up areas in China	A simple indicator accounting method is proposed to provide experience and reference for other countries to evaluate and internationally compare the same indicators	Data support is provided for comprehensive evaluation of sustainable urban development at the national scale in China
SDG 14.1.1	Construction and application of an integrated eutrophication assessment model for typical coastal waters of China	Coastal Waters, China		Construct the latest comprehensive assessment system suitable for evaluating coastal eutrophication in China	Participate in the establishment of marine industry standards for the assessment of coastal eutrophication in China; Issue international reports on eutrophication assessment in the Northwest Pacific Action Plan (NOWPAP) region together and propose it to the United Nations Environment Programme (UNEP)
SDG 14.2.1	Ecosystem health assessment in Jiaozhou Bay, China	Jiaozhou Bay, China		Build the evaluation index system for typical waters in China	
SDG 15.1.2	Evaluating the effectiveness of the management of protected areas: An example from Qianjiangyuan National Park in China	Qianjiangyuan National Park, China	Qianjiangyuan National Park ecosystem and biodiversity datasets		Countermeasures for biodiversity conservation and management in Qianjiangyuan National Park
SDG15.5.1	Evaluation of the Red List Index of threatened species in China	China	Chinese species Red List Index data		
SDG15.5.1	Assessment of giant panda habitat fragmentation	Giant Panda Habitat, China	The data describes the current distribution and past changes in the giant panda habitat in China over the past 40 years		Support is provided to assess evolutionary characteristics and suggestions are offered for protecting giant panda habitats

Big Earth Data for SDGs

Big Earth Data for SDGs

The core of the 2030 Agenda for Sustainable Development is the 17 Sustainable Development Goals (SDGs). China attaches great importance to the implementation of the agenda and makes important contributions to addressing global challenges and achieving common development through practical actions. The 2030 Agenda for Sustainable Development is an ambitious undertaking and requires support from different sectors of society. The role of science and technology in particular is critical to facilitate knowledge-driven decisions and science-based policy development processes. Among numerous technologies and disciplines, big data technology, which is growing rapidly, is playing a distinct and significant role.

Data-intensive Paradigm

The rapid development of science and technology, with its growing acceptance and social demand, has enabled a revolution focused on collecting, storing, and utilizing data generated from human activities. Semi-structured and unstructured data have emerged in large volumes as the production and storage of data is no longer limited by time and space, and this has triggered an explosive growth of data. The volume and complexity of data is beyond the capabilities of traditional data management systems and processing models, which has given rise to the concept of big data.

This data revolution includes open data flows, the rise of crowdsourcing, the emergence of new data-gathering information and communications technology, the explosive growth of big data availability, and the popularization of artificial intelligence and the Internet of Things. The data revolution is affecting global production, distribution, and consumption patterns, and is changing human lifestyles, economic mechanisms, and national governance models. Meanwhile, computational science and data sciences have made real-time processing and analysis of big data a reality. New data obtained through data mining can be used as a supplement to official statistics and survey data to promote the accumulation of information on human behavior and other empirical information. The combination of new and traditional data can create high-quality information that is more detailed, timely, and relevant.

Data is one of the most significant elements that may affect decision-making processes. Using advanced mining and analysis functions on long-term, macro and micro multi-source data obtained through big data technology, it is possible to better monitor and evaluate the progress of implementing SDGs, and propose more scientific and targeted development guidance.

Big Earth Data

As an important part of big data, Big Earth Data is becoming a new frontier of Earth science, and is playing a significant role in promoting the in-depth development of Earth science and major scientific discoveries.

Big Earth Data is a new data-intensive research method that consists of big data with a spatial reference, including data related to land, oceans, the atmosphere, and human activities. Big Earth Data is generated by a variety of Earth observation methods, field surveys, and ground sensor networks. It bears the general characteristics of big data—large volume, multi-source, multi-temporal—and additionally has the characteristics of high instantaneity, arbitrary spatiality, and physical correlation, with Earth observation, communication, computation, and network technologies at its core.

Big Earth Data is not limited to scientific research, but also contributes to the sustainable development of our society and serves the SDGs. An important feature of Big Earth Data is the integration of multi-source data, which can provide more relevant and comprehensive information from complex and frequent analysis. The development of Big Earth Data will usher in more open and transparent data policies, so that humankind can hope for a better future for ourselves and the planet.

Big Earth Data for Implementing SDGs

At present, the UN, national governments, and international organizations are developing systems for monitoring and evaluating SDG indicators. However, one of the biggest challenges in implementing these systems is the lack of data to monitor the progress of various SDGs. Incomplete and inconsistent data statistics and the lack of systems for observing indicators are the main reasons for the lack of data and the low quality of existing data. Furthermore, indicators require multidisciplinary information, which is difficult to integrate and analyze using traditional systems, complicating the monitoring of SDG indicators.

Among the SDGs, many targets that are closely related to the environment and resources of the Earth surface are characterized by large-scale, periodic changes. Therefore, the Chinese Academy of Sciences (CAS) has launched research on Big Earth Data for SDGs, aiming to utilize Big Earth Data to expand upon the capabilities of inter-disciplinary science. The research systemically and holistically studies a series of major scientific issues improving scientific understanding of the Earth system to produce major breakthroughs, discoveries, and technological innovations in different scientific domains.

Applying Big Earth Data as a Technology Facilitation Mechanism (TFM) for SDGs, the research proposes to conduct research in relation to SDG 2 (Zero Hunger), SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 14 (Life below Water), and SDG 15 (Life on Land). The macro and dynamic monitoring capabilities of Big Earth Data provide an important tool for evaluating sustainable development. It can integrate databases, model libraries, and decision-making methods for resources, environment, ecology, and biology, building a sustainable development evaluation index system and decision support platform. These tools can effectively monitor sustainable development within economic, social, and environmental aspects, which helps generate richer, more relevant information for decision support.

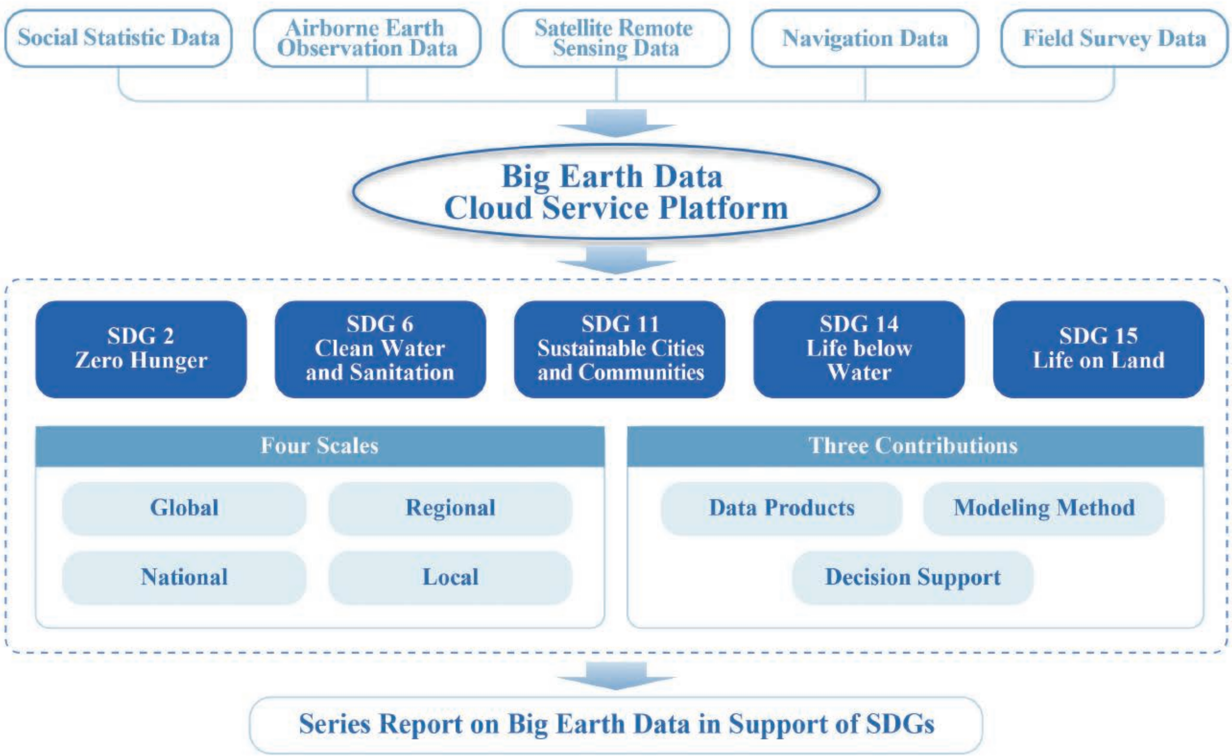


Figure 1-1. Framework of Big Earth Data for SDGs.

The research on Big Earth Data for SDGs is committed to providing assistance and facilitating SDGs in multiple capacities:

(1) Becoming a global data provider by constructing the Big Earth Data Sharing Service Platform to facilitate SDG implementation globally.

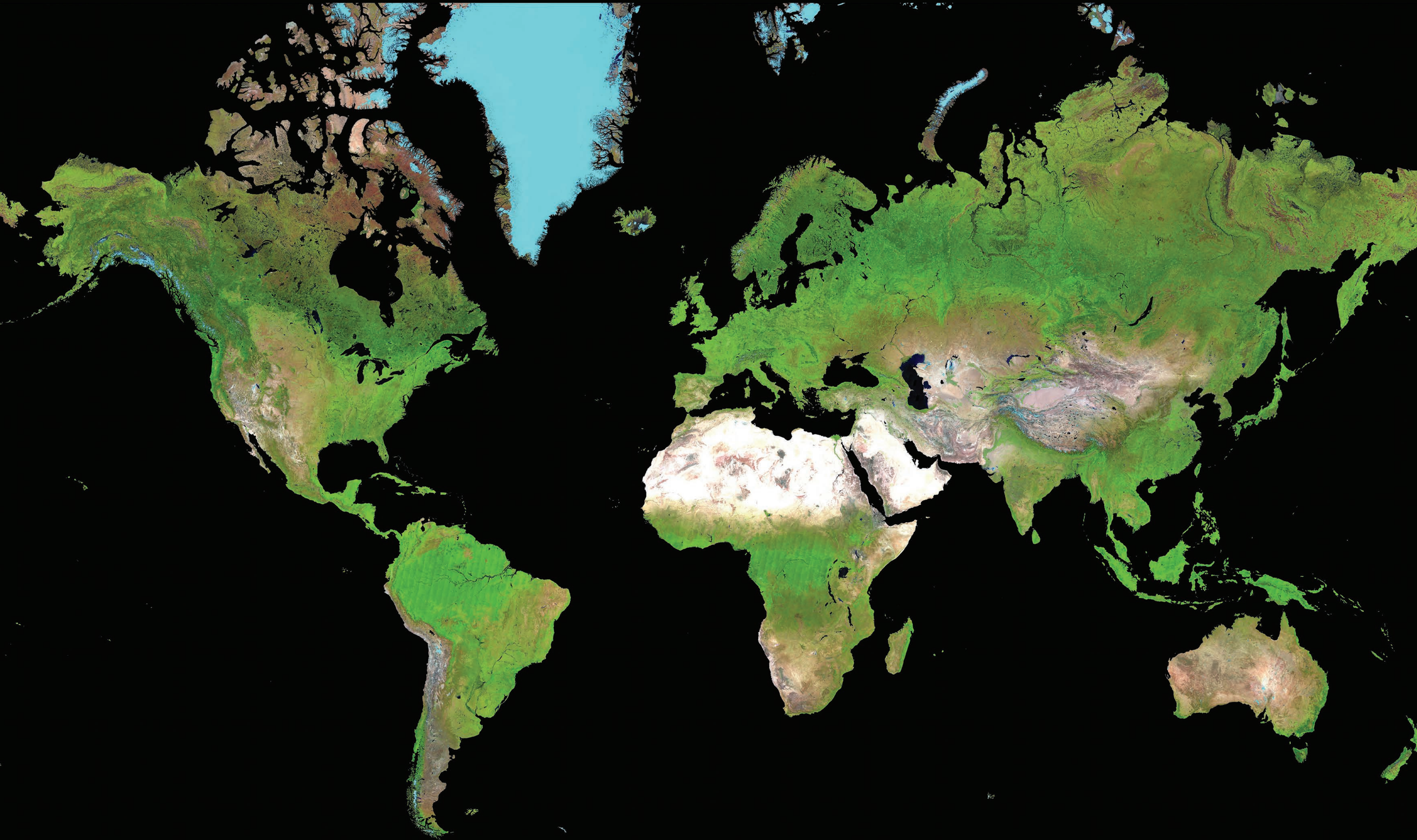
(2) Constructing an assessment and monitoring system for selected indicators of SDGs 2, 6, 11, 14, and 15.

(3) Evaluating and demonstrating projects on Big Earth Data utilization for SDGs in three broad aspects: development of data products, development of models and methods, and decision support.

(4) Publishing the Series Report on *Big Earth Data in Support of the Sustainable Development Goals* based on data collection and analysis, conducting regular evaluations of the progress of SDGs, and forming new ideas for global assessment of SDGs.

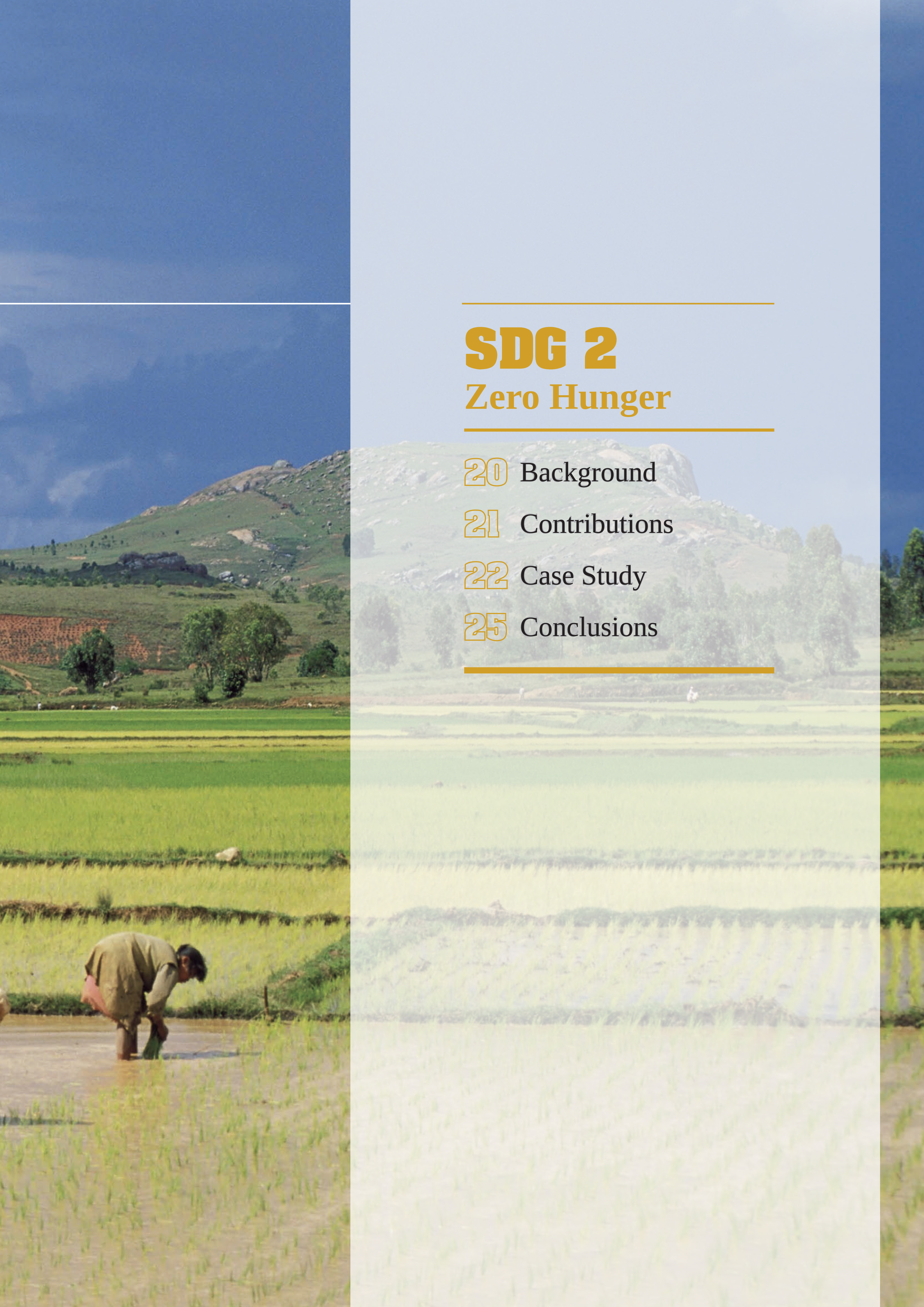
Data sharing is a key element to ensure support of Big Earth Data for SDGs, and therefore demands elimination of data islands and improvements in the efficiency of data exchange and sharing. CAS is working to develop and operate a Data Sharing Service Platform that breaks the policy barriers of data sharing, promotes the formation of a new model for online data sharing, improves the data sharing evaluation system, and establishes operable intellectual property protection mechanisms. These include data sharing indicators and verified authenticity, accuracy, and timeliness of shared data. The system also ensures that the data is discoverable, accessible, interactive, reusable, and citable. At present, the total amount of data shared on this platform is approximately 5 PB. As the hardware of the platform develops, about 3 PB of data will be updated each year.

Big Earth Data is a technological innovation method, and a TFM for SDGs will be developed, improved, and established through a series of major scientific studies with a systematic and holistic concept, contributing to human understanding of Earth, and realizing new breakthroughs in serving global sustainable development.



Global Remote Sensing Imagery

2 ZERO HUNGER



SDG 2
Zero Hunger

2 ZERO HUNGER

Background

The eradication of hunger and the guarantee of food security is one of the fundamental goals of global sustainable development. At present, the proportion of global population suffering from malnutrition has risen after years of continuous decline. Climate change, wars, conflicts and unbalanced economic development in many regions of the world account for the trend and place high levels of uncertainty on global food security.

SDG 2 aims to end all forms of hunger, achieve food security and improved nutrition and promote sustainable agriculture. It involves eight specific targets and thirteen indicators related to nutrition demands, sustainable food production, and national actions, for the purpose of guiding governmental regulations and establishing a sustainable food supply system that meets demands.

Assessment of the indicators in SDG 2 is led by the Food and Agriculture Organization (FAO), World Health Organization (WHO) and United Nations International Children's Emergency Fund (UNICEF). Data used in the assessment is mostly acquired through surveys and census by statistical departments of all countries. However, there has been a consensus that the traditional means for surveys and censuses is inadequate in terms of timeliness, spatial resolution, and costs. Earth observation technologies have innate advantages in monitoring indicators related to natural systems, such as food production and environmental impacts. Existing research has adopted Earth observation technologies for long-term monitoring of factors related to food production such as distribution of farmlands and grain yield. Such factors indirectly reflect, rather than directly assess, indicators related to SDG 2.

The research focuses on Tier II indicator related to sustainable food production system estimation (Table 2-1), and builds up methodologies to monitor the spatiotemporal patterns of indicator and sub-indicator by integrating multidisciplinary models based on Big Earth Data. Methods are used to estimate the situations of SDG 2.4.1 for the purpose of supporting the establishment of a sustainable food supply system and realization of the goal of zero hunger.

Table 2-1. Focused SDG 2 indicator

Target	Indicator	Tier
2.4 By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters, and that progressively improve land and soil quality.	2.4.1 Proportion of agricultural area under productive and sustainable agriculture.	Tier II

Contributions

Focusing on the difficulties in obtaining timely information on food production systems using surveys, this study promoted methodologies to estimate sub-indicators of SDG 2.4.1 by integrating multi-source data including remote sensing data, statistical data, and data from ground surveys. Methods were applied at national scale to create a data product to evaluate progress towards sustainable food production systems. This product provides a framework for comparison among regions, revealing sustainability problems and providing decision-making support (Table 2-2).

Table 2-2. Case and its contributions to SDG 2

Indicator	Case	Contributions
2.4.1 Proportion of agricultural area under productive and sustainable agriculture.	Assessing progress towards sustainable cropping systems: The case of China.	Method and model: Methodologies for assessing land productivity, irrigation water consumption, and excess fertilizer application by integrating multi-source data and multidisciplinary models. Decision support: Reveal the progress of sustainable use of cropland in China and the driving forces, and propose suggestions on promoting sustainability of crop production systems.

2 ZERO HUNGER

Case Study

Assessing progress towards sustainable cropping systems: The case of China

Scale: National

Study area: China

Developing agriculture to ensure long-term food supply contributing to economic and social development, while minimizing environmental impacts is at the heart of the challenge. Quantitatively assessing the sustainability of agricultural systems is therefore critical and requires spatial and temporal monitoring of three key aspects, economic, environmental, and social, and examining the interactions between them. This is a complex undertaking and requires innovative data infrastructure such as the Big Earth Data infrastructure that provides one of the best implementations to accomplish this task.

Target 2.4: By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding, and other disasters, and that progressively improve land and soil quality.

Indicator 2.4.1: Proportion of agricultural area under productive and sustainable agriculture.

Method

By integrating remote sensing methodologies, spatial allocation models, global crop water models, and mass balance models, analysis estimates three sub-indicators of SDG 2.4.1—land productivity, water use (represented by irrigation water consumption), and fertilizer pollution risk (represented by excess nitrogen and phosphorus)—for China from 1987 to 2015. The sub-indicators were calculated for a total of 14 major crops, over 76% of the harvest area in China that accounts for about 87% of kilocalorie production in the region. "Environmental intensity"—environmental impacts per kilocalorie produced—was used to develop a matrix to determine level of sustainability, to facilitate comparison among different agricultural zones and across indicators. Sustainability criteria were proposed according to the definition from the FAO's metadata for SDG 2.4.1, which is based on two aspects: current state and trends. A decrease in intensity suggests a more sustainable level. The trends of each sub-indicator and the integrative patterns in terms of environmental intensity were estimated for the entire study area.

Data used in this case

For this study the Big Earth Datasets are composed of the 1:100,000 National Land use/cover Database of China based on Landsat, China-Brazil Earth Resources satellite (CBERS) and HJ-1 satellite data; MODIS time series vegetation index data; statistical data including national crop harvest area and yield, irrigation area, and fertilizer application; field survey data including pollution census data and agricultural census data; and information on crop phenology and fertilizer application rate obtained from literature.

Results and analysis

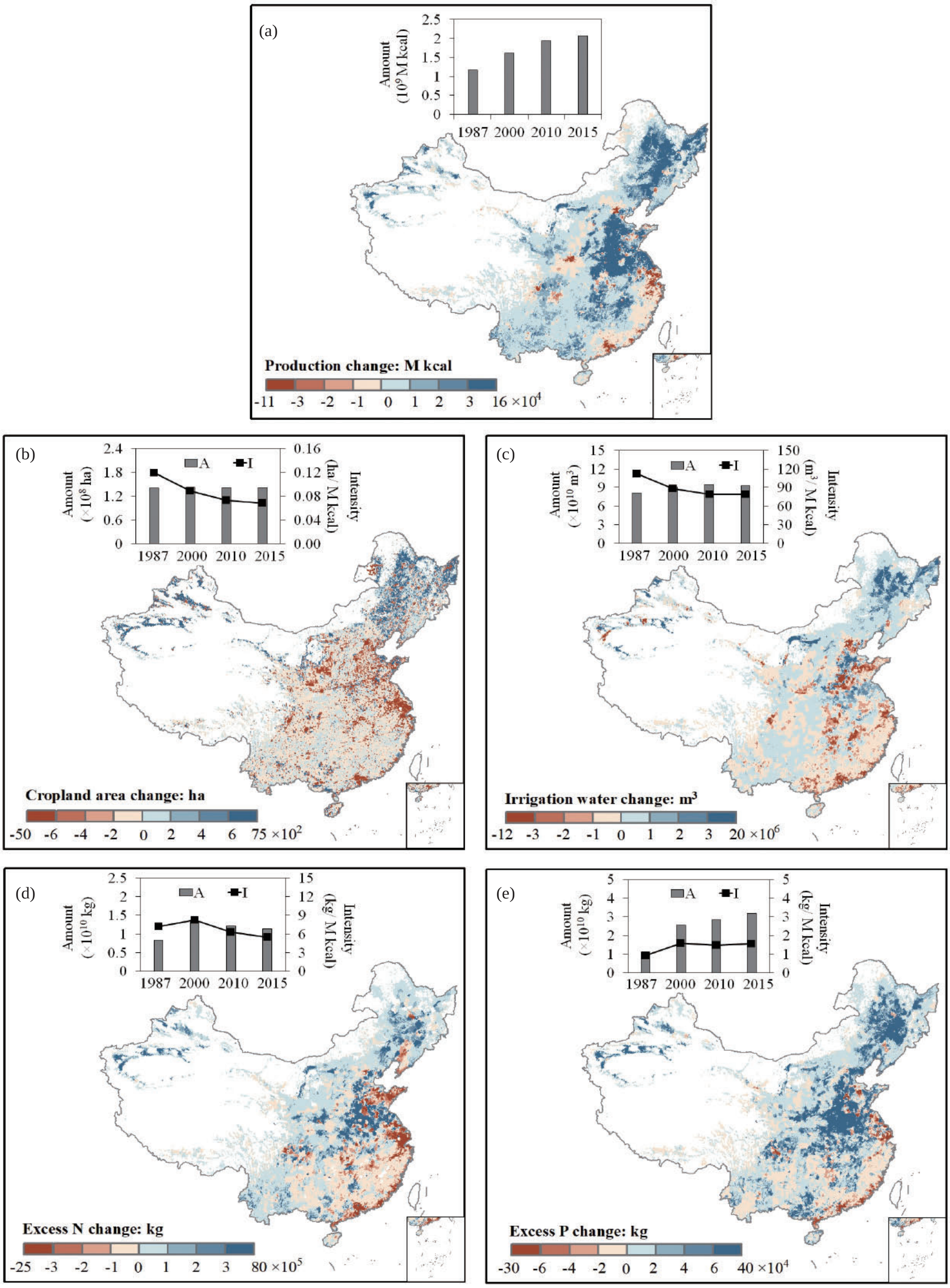


Figure 2-1. Spatial distribution of changes in crop kilocalorie production (a), cropland area (b), irrigation water (c), excess N use (d), and excess P use (e) from 1987 to 2015 in China. Inset plots indicate the changes in amount (A) and intensity (I) for these indicators in 1987, 2000, 2010, and 2015 (data for Taiwan Province is missing).

The study found that from 1987-2015, environmental intensity for land use (-43%), irrigation water consumption (-30%), and excess N application (-24%) decreased whereas excess P application (+66%) increased. However, all indicators declined after 2000. Collectively, the intensity of all four indicators declined across 26% of cropland, meaning that these croplands had achieved at least an acceptable level of sustainability across the four indicators. Environmental intensity was found to have increased in only 3% of cropland for all four indicators collectively. Generally, regions with lower land intensity had greater improvement across all other indicators. Overall these results suggest that China's food supply has become more environmentally efficient over time.

Recognizing drivers of change in sustainability helps develop future strategies. Analysis indicates that farm management explained >90% of changes in crop production and environmental impacts. Precision agricultural management, such as Science Technology Backyard platforms, has helped China's cropping systems to become more sustainable.

Meanwhile, nationwide loss of fertile cropland to urban expansion was offset by cropland expansion in arid and low-productivity northern regions, where land and irrigation water intensity were much higher than the national average. Continued spatial redistribution of croplands, which was already observed, may further challenge China's food security. Coordinating land-use change and farm management are thus critical for delivering agricultural sustainability in China, and also other rapidly urbanizing regions of the world.

Figure 2-2. High-standard cropland in Xinjiang Uygur Autonomous Region of China.

Highlights

- *For the period of 1987-2015, about one quarter of croplands in China improved in efficiency in terms of land use, irrigation water consumption, and excess fertilizer application; since 2000, national average intensity of all three indicators decreased, indicating a more environmentally efficient cropping system in China.*
- *Farm management explained >90% of the changes; meanwhile, land-use change primarily driven by urbanization challenged the trends. Coordinating land-use change and farm management are critical for delivering agricultural sustainability in China and other rapidly urbanizing regions of the world.*

Outlook

Applying the above methodologies in other countries can help to gradually improve the efficiency of their productivity and move towards a more sustainable cropping system.

Further employing Earth observation technology in the estimation of other sub-indicators, and exploring methodologies for fusing social and economic data with Earth observation data, will help develop mechanisms to coordinate different sources of data in the estimation.

Exploring interconnections between SDG 2.4.1 and other indicators particularly in SDG 6, SDG 11, SDG 13, will provide improved understanding of how different goals influence each other and provide valuable insights on underlying factors locally, helping to promote region-specific strategies towards sustainability and to support decision making.

2 ZERO HUNGER

Conclusions

Sustainable food production systems are critical for achieving SDG 2. Earth observation technologies have unique advantages in monitoring food production systems, for measuring distribution of agricultural production, food yield and fluctuations, as well as understanding environmental impacts on agricultural production. The high temporal and spatial resolution of Earth observation data coupled with data from statistical surveys and other economic and social data provide progressive monitoring and evaluation of indicators to facilitate actions and decisions towards sustainable agriculture.

The research focuses on Tier II indicator related to sustainable food supply in SDG 2, namely SDG 2.4.1. The case study presented in this report propose methods to evaluate indicator and sub-indicator by integrating multi-source data, to improve the monitoring and assessment of sustainability in China.

The estimation of sub-indicators of productive and sustainable agriculture shows that environmental intensity (land use, irrigation water consumption, and excess fertilizer application) in China has been declining since 2000, indicating a movement towards a more sustainable cropping system. Meanwhile, nationwide cropland displacement from high-quality lands to marginal ones primarily driven by urbanization challenged this trend. Farm management and land-use planning must be coordinated to further deliver a sustainable food supply in China and other urbanizing regions.

This report proposes some key areas, problems, and countermeasures for a sustainable food production system for achieving SDG 2.

In the future, the research will:

(1) Make full use of the current international linkages and collaboration networks to cooperate with international organizations and third-party organizations to strengthen the application of Big Earth Data in SDG 2, establish a mechanism for data sharing and technology promotion, and advance the work of indicator evaluations in developing countries with serious food problems and relatively poor technical forces.

(2) Focus on key issues of the global food production system including small-scale producers and productive, sustainable agriculture; examine interactions between SDG 2 and SDG 13; address challenges to food security due to changing climate; and provide decision making support to achieve global food security within a changing world.

6 CLEAN WATER AND SANITATION

SDG 6

Clean Water and Sanitation

Background

Water is a key resource for sustaining life on this planet and clean water is essential for the development of human society. A significant portion of the human population still lacks access to clean drinking water. SDG 6 defines an important goal for global sustainable development, proposing eight targets and eleven indicators, including water resources, water environment, water ecology, and international cooperation related to water. UN-Water, WHO, and other international organizations have jointly implemented the Integrated Monitoring of Water and Sanitation Related SDG Targets program for SDG 6 indicators.

Data is the biggest bottleneck that restricts monitoring of the SDG 6 indicators. There are five Tier II indicators among the eleven specific indicators for SDG 6 that have clear methods but lack relevant data sources. The evaluation methods recommended in the metadata documents and assessment reports for SDG 6 indicators are mainly based on statistical and census data. These methods are limited by the cost and cycle of sampling surveys, which results in limited spatiotemporal resolution. Additionally, differences in statistical systems and methods among different countries create consistency issues, making evaluation of these indicators challenging at global scales.

These limitations call for innovative evaluation methods to both improve spatiotemporal accuracies of indicators and provide multi-scale perspectives. This is only possible by diversifying data sources. Big Earth Data therefore becomes highly relevant for indicator evaluation.

Presently, a large number of applications utilize satellite remote sensing data and data from ground observations to monitor indicators related to various aspects of water quality and water ecological environments. For example, large-scale dynamic monitoring for indicator SDG 6.3.2 is performed by measuring the chlorophyll content in lakes and large reservoirs through remote sensing data. Moreover, this method is coupled with analysis of samples to determine water quality changes.

Table 3-1. Focused SDG 6 indicator

Target	Indicator	Tier
6.3 By 2030, improve water quality by reducing pollution, eliminating dumping and minimizing release of hazardous chemicals and materials, halving the proportion of untreated wastewater and substantially increasing global recycling and safe reuse.	6.3.2 Proportion of bodies of water with good ambient water quality.	Tier II

Contributions

Big Earth Data was employed in a supporting role for the realization of SDG 6 targets. SDG 6.3.2 was monitored at a high resolution by using Internet data, statistics, and other data sources. This was also accomplished using spatiotemporal data fusion method.

Table 3-2. Case and its contributions to SDG 6

Indicator	Case	Contributions
6.3.2 Proportion of bodies of water with good ambient water quality.	Analysis of surface water quality in China.	Data product: The proportion of good ambient water quality at provincial levels in China in 2016 and 2017.

6 CLEAN WATER AND SANITATION

Case Study

Analysis of surface water quality in China

Scale: National

Study area: China

Surface water quality is important for both human consumption and maintaining a healthy and functioning ecosystem. Pollution is one of the main causes of water quality degradation in surface water bodies throughout the world. The rapid economic development in China during the past 40 years has considerably increased the amount of pollutants released into water bodies. The Chinese government has made a considerable effort to improve water quality. The Central Government of China has developed national standards for surface water environmental quality, and established a water quality monitoring network covering all major river basins across the country. The national standard identifies 24 main indicators, which also provide the basis for the SDG 6.3.2 indicator proposed by UN-Water. This case study focuses on the water quality of major rivers, lakes, and reservoirs, and uses data collected from national monitoring networks accessible from their website. Herein, a statistical spatial index of surface water quality was developed for China at provincial and municipal scales.

Target 6.3: By 2030, improve water quality by reducing pollution, eliminating dumping, and minimizing release of hazardous chemicals and materials, halving the proportion of untreated wastewater, and substantially increasing recycling and safe reuse globally.

Indicator 6.3.2: Proportion of bodies of water with good ambient water quality.

Method

Surface water quality is classified into six categories by Environmental Quality Standards for Surface Water (GB3838-2002). Classes III, II, and I represent progressively higher classes for surface water quality. The water quality data was collected online from websites administered by local environmental protection departments, where the observation data is regularly updated. An index was calculated by determining the proportion of water bodies for each water quality class within sub-national administrative boundaries.

Data used in the case

◎ Observation data for surface water quality is issued online by environmental protection monitoring departments administered by provinces and municipalities.

Results and analysis

The above methodology was employed to calculate the proportion of each category of surface water for provincial and municipal administrative units in China during the 2016 and 2017 period. The proportions of water bodies with good ambient water quality in China was 67.8% in 2016. The proportion of Class I, II, III, IV, V, and inferior V water bodies was 2.4%, 37.5%, 27.9%, 16.8%, 6.9%, and 8.6%, respectively, with Class II and III in the majority. The number rose to 67.9% in 2017, and the proportion of inferior V water bodies decreased by 0.3% compared to 2016, suggesting that the water quality has improved. Spatially, the surface water quality in the western region of China was superior compared to the central and eastern regions. The Xinjiang Uygur Autonomous Region and Tibet Autonomous Region maintained the highest surface water quality during the 2016 and 2017 periods. After years of centralized treatment, the quality of surface water in China is observed to be gradually improving. However, there is still much work to be completed in water pollution control, such as differentiated governance and investigating pollution sources.

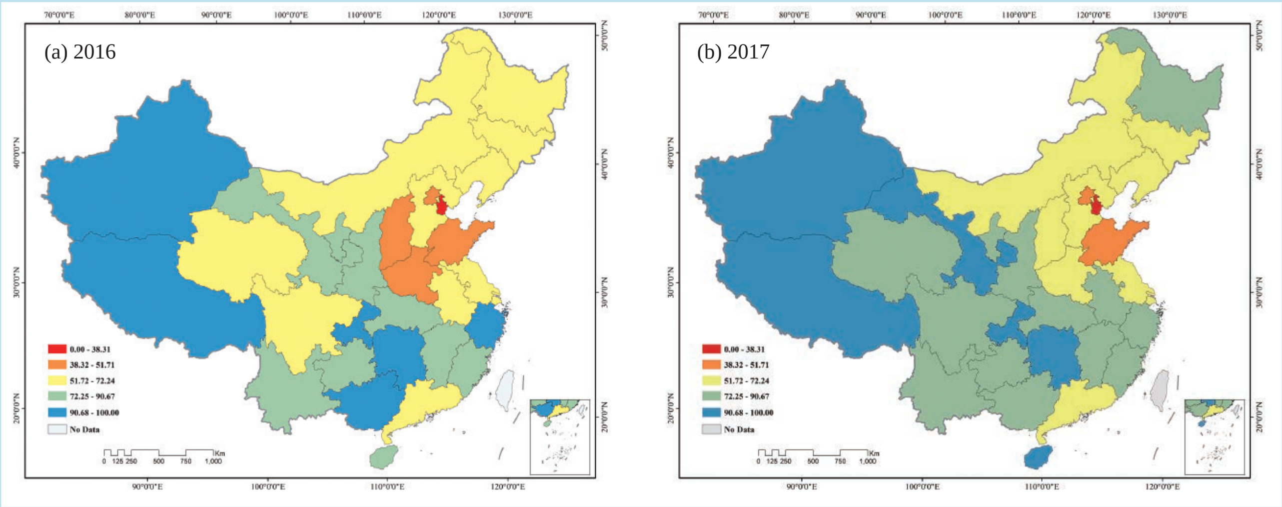


Figure 3-1. Proportion index for water quality at provincial scales in China in 2016 and 2017.

Highlights

- *In 2016 and 2017, the proportion of bodies of surface water with good ambient water quality in China were 67.8% and 67.9% , respectively.*
- *The surface water quality in China's western region was superior compared to the central and eastern regions.*

Outlook

The monitoring result will be updated each year. A more comprehensive analysis is being planned by adding data from 2018 to 2020. This will allow for estimation of high surface water quality trends for ambient water quality.

A comparative analysis of water quality monitoring standards is also being designed for other countries and regions. This is necessary to explore the feasibility of using networks to acquire observation data for surface water quality analysis. This will allow for additional applications in countries and regions that maintain a water quality database.

6 CLEAN WATER AND SANITATION

Conclusions

Rapid and accurate monitoring of SDG 6 indicators represents an important foundation for providing and managing sustainable water sources and sanitation. Currently, there are suggested calculation methods for all eleven indicators in SDG 6. Current and future work will focus on examining existing calculation methods that use multi-source data integration. This is necessary to obtain spatiotemporally continuous data to meet the requirements for monitoring and evaluation.

The Big Earth Data framework has numerous advantages in spatiotemporal resolution, accessibility, and accuracy compared with traditional statistical data. The application of Big Earth Data methods, represented by satellite remote sensing and mobile Internet data, has comprehensively improved the spatial accuracy, sampling density, and frequency of SDG 6 indicators. Moreover, this methodology has improved the temporal resolution and accuracy of evaluation results.

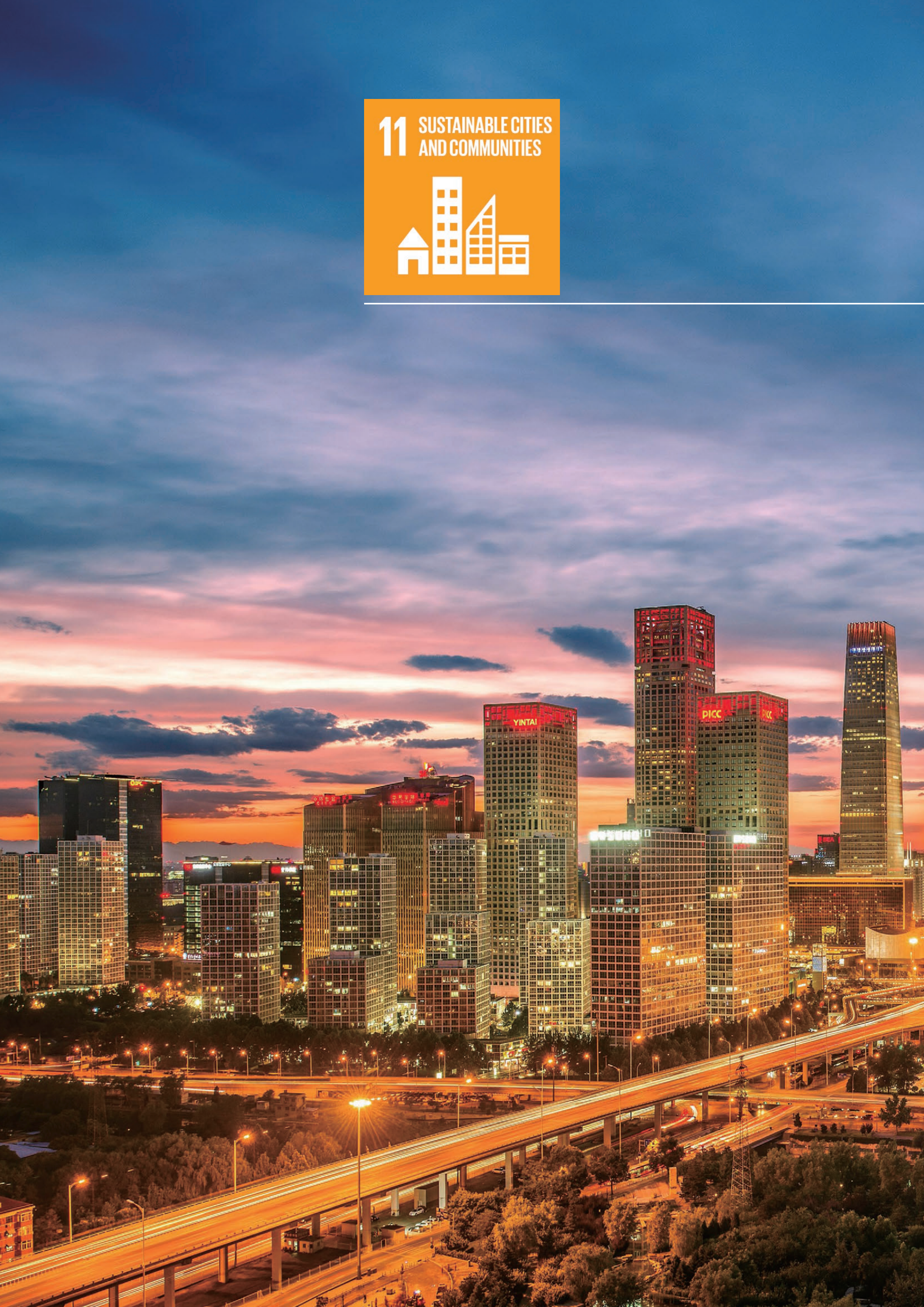
The SDG 6 cases selected in this report suggest that Big Earth Data plays an important role in improving the monitoring capability of SDG indicators. However, these results also expose the issues associated with spatiotemporally continuous data acquisition, and multi-source heterogeneous data matching. There is also a discrepancy in the connection between independent monitoring and evaluation results and the actual needs of the local government management department. In view of this, it is advisable to continue in-depth work in the following areas in the future.

(1) There is a need to strengthen data collection and processing, develop universal analysis methods, and standardize processing and modules. Moreover, future work should realize seamless connection and simplification of applications for data from big networks, remote sensing, and statistical surveys. This will aid in realizing continuity and sustainability for monitoring and evaluating all indicators.

(2) Future studies should also aim to promote extensive and in-depth cooperation with international, national, and social organizations. Technical methods and systems should be applied to aid in promoting the global realization of SDG 6, especially in the countries and regions involved in the joint construction of the Belt and Road.

Sanjiang Plain Wetland, China

11 SUSTAINABLE CITIES AND COMMUNITIES



SDG 11

Sustainable Cities and Communities

Background

According to UN statistics, the proportion of the global urban population has increased from less than 30% in 1950 to 55% in 2018 and is expected to rise to 68% by 2050. In 2016, more than one billion people lived in slums or informal settlements, more than half of whom (589 million) were in East Asia, Southeast Asia, Central Asia, and South Asia. Although over 75% of global gross domestic product (GDP) is generated from urban areas, they account for 60-80% of energy consumption and 75% of carbon emissions. Rapid urbanization poses enormous challenges to humanity and results in an increasing number of slum dwellers due to housing shortages, traffic congestion, increased air pollution and sewage, inadequate freshwater supply, waste generation, and inadequate basic services and infrastructure. Unplanned urban expansion renders cities particularly vulnerable to climate change and natural disasters.

SDG 11 was created as a response to the above issues and aims to make cities and human settlements inclusive, safe, resilient, and sustainable. SDG 11 includes seven targets for technology, three targets for cooperation, and a total of 15 indicators. Cities are one of the most challenging areas for sustainable development. Domestic and overseas studies have shown that Big Earth Data technology has great potential and benefits in providing updated Earth surface information with good spatiotemporal resolution, accessibility, and accuracy. This section focuses on 5 of the 15 indicators for SDG 11 using the Big Earth Data approach, and includes: urban public transport, urbanization, cultural and natural heritage, $PM_{2.5}$, and urban public space (Table 4-1).

Table 4-1. Focused SDG 11 indicators

Target	Indicator	Tier
11.2 By 2030, provide access to safe, affordable, accessible, and sustainable transport systems for all. Improve road safety by expanding public transport with special attention to the needs of those in vulnerable situations, such as women, children, the elderly, and persons with disabilities.	11.2.1 Proportion of the population that has convenient access to public transport, by sex, age, and persons with disabilities.	Tier II
11.3 By 2030, enhance inclusive and sustainable urbanization and the capacity for participatory, integrated, and sustainable human settlement planning and management in all countries.	11.3.1 Ratio of land consumption rate to population growth rate.	Tier II
11.4 Strengthen efforts to protect and safeguard the world's cultural and natural heritage.	11.4.1 Total expenditure (public and private) per capita spent on the preservation, protection, and conservation of all cultural and natural heritage, by type of heritage (cultural, natural, mixed and World Heritage Centre designation), level of government (national, regional and local/municipal), type of expenditure (operating expenditure/investment) and the type of private funding (donations in kind, private non-profit sector and sponsorship).	Tier III
11.6 By 2030, reduce the adverse per capita environmental impact of cities, including assessing air quality and municipal and other waste management.	11.6.2 Annual mean levels of fine particulate matter (e.g., $PM_{2.5}$ and PM_{10}) in cities (population weighted).	Tier I
11.7 By 2030, provide universal access to safe, inclusive, and accessible, green and public spaces, particularly for women and children, the elderly, and persons with disabilities.	11.7.1 Average share of the built-up area of cities that is open for public use to citizens regardless of sex or age, and to persons with disabilities.	Tier II

Contributions

The research mainly monitors and evaluates five indicators (Table 4-1) for SDG 11 at national scale. It provides access to Chinese data products, methodological models, and decision support for monitoring SDG 11 indicators. Detailed information is provided in Table 4-2.

Table 4-2. Cases and their contributions to SDG 11

Indicator	Case	Contributions
11.2.1 Proportion of the population that has convenient access to public transport, by sex, age, and persons with disabilities.	Proportion of the population with easy access to public transportation in China.	Data product: China's regional public transport information data. Method and model: A simple indicator accounting method is proposed to provide experience and reference for other countries to evaluate and compare the same indicators. Decision support: Provide data support for comprehensive evaluation of sustainable urban development at the national scale in China.
11.3.1 Ratio of land consumption rate to population growth rate.	Monitoring and assessing urbanization progress in China.	Data product: Global 10-meter resolution high-precision spatial distribution information for urban impervious surfaces in 2015 (the base year for SDGs). Method and model: A method is proposed for rapidly extracting the information for global urban impervious surfaces using multi-source, ascending/descending orbits, multi-temporal SAR and optical data combined with texture and phenological characteristics. China's localized practices are evaluated for SDG 11. Decision support: Decision support is provided for comprehensive evaluation of sustainable urban development at the national scale in China.
11.4.1 Total expenditure (public and private) per capita spent on the preservation, protection, and conservation of all cultural and natural heritage, by the type of heritage (cultural, natural, mixed, and World Heritage Centre designation), the level of government (national, regional, and local/municipal), the type of expenditure (operating expenditure/investment) and the type of private funding (donations in kind, and private non-profit sector and sponsorship).	Preliminary study and suggestions for modifying indicator SDG 11.4.1.	Data product: Statistical data of "total per capita expenditure" and "expenditure per unit area" of national scenic spots in eastern, central and western China; 25-year time series datasets on the Huangshan World Heritage Site Remote Sensing Ecological Index (RSEI). Method and model: A method concerning "increasing the capital investment per unit area to preserve and protect world cultural and natural heritage" is proposed.
11.6.2 Annual mean levels of fine particulate matter (e.g., $PM_{2.5}$ and PM_{10}) in cities (population weighted).	Monitoring and analyzing fine particulate matter ($PM_{2.5}$) in China.	Data product: China's 2010-2018 annual average $PM_{2.5}$ products.
11.7.1 Average share of the built-up area of cities that is considered as open space for public use by all citizens, regardless of sex, age, or disability.	Proportion of urban open public space in China.	Data product: Area indicator evaluation datasets for urban built-up areas in China. Method and model: A simple indicator accounting method is proposed to provide experience and reference for other countries to evaluate and internationally compare the same indicators. Decision support: Data support is provided for comprehensive evaluation of sustainable urban development at the national scale in China.

11 SUSTAINABLE CITIES AND COMMUNITIES

Case Study

Proportion of the population with easy access to public transportation in China

Scale: National

Study area: China

Public transportation is an essential lifeline for citizens that guarantees movement of people and goods and contributes to the economic productivity of urban centers and ensures proper functioning of the city. It plays an important role in promoting the development of various industries, the prosperity of economic and cultural activities, and contact between urban and rural areas. A good urban public transportation system is synonymous with economic growth and quality of life in many cities. Moreover, public transportation is a key factor for achieving most SDGs, especially those related to education, food security, health, energy, infrastructure, and the environment. However, it is difficult to acquire information and quantify public transportation networks within the complex urban space. Big Earth Data provides a viable solution to the challenges of acquiring and processing the information gathered from complex environments.

Target 11.2: By 2030, provide safe, affordable, accessible, and sustainable transportation systems for all, improve road safety, especially to expand public transportation. Special attention should be paid to the needs of vulnerable people, women, children, the disabled and the elderly.

Indicator 11.2.1: Proportion of the population with easy access to public transportation, classified by age, sex, and disability.

Method

The SDG 11.2.1 indicator method extracts public transport (transit, subway) station data based on the national public transportation network vector map. This method involves the creation of 500 m buffers, which are then overlapped with high spatiotemporal resolution population products to calculate the proportion of the population covered by the buffer in the kilometer grid. Finally, the proportion of the population that has easy access to public transportation within the urban built-up area is calculated based on spatial data.

Data used in this case

◎ National public transportation network vector map (2015).
◎ National 100-meter resolution land use data.
◎ National 1-kilometer resolution population distribution product.

Results and analysis

The population coverage within 500 m of public transportation stations in the following provinces (excluding Taiwan Province) was analyzed using public transport station and population kilometer grid products for prefecture-level cities across the country. Overall, the proportion of the population with convenient access to public transportation at the provincial level was 64.28% on average. Moreover, the proportions in eastern provinces were generally higher than those in the central and western provinces. The proportions in the southern provinces were also generally higher than in the northern provinces. Macao, Shanghai, and Hong Kong reached 100%, and the 500 m buffer for traffic stations covered the entire population in the built-up area. Beijing, Tianjin, Zhejiang, Fujian, Sichuan, Jiangsu, Guangdong, Chongqing, Liaoning, Guangxi, Hunan, Anhui, Shaanxi, Qinghai, Jiangxi, and Guizhou featured higher percentages compared to the national average. There were 14 provinces that featured percentages below the national average: Shandong, Hebei, Hainan, Hubei, Shanxi, Jilin, Heilongjiang, Henan, Ningxia, Yunnan, Gansu, Tibet, Xinjiang, and Inner Mongolia.

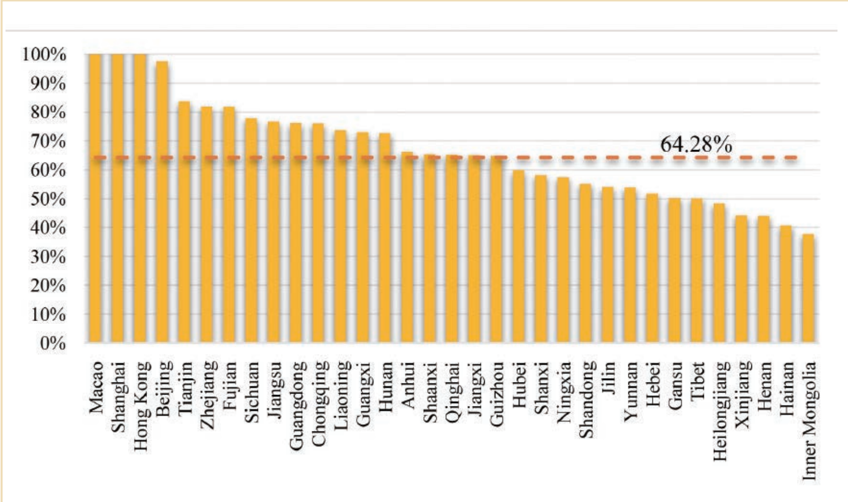


Figure 4-1. Proportion of the population with easy access to public transportation in each province (data for Taiwan Province is missing).

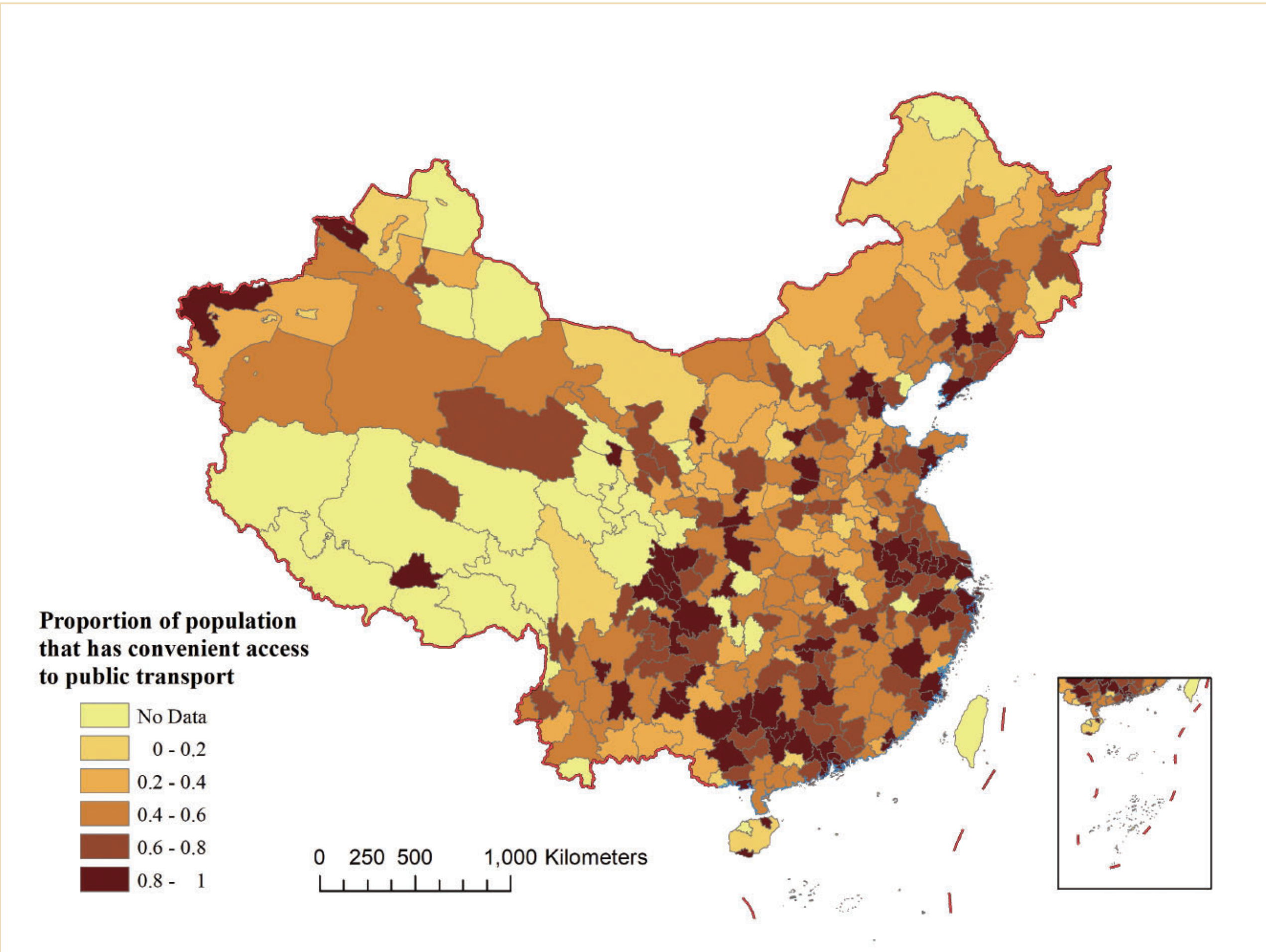


Figure 4-2. Proportion of the population in prefecture-level cities with easy access to public transportation (data for Taiwan Province is missing).

At the prefecture-level city scale, the number of people that have easy access to public transportation in densely populated cities is generally higher than in sparsely populated cities. Furthermore, the population in provincial capitals with access to transportation is generally higher than other non-provincial capitals. In some northwestern cities, the number of people with easy access to public transportation is relatively high due to the high urban population density and their distribution along urban roads.

Highlights

- *The proportion of the population with convenient access to public transportation at the provincial level was 64.28% on average. This proportion was observed to be generally higher in eastern provinces compared to the central and western provinces. Moreover, the southern provinces generally had a greater degree of transportation access compared to the northern provinces.*
- *At the prefecture-level city scale, the proportion of the population having easy access to public transportation in densely populated cities was generally higher than in sparsely populated cities. Moreover, the number of people with transportation access was generally greater in provincial capitals in comparison to other non-provincial capitals.*

Outlook

The calculation method adopted by this indicator is simple, and navigation and land use data are easy to obtain. This type of analysis allows for other countries to follow and monitor the indicator, which can be used for global comparison.

The bus line network vector dataset can be dynamically updated as needed. The land use products are updated every 3 to 5 years, which meets the requirements for future high spatiotemporal resolution evaluation.

The population data used herein is not yet available for classification by age, sex, and disability. The next step is to develop a spatial population dataset for different groups using big data gathered from mobile phone platforms and Internet sources. This is necessary to provide improved support for indicator monitoring and evaluation.

Monitoring and assessing urbanization progress in China

Scale: National

Study area: China

The most notable features of urbanization include urban expansion and demographic change. A large amount of land resources are lost due to rapid urbanization. These lost resources have great societal, economic, and environmental value. Additionally, the physical growth of urban areas is often disproportionate in relation to population growth, resulting in low land use efficiency. Therefore, it is important to understand and coordinate human-land relationships by acquiring information on both urban land consumption and population growth. This is necessary to effectively monitor and assess the urbanization process. The SDG 11.3.1 indicator is defined as the ratio of land consumption rate (LCR) to population growth rate (PGR) and is used to describe the relationship between urban expansion and demographics.

This indicator involves a focus on the following factors. (1) Global high-resolution urban land mapping is used to precisely delineate the urban footprint, which provides data support for monitoring and evaluating SDG 11.3.1. (2) There is a focus on quantitatively assessing the relationship between LCR and PGR for 340 prefecture-level cities in China. Furthermore, the sustainable development of Chinese cities is assessed on a national scale. This research is significant for providing spatial data and decision support for SDG 11 urban sustainable development.

Target 11.3: By 2030, enhance inclusive and sustainable urbanization and capacity for participatory, integrated, and sustainable human settlement planning and management in all countries.

Indicator 11.3.1: Ratio of land consumption rate to population growth rate.

Method

The ratio between urban LCR and PGR is based on the SDG indicator framework and is calculated as the following.

(1) LCR is calculated as:

$$LCR = \frac{LN(Urb_{t+n}/Urb_t)}{(y)}$$

where Urb_t is the total extent of the urban agglomeration in km^2 for the past/initial year, Urb_{t+n} refers to the total extent of urban agglomeration in km^2 for the current year, and y expresses the number of years between the two measurement periods.

In urban remote sensing, scientists have discovered that urban impervious surfaces extracted from remote sensing images can accurately reflect urban surface information and land use intensity. In this case, the urban impervious surface is extracted from multi-temporal Landsat TM/ETM+ imagery acquired from 1990 to 2010. In this study, an effective urban land extraction method was proposed for the 2015 product using ascending/descending orbits of Sentinel-1A synthetic aperture radar (SAR) data and Sentinel-2 multispectral instrument optical data acquired from January 1, 2015, to June 30, 2016. The method includes an assessment of textural and phenological features.

(2) PGR is calculated as:

$$PGR = \frac{LN(Pop_{t+n}/Pop_t)}{(y)}$$

where Pop_t is the total population within the city in the past/initial year, Pop_{t+n} refers to the total population within the city in the current/final year, and y expresses the number of years between the two measurement periods.

In China, the population spatialization method is used to obtain the spatial distribution for population. Firstly, nine independent variables related to population are constructed using land use data and Defense Meteorological Satellite Program (DMSP) and Operational Linescan System (OLS) nighttime light data. Secondly, geographically weighted regression is used to construct a population spatialization model. Lastly, a gridded population distribution is acquired with a spatial resolution of 1×1 km.

(3) The ratio of LCR to PGR (LCRPGR) is estimated as follows:

$$LCRPGR = \left(\frac{Land\ consumption\ rate}{Annual\ population\ growth\ rate}\right) = \left(\frac{LCR}{PGR}\right)$$

Data used in this case

◎ Ascending/descending orbits of Sentinel-1A SAR data (150,000 scenes) and Sentinel-2A optical data (340,000 scenes). Data is acquired for the dates ranging from January 1, 2015, to June 30, 2016. The data also includes Landsat imagery acquired from 1990 to 2010, and DMSP/OLS nighttime light data acquired in 1992, 2000, and 2010. Lastly, data relating to the Shuttle Radar Topography Mission (SRTM) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Digital Elevation Model (DEM) are also included.

◎ Land use/land cover data with 30-meter spatial resolution acquired in 1990, 2000, and 2010.

◎ The fourth, fifth, and sixth China Census data (county level) as well as UN city population data.

Results and analysis

Under the SDG indicator framework, based on the methods for calculating SDG indicator 11.3.1, the research result illustrates the urbanization progress of China from one perspective.

(1) High-resolution global urban impervious surface mapping

Figure 4-3 displays the global 10-meter resolution urban impervious surface distribution. The product results were compared with other urban land products, such as the Global Human Settlement Layer (GHSL), global land cover datasets at a 30-meter resolution (GlobeLand30), National Land Cover Database (NLCD), and CORINE Land Cover (CLC). In comparison with other methods, the product featured in this case was generated through fusion of optical and SAR data. The results reveal that the product provided a high correlation coefficient (R^2>0.80) and high accuracy with an overall accuracy (OA) greater than 86%, a user accuracy (UA) greater than 82%, and a product accuracy (PA) greater than 90% at the global scale.

The method presented in this case has numerous advantages. 1) The method effectively resolves some limitations and problems for extracting impervious surfaces from single data sources and further improves extraction accuracy. 2) The method employs Big Earth Data processing technology and is based on different sensors (e.g., SAR and optics) and imaging modes (e.g., ascending/descending orbits). The method also employs 150,000 Sentinel-1A (S1) and 340,000 Sentinel-2 (S2) images. 3) The method achieves rapid fully automated urban impervious surface extraction. 4) Lastly, the methodology is useful for identifying human settlements located in low latitude areas.

(2) Analysis of China's urban expansion and population migration

LCR, PGR, and LCRPGR were calculated for 340 prefecture-level cities in China during 1990-2000 and 2000-2010 to monitor the progress of SDG 11.3.1 (Figure 4-4). Results from monitoring the SDG 11.3.1 indicator in China reveal that the

Figure 4-3. Global 10-meter resolution urban impervious surface distribution (2015).

ratio between LCR to PGR increased from 1.41 in 1990-2000 to 1.94 in 2000-2010. Therefore, compared with 1990-2000, the growth rate of built-up areas in 2000-2010 was faster than the rate of population growth. Additionally, it also found cities with higher LCRPGR (LCRPGR>3), including 19 cities in 1990-2000, and 47 in 2000-2010. These results suggest that the expansion of urban space in these cities needs to be effectively controlled.

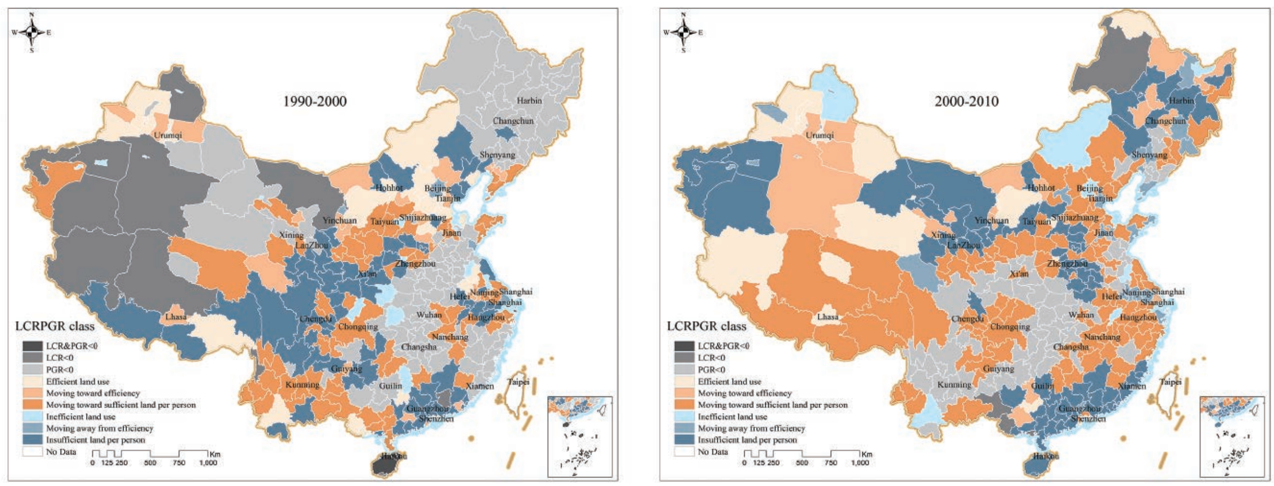


Figure 4-4. Spatial distribution of SDG 11.3.1 at 342 prefecture-level cities in China during 1990-2000 and 2000-2010.

Highlights

- *The case product is observed to feature high accuracy, with OA values greater than 86%. Therefore, the proposed method and the high-precision, high-resolution, global urban impervious remote sensing product can provide spatial data and decision support for the 2030 Agenda for Sustainable Development.*
- *The growth rate of built-up areas in 2000-2010 was faster than the population growth in 1990-2000. Higher LCRPGR values (LCRPGR>3) were observed in 1990-2000. There were 19 cities in 1990-2000, and 47 cities in 2000-2010. Results suggest that the expansion of urban space in these cities needs to be effectively controlled.*

Outlook

Future work will focus on measuring and monitoring the SDG 11.3.1 indicator and "LCRPGR" values for 1,860 cities with populations greater than 300,000 at the global scale. In the future, other urbanization indicators will be integrated to assess the overall progress and trend of urbanization. In addition, combined with the economic and environmental data of these cities, more comprehensive spatiotemporal monitoring of urban sustainable development will be conducted using Big Earth Data.

SDG 11 is directly related to at least 11 other SDGs. About one-third of all SDG indicators can be measured at the city level, making cities an important unit for measuring, monitoring, and tracking SDG progress. Future work will include cross-over and comprehensive assessment studies between SDG 11 and other SDGs.

Global urban impervious surface products can aid developing countries that do not have the technical and financial resources to monitor their urban development. These products will enable developing countries to describe the relationship between land use and PGR in urban environments. The high-resolution global urban impervious layer data will be updated every three years.

Preliminary study and suggestions for modifying indicator SDG 11.4.1

Scale: National

Study area: China

The UN has proposed to "strengthen efforts to protect and safeguard the world's cultural and natural heritage" per SDG 11.4. An indicator has been provided to accomplish this goal, which is described as "the total expenditure per capita (public and private)". International cultural and natural heritage sites are distributed throughout the world in different countries with diverse cultural backgrounds and different levels of economic development. This variance in conditions and culture between different countries makes it difficult to use indicator SDG 11.4.1 since the measurement depends on localized factors. The amount of total expenditure per capita in a country is related to factors such as: (1) the total number of all cultural and natural heritage sites in the country and its total area, (2) the funding invested in each cultural or natural heritage site, and (3) the population of each country. This case study proposes a method that uses in-depth interpretation of the evaluation target system, convenient access to reliable data, and compliance with actual measures to measure capital investment, especially for natural and mixed heritage sites. This value can be calculated from the expenditure per unit area of the heritage site. Per unit area investment = total capital investment / area of heritage site (km^2 or ha). The calculation results can be used to measure "increased capital investment". It is recommended that the indicators given in SDG 11.4 be summarized as a new indicator, SDG 11.4.1. This new indicator can be described as the "increase in capital investment per unit area to protect and safeguard the world's cultural and natural heritage".

Target 11.4: Strengthen efforts to protect and safeguard the world's cultural and natural heritage.

Indicator 11.4.1: Total expenditure (public and private) per capita spent on the preservation, protection, and conservation of all cultural and natural heritage, by type of heritage (cultural, natural, mixed, and World Heritage Centre designation), level of government (national, regional, and local/municipal), type of expenditure (operating expenditure/investment) and type of private funding (donations in kind, private non-profit sector and sponsorship).

Method

(1) The method involves the calculation of capital investment per unit area. The investment per unit area in the protected area reflects the protection intensity of a country or a single world heritage site. This is given as:

$$\mathrm{TEPUA}=\frac{\Sigma \mathrm{PuE}+\Sigma \mathrm{PrE}}{\mathrm{A}}$$

where the total expenditure per unit area (TEPUA) is the total expenditure (public and private) per unit area on the preservation, protection, and conservation of all cultural and natural heritage. The public expenditure (PuE) is the expenditure for the preservation and conservation of cultural and natural heritage by government departments at all levels. The private expenditure (PrE) is the private expenditure for the preservation, protection, and conservation of cultural and natural heritage. Area (A) is the total area for the regional protection area.

(2) The method involves a calculation of RSEI, which is used to measure changes in the ecological environment, and its formula is given as:

$$\mathrm{RSEI}=1-\mathrm{PCA}\ (f\ (\mathrm{NDVI},\ \mathrm{WET},\ \mathrm{NDSI},\ \mathrm{LST}))$$

where PCA refers to principal component analysis, NDVI is the normalized difference vegetation index, WET is the wetness component of the tasseled cap transformation, NDSI is the normalized difference soil index, and LST is the land surface temperature. Together they represent greenness, humidity, dryness, and heat.

(3) The case methodology also incorporates a sample selection method. China's national parks have a strong management system. The current management model for natural and cultural heritage has evolved from the original national park management model and there are similarities between the two management systems. This project calculated and summarized capital investment with the aid of geographic information system methods and technologies. The calculation involved income and expenditure statistics and area data for 244 national parks from

2006 to 2017. The aim was to discuss the measurability and operability of the indicator for specific cases.

(4) The method also included an analysis of the relationship between capital investment and the ecological environment. A typical case in Huangshan was used as a demonstration. This case also compared the TEPUA curve with the RSEI curve and analyzed the relationship between capital investment and the ecological environment.

Data used in the case

◎ Statistics for revenue and expenditure, area, and tourist volume for 244 national parks in China from 2006 to 2017.

◎ Vector data for 244 national parks and the World Heritage of China.

◎ Income and expenditure data for Huangshan from 1992 to 2017.

◎ Landsat series satellite image data from 1992 to 2017. GF series remote sensing data and ground survey data for Huangshan.

Results and analysis

A total of 244 national parks in China were selected as study areas, and these were divided into eastern, central, and western regions. The per capita expenditure and unit area expenditure were then calculated and compared for each district (Figure 4-5; Figure 4-6).

According to Figure 4-6, the average unit area investment in China was observed to increase annually. The total expenditure per square kilometer of China's national parks increased from ¥250,000 RMB in 2006 to ¥650,000 RMB in 2017. The investment in the eastern and central region was higher than in the western region. According to Figure 4-5, per capita investment was significantly higher in the west than in the eastern region after 2012. The amount of capital investment in the eastern region was much higher than in the western region, and the population density in the west was much lower compared to the eastern region. However, Figure 4-5 reveals that the per capita investment in the west was higher than in the east. Therefore, it was more reasonable to measure the strength of protection using "investment per unit area" rather than "total expenditure per capita".

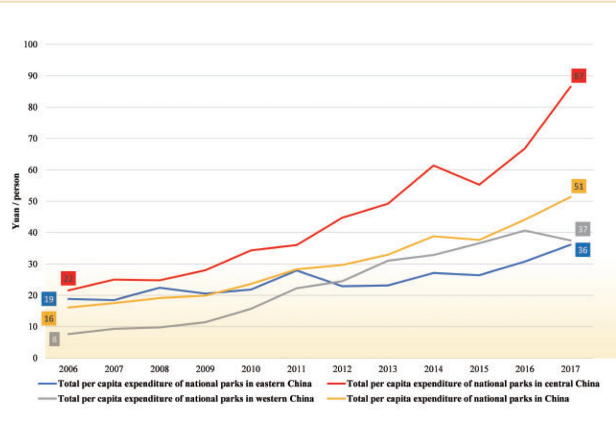


Figure 4-5. Statistics for the per capita expenditure of China's national parks.

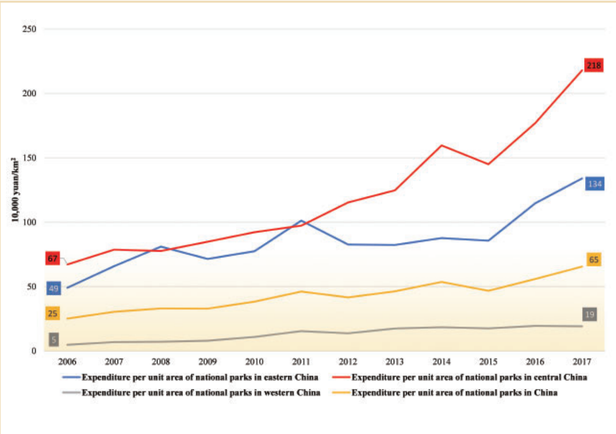


Figure 4-6. Statistics for the per unit area expenditure of China's national parks.

For example, Huangshan was listed in the World Heritage List in 1990. Huangshan Mountain has three laurels, including: The World Cultural and Natural Heritage Site, the World Geopark, and the World Biosphere Conservation. A typical analysis was performed to assess the protection intensity and capital investment of the site. Figure 4-7 displays a distribution map of the Huangshan RSEI from 1992 to 2017.

Figure 4-8 reflects the changes in resource conservation investment and the ecological environment in Huangshan over

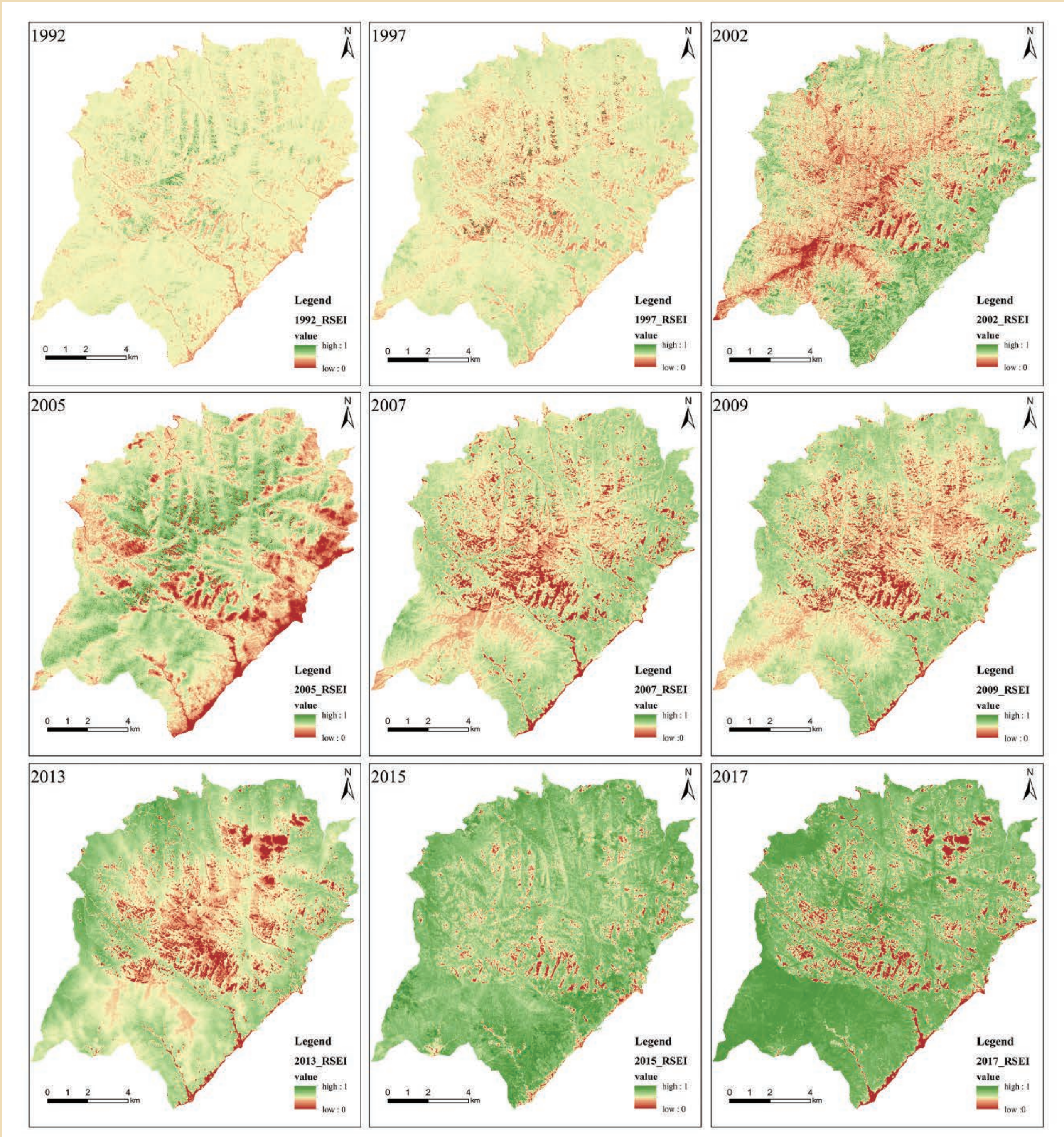


Figure 4-7. RSEI for the Huangshan Scenic Area (1992-2017).

the past 25 years. An analysis of Figure 4-8 reveals that the two trends are consistent. In general, the ecological environment in the Huangshan Scenic Area was observed to improve due to the increase in resource conservation investment. Resource protection accounted for 23% of the proportion of expenditures for different projects in Huangshan from 1990 to 2017. This factor played a powerful role in protecting the ecological environment of the heritage site.

Figure 4-8. Changes in resource conservation input and RSEI for the Huangshan Scenic Area (the dotted line is the actual value and does not participate in the moving average).

Highlights

- *It is more reasonable to measure the strength of protection by "investment per unit area" rather than "total expenditure per capita".*
- *The ecological environment in the Huangshan Scenic Area was observed to improve due to the increase in resource conservation investment. This case demonstrates the importance of investing in resource conservation measures.*

Outlook

Currently, there is an urgent need to establish a scoring standard (e.g., 0-5) for investment per unit area at the global scale to measure the strength of capital investment. The "total expenditure per unit area" of heritage sites can more scientifically and reasonably reflect the protection efforts of "increased investment" on world heritage sites in comparison with the "total expenditure per capita" method. However, different countries, regions, and heritage sites may require different input funds in order to measure the total expenditure per unit area. There is a need to consider the issue from a global perspective, beginning with the "interference minimization principle" of world heritage sites. A guideline or scoring standard can be established for investment per unit area to measure the strength of capital investment.

Direct and universal indicators are needed to measure the effect of investment on heritage site protection. In this case, the Huangshan World Heritage Site in China was used as an example. RSEI revealed that the ecological environment in Huangshan Reserve had improved due to the increased investment in resource conservation. However, this is only one example. A determination of whether the quantitative relationship between capital investment and ecological environment can be measured by the RSEI will require a comprehensive study of several additional cases. This can be accomplished through international cooperation, and the establishment of a sharing mechanism for statistical data.

Monitoring and analyzing fine particulate matter ($PM_{2.5}$) in China

Scale: National

Study area: China

Fine particulate matter ($PM_{2.5}$) is a primary air pollutant in China that is responsible for negatively impacting the health of local populations. Since 2012, several national environmental protection departments have paid close attention to the spread of $PM_{2.5}$. Additional ground-measurement stations are constructed on an annual basis for monitoring the pollutant. The historical data on this pollutant is also lacking and is difficult to obtain; therefore, it is difficult to conduct any study on the epidemiological and health effects of fine particles.

Satellite remote sensing has the advantages of long-term time series data and broad spatial coverage, which can compensate for the lack of site observations. Remote sensing imagery has been widely used by scientists to estimate the concentration of $PM_{2.5}$.

Target 11.6: By 2030, reduce the adverse per capita environmental impact of cities, including assessing air quality and municipal and other waste management.

Indicator 11.6.2: Annual mean levels of fine particulate matter (e.g., $PM_{2.5}$ and PM_{10}) in cities (population weighted).

Method

Many methods have improved the estimation of $PM_{2.5}$ using Aerosol Optical Depth (AOD). These methods employ different characteristics to obtain historical $PM_{2.5}$ concentrations, which have applications in the evaluation of public health risks. The objective of this study was to analyze the changes of $PM_{2.5}$ in key cities in China in recent years. This was accomplished by calculating the average annual concentration of $PM_{2.5}$ in the built-up areas of key cities from 2010 to 2018 according to the population weight. Calculations were obtained using the following equation:

$$C_{agg}=SUM(C_{nat}\times P_{nat})/SUM(P_{nat})$$

where C_{agg} is the estimation at the global scale, C_{nat} is the estimation at the country scale, and P_{nat} is the national population.

Data used in this case

Remote sensing data and related products included MODIS AOD and MODIS NDVI in the time series. Monitoring data included atmospheric composition of China's environmental monitoring stations, meteorological data, and reanalysis by ECMWF.

Results and analysis

The MODIS AOD products from the National Aeronautics and Space Administration (NASA) Terra and Aqua satellites were used to estimate the $PM_{2.5}$ concentration from 2010 to 2018 in China (Figure 4-9). In general, the spatial pattern of the annual $PM_{2.5}$ over China showed high correlation with the accumulation of both population and industries. Elevated $PM_{2.5}$ levels were mostly concentrated on those cities or city-clusters with higher urbanization or industrialization in central and eastern China. Temporally, the annual nationally averaged $PM_{2.5}$ presented an overall decreasing trend from 2013 to 2018. This clearly demonstrates the effectiveness of comprehensive pollution control measures conducted by the Chinese government in recent years.

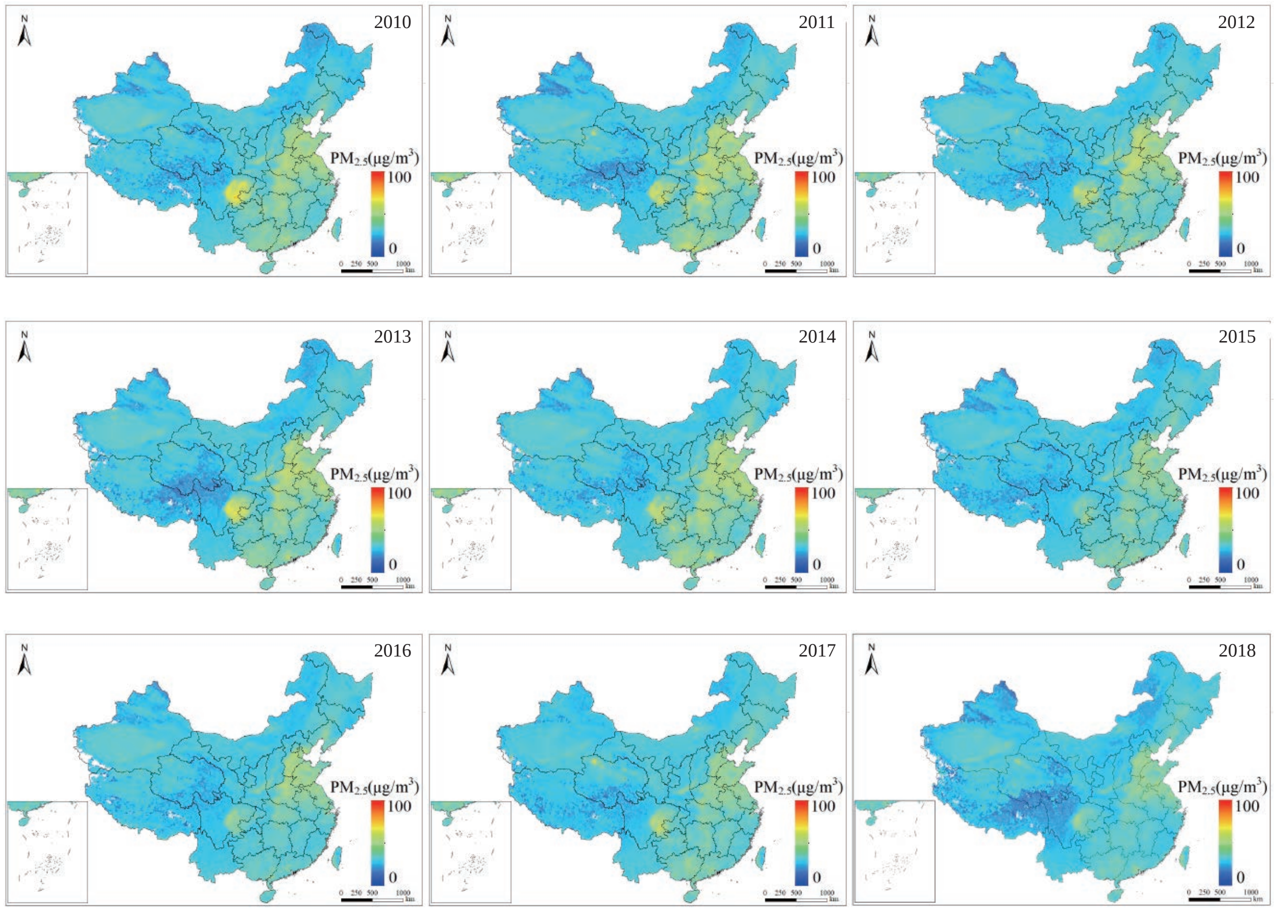


Figure 4-9. Annual average distribution of $PM_{2.5}$ in China from 2010 to 2018.

Highlights

- *Average annual $PM_{2.5}$ data products have been developed for the period from 2010 to 2018.*
- *The Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta, and Chengdu-Chongqing regions showed an overall decreasing trend from 2010 to 2018.*

Outlook

Deep learning methods will continue to be explored in the future. More relevant indicators and parameters will be introduced to improve estimation accuracy. The mechanism and source distribution of pollutants in the atmosphere will also be explored to promote atmospheric research.

In terms of application and promotion, the atmospheric environment affects human health, which is the primary concern of the public. We will improve and promote the progress and application of $PM_{2.5}$, Ozone and other products closely related to public health through the construction of high spatial and temporal resolution data. Meanwhile, it also needs the guidance and support from the government, society and other users.

Proportion of urban open public space in China

Scale: National

Study area: China

Open public spaces provide valuable services such as entertainment opportunities, aesthetic enjoyment, and environmental and agricultural functions for urban residents. These spaces serve as a prerequisite for improving city functions, promoting health, and developing efficient urban ecosystems with better quality of life for residents. Public space is also linked to benefits such as increased social security and cohesion, greater equality, and improved health and well-being. Open public spaces are the key to realizing SDG 3 (Good Health and Well-being), SDG 5 (Gender Equality), SDG 8 (Decent Work and Economic Growth), and SDG 13 (Climate Action). Urban public space planning and management provides a feasible path for urban space transformation and quality improvement.

Target 11.7: By 2030, provide comprehensive, convenient, green public space for all, especially for women, children, the elderly, and those with disabilities.

Indicator 11.7.1: Average proportion of open public space provided for all people in urban built-up areas.

SDG 11

Method

The "urban land" sub-category is extracted from land use data to establish the national built-up area spatial database. Open public spaces (including public green spaces and squares) are extracted from within defined urban boundaries based on built-up areas from national navigation vector data, and road data at all levels (e.g., highway, national highway, provincial highway, county road, township road, and urban streets). Road data is converted from line to polygon structures according to Chinese road width specifications. The specific calculation process is described as the following. (1) A national kilometer grid is generated and a Fishnet function is defined. The grid transformation method is then used to generate the national kilometer grid. (2) The national grid is overlapped with public green space spatial data to generate kilometer grid public green space spatial data. (3) High-speed, provincial, county, and other urban roads are converted into polygon data according to national road construction width specifications. This data is then overlapped with a national grid to generate kilometer grid road spatial data. (4) Road data and public green space data are integrated at the grid scale and divided by the total urban built-up area to determine the urban open public space area. (5) The results are converted from the kilometer grid scale to county, city, provincial, and national scales based on spatial statistical analysis.

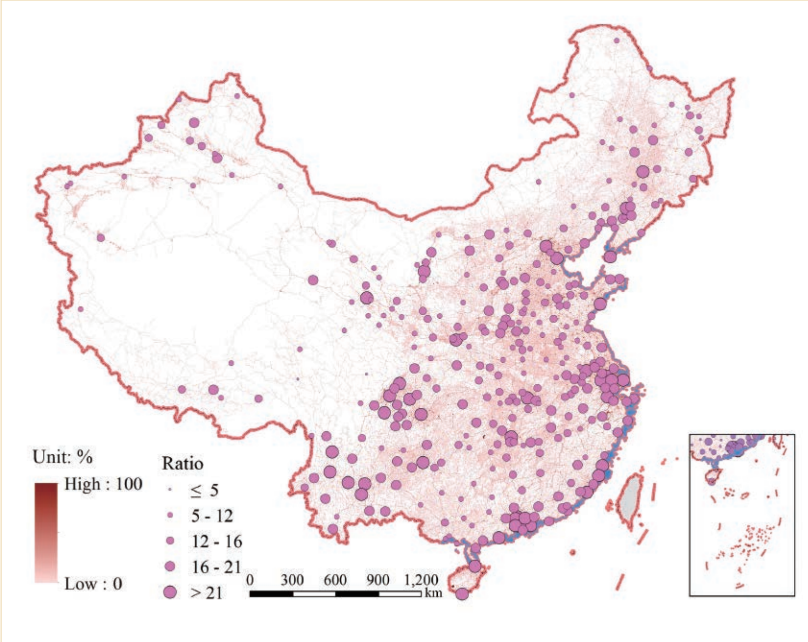
Data used in this case

◎ The case data includes navigation data for China acquired in 2015, which includes public green spaces, public squares, and roads at all levels (e.g., highway, national highway, provincial highway, county road, township road, and urban streets). The data was stored in a PostgreSQL database.

◎ The case data also includes land use data for China in 2015 with a 100-meter resolution. Data was obtained from China's Land use Status Remote Sensing Monitoring Database, CAS. It is generated by visual interpretation based on Landsat 8 images.

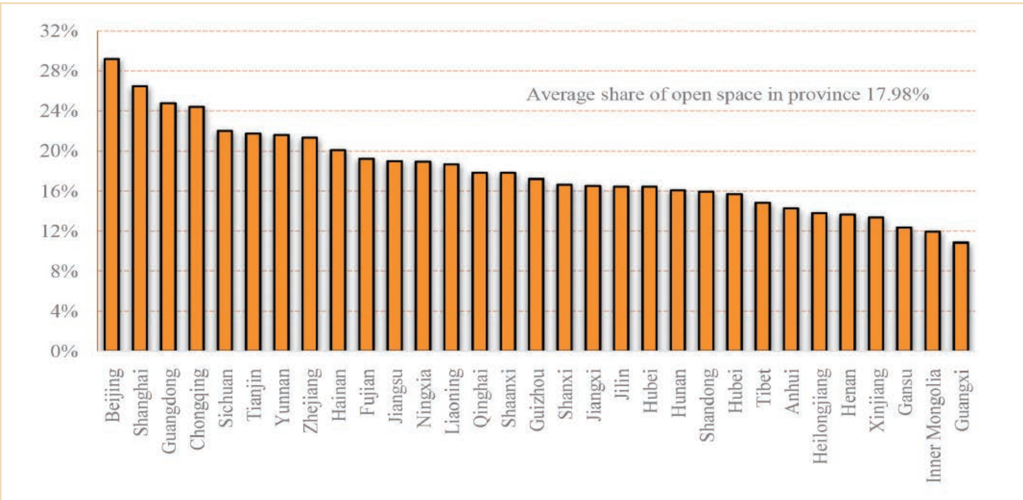
Results and analysis

This case study evaluated the open public spaces for all prefecture-level cities in China. The preliminary conclusion from the analysis was that at the provincial level, the average proportion of open public space in the built-up areas of Chinese cities was 17.98% (excluding Hong Kong, Macao, and Taiwan Province). Beijing featured the highest proportion of open public spaces (29.18%), while Guangxi had the lowest percentage (10.82%). A total of 18 provinces, including Qinghai, Shaanxi,



↑ Figure 4-10. Proportion of open public space in major prefecture-level cities in China.

Guizhou, Shanxi, Jiangxi, Jilin, Hubei, Hunan, and Shandong, had a lower amount of open public space areas compared to the national average. At the city level, the proportion of open public spaces in the eastern cities was higher than in the central and western cities. Moreover, provincial capitals had higher proportions of open spaces compared to other cities in the province. The proportion of open public spaces in the Beijing-Tianjin-Hebei agglomeration, Yangtze River Delta urban agglomeration, the Pearl River Delta urban agglomeration, Sichuan Basin urban agglomeration, and the Yunnan-Guizhou urban agglomeration were higher than in the surrounding cities. Urban open public spaces were mainly composed of parks, squares, green spaces, and other public spaces and roads. The largest urban open spaces based on the density of urban roads were found in the Jing-Jin-Ji urban agglomeration, Yangtze River Delta urban agglomeration, and the Pearl River Delta urban agglomeration. Green public spaces were mostly found in the Sichuan Basin urban agglomeration and the Yunnan-Guizhou urban agglomeration.



↑ Figure 4-11. Proportion of urban open public spaces for different provinces.

Highlights

- *At the provincial level, the average proportion of open public spaces in the built-up areas of Chinese cities was 17.98% (excluding Hong Kong, Macao, and Taiwan Province). Beijing had the highest proportion of open public space (29.18%), while Guangxi had the lowest proportion (10.82%).*
- *At the city level, the proportion of open public space in eastern cities was higher than in the central and western cities. Moreover, the provincial capitals had a higher proportion of open space than other cities in the province.*

Outlook

The navigation data for China can be updated in real time, and land use products are updated every 3-5 years. This is enough to meet the requirements for future high temporal resolution evaluation.

The method adopted in this case is simple, and navigation and land use data are relatively easy to obtain. This enables the methodology to be easily reproducible in other countries and allows for international comparison.

The open space described in this study does not consider diverse categories of open space, and this needs to be addressed in the future.

It is still challenging to classify information based on gender, age, disability, and other demographic characteristics. The next step is to develop spatial data products for population based on different groups utilizing big data such as mobile phone platforms and Internet sources.

Conclusions

These case studies propose methods for rapid extraction of global impervious surface using multi-source Big Earth Data. A new method was proposed to estimate near-surface $PM_{2.5}$ (SDG 11.6.2, Tier I) using aerosol optical thickness retrieved from satellites. This method was observed to improve the accuracy and spatiotemporal resolution of $PM_{2.5}$ remote sensing estimation and provides a new data product for the evaluation of urban air quality.

High-resolution remote sensing and navigation vector data was examined in terms of urban public transport (SDG 11.2.1, Tier II), urban land use efficiency (SDG 11.3.1, Tier II), and urban public space (SDG 11.7.1, Tier II) indicators. These datasets were used to develop a high spatiotemporal resolution method for extracting information related to urban public transport, open public spaces (e.g., green space, squares, roads), urban built-up areas, and population distributions. This allowed for the creation of high-resolution regional data products for China.

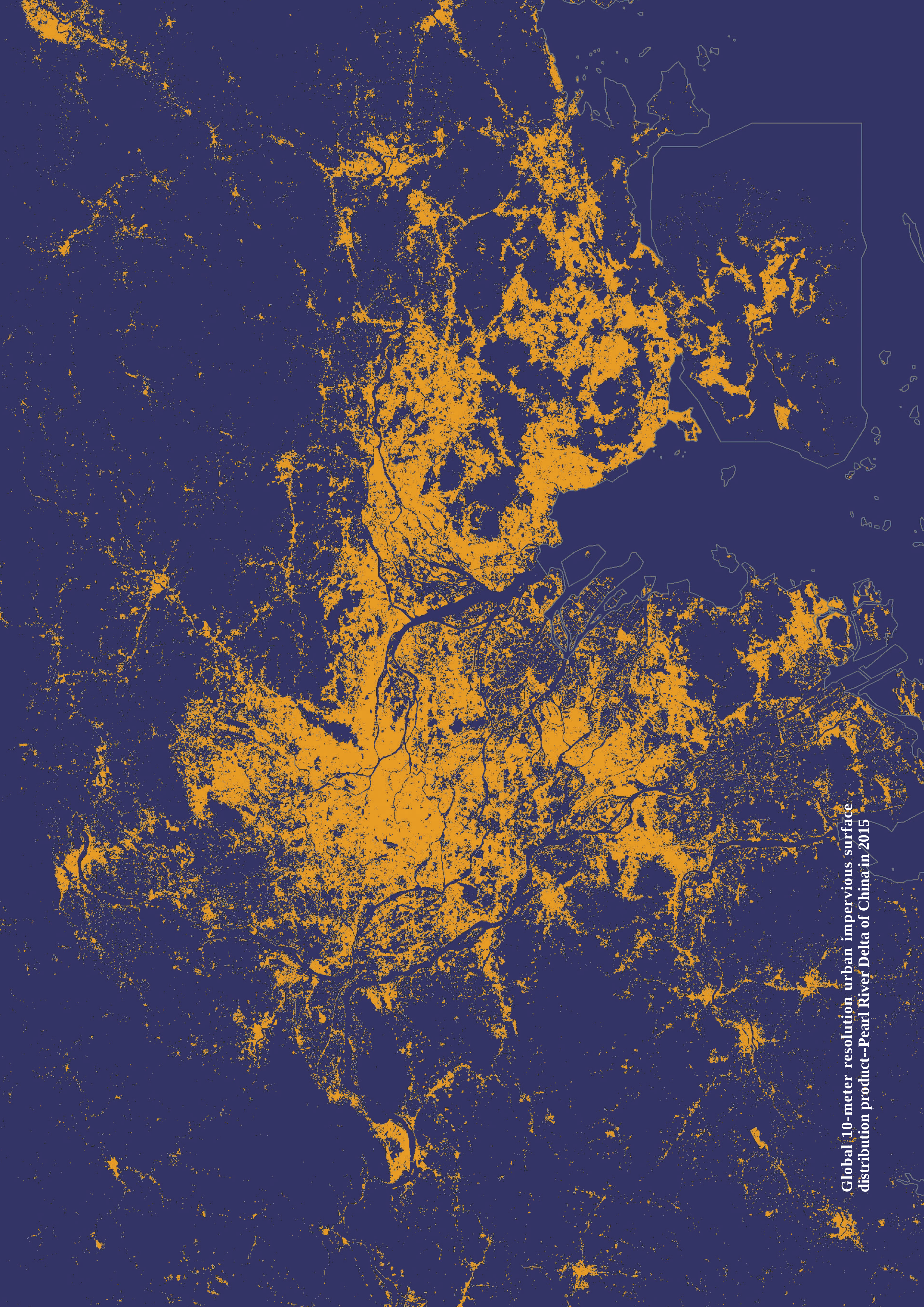
In this chapter, a new indicator was proposed for preserving and protecting world cultural and natural heritage sites (SDG 11.4.1, Tier III). This indicator is defined as the “increase in capital investment per unit area to preserve and protect world cultural and natural heritage”. A corresponding evaluation model was developed and a case study was conducted in China.

Sustainable development in urban areas is crucial for resource and environmental disaster management challenges and for the future development in cities. The following studies are being planned to develop methodologies for comprehensively evaluating indicators.

(1) There are plans to further tap into the potential of Big Earth Data by developing new evaluation models and producing high-quality evaluation datasets.

(2) Multi-indicator coordinated trade-off research will be carried out around city-related indicators with SDGs as the framework. Active cooperation with government departments will be carried out to comprehensively evaluate the sustainability of major Chinese cities and serve government decision-making.

(3) SDG 11 indicator evaluation models and methods supported by Big Earth Data will be standardized, and new data and methods will be promoted to the international community. Data and technical support will be provided for developing countries to help monitor and comprehensively evaluate SDG 11 indicators.



Global 10-meter resolution urban impervious surface distribution product--Pearl River Delta of China in 2015


14 LIFE BELOW WATER

SDG 14

Life below Water

Background

Oceans are an important part of the global ecosystem. They provide food and livelihoods for billions of people, absorb atmospheric heat and more than a quarter of carbon dioxide, and produce about half of the oxygen in the atmosphere. In recent decades, human activities and global climate change have adversely affected the stability of marine ecosystems, especially the coastal-ocean ecosystem. Environmental problems like acidification, hypoxia, and eutrophication have increased considerably, while ecological disasters such as harmful algal blooms (HABs) and jellyfish blooms occur more frequently. Coastal fishery resources are being exhausted extensively, and marine biodiversity is also under stress from ocean acidification and terrigenous pollutants. Therefore, marine ecosystems and environments are under major threats and the sustainable development of coastal areas and their economic outcomes face serious challenges. Policies and treaties that encourage the responsible exploitation of marine resources are critical to address these threats.

Several large marine studies have been initiated in China and helped gather data and improve theoretical understanding of marine ecosystems. However, there are still shortages in the comprehensive assessment of marine pollution, acidification, coastal ecosystem health management, and sustainable utilization of marine resources. It is hard to meet SDG 14, “conserve and sustainably use the oceans, seas and marine resources for sustainable development”, at the present stage. This research is targeting development of basic data products and data platforms to facilitate access to information for sustainable development in marine environments.

Table 5-1. Focused SDG 14 indicators

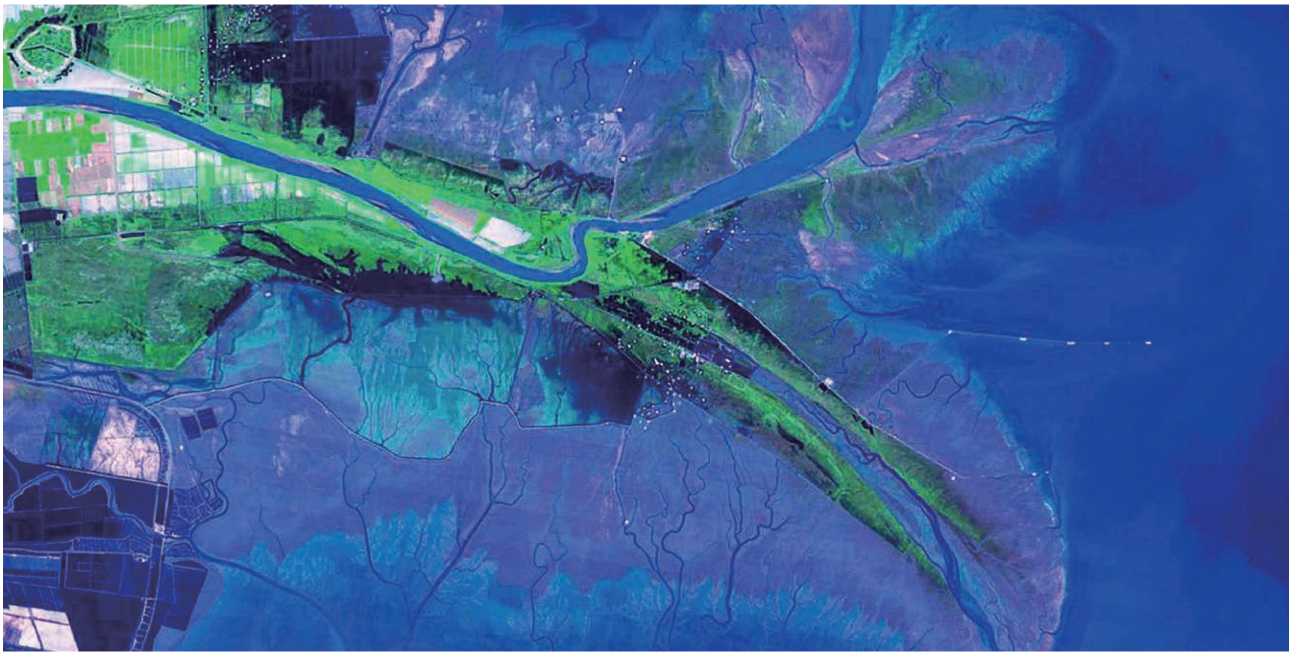
Target	Indicator	Tier
14.1 By 2025, prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution.	14.1.1 Eutrophication index and concentration of floating plastic pollutants.	Tier III
14.2 By 2020, sustainably manage and protect marine and coastal ecosystems to avoid significant adverse impacts, including by strengthening their resilience, and take action for their restoration in order to achieve healthy and productive oceans.	14.2.1 Proportion of national special economic zones implementing ecosystem-based management measures.	Tier III

Contributions

The research on Big Earth Data for SDGs is committed to realizing SDG 14 through studies focused on four key priority areas, namely: assessment of marine pollution, detection of ocean acidification, marine ecosystem health management and sustainable exploitation of marine resources. The research developed new datasets, models, and methods to calculate specific indicators for these four key areas (Table 5-2).

Table 5-2. Cases and their contributions to SDG 14

Indicator	Case	Contributions
14.1.1 Eutrophication index and concentration of floating plastic pollutants.	Construction and application of an integrated eutrophication assessment model for typical coastal waters of China.	Method and model: Construct the latest comprehensive assessment system suitable for evaluating coastal eutrophication in China. Decision support: Participate in the establishment of marine industry standards for the assessment of coastal eutrophication in China; Issue international reports on eutrophication assessment in the Northwest Pacific Action Plan (NOWPAP) region together and propose it to UNEP.
14.2.1 Proportion of national special economic zones implementing ecosystem-based management measures.	Ecosystem health assessment in Jiaozhou Bay, China.	Method and model: Build the evaluation index system for typical waters in China



Yellow River Estuary

14 LIFE BELOW WATER

Case Study

Construction and application of an integrated eutrophication assessment model for typical coastal waters of China

Scale: Local

Study area: Coastal Waters, China

Land-based human activities are increasing and producing a large amount of pollutants, which have led to rapid deterioration of the eutrophication status in coastal areas via river discharges, underground waste input, or atmospheric deposition. Confronted with nutrient pressure, coastal ecosystems have responded through ecological signals, such as hypoxia and HABs. Based on the framework of "Pressure-State-Response", an integrated eutrophication assessment model was developed, which reflects both water quality (the pressure part) and ecological effect (the response part). By using this model, estuaries and bays along China's coast were assessed at multiple scales, not only to understand the human pressure and ecological symptoms, but also to define a comprehensive eutrophication status. Such a model and evaluated results provide scientific and technical support for decision making processes in eutrophication management.

Target 14.1: By 2025, prevent and significantly reduce marine pollution of all kinds, particularly from land-based activities, including marine debris and nutrient pollution.

Indicator 14.1.1: Eutrophication index and concentration of floating plastic pollutants.

Method

The model considers different sensitivities and hydrologic conditions in different areas to reflect the characteristics of different anthropogenic pressures. The study considered primary and secondary ecological responses to detect the degree and estimate the stage of coastal eutrophication. The human management response part was added in the model by combining data on human pressures with ecological responses to comprehensively evaluate the trophic status in varied coastal areas. The framework of the model ensured the comprehensive and objective assessment of coastal areas.

Data used in this case

Indicators of nutrients in typical coastal areas of China—Chl-*a*, biomass, and dissolved oxygen—were obtained from the CAS Big Earth Data Program database, and some other data were collected from published literature, as well as related bulletins of China.

Results and analysis

In each case, the anthropogenic pressures and the ecological responses were individually evaluated initially. For example, in Jiaozhou Bay and adjacent areas, the results (human pressure, Figure 5-1 left, and ecosystem symptom HABs, Figure 5-1 right) indicate that there were spatial shifts in ecosystem symptoms, as the area experiences frequent HAB starting within the bay moving outwards in response to human activities that were also observed to have rapidly increased within the same period outside the bay. These results provide valuable information on HAB timings and patterns to devise a management plan.

Furthermore, as shown in the Figure 5-2, the eutrophication status of each case was evaluated comprehensively, considering both human pressures and ecological responses. The results also indicate that the eutrophication problems in the inner bays and big estuaries were very serious where anthropogenic activities are concentrated in China (Figure 5-2). These areas include Bohai Bay, Jiaozhou Bay, Laizhou Bay, and Changjiang River Estuary, and more. In these areas, response strategies should be developed to reduce terrigenous nutrients and facilitate ecological restoration.

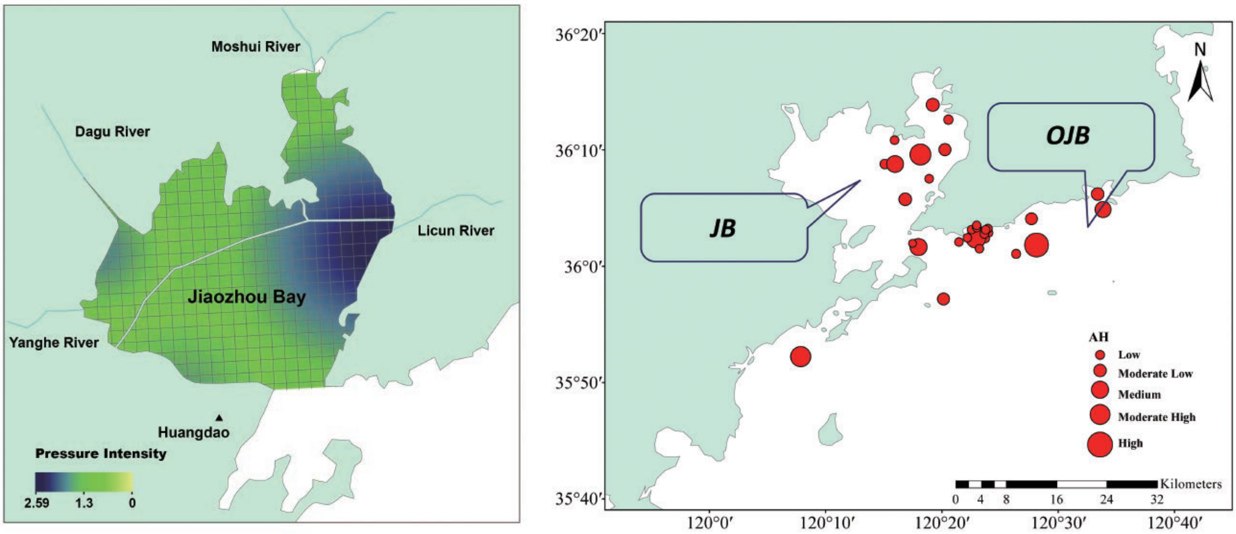
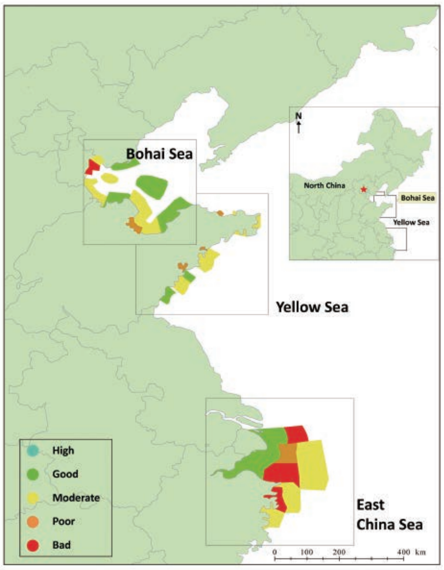


Figure 5-1. Assessment of human pressure and typical eutrophication symptoms (HABs) in Jiaozhou Bay, China (JB: Jiaozhou Bay; OJB: Waters outside Jiaozhou Bay).



Factors	Combination Matrix							Eutrophication status	
Water quality				1	2			1 High	
Ecological response				1	1				High
Water quality		1	2	3	3	4		2 Good	
Ecological response		2	2	1	2	1			Good
Water quality	1	1	2	3	4	4	5	3 Moderate	
Ecological response	3	4	3	3	2	3	2		Moderate
Water quality		2	2	3	4	5		4 Poor	
Ecological response		4	5	4	4	3			Poor
Water quality			3	4	5	5		5 Bad	
Ecological response			5	5	4	5			Bad

Figure 5-2. Evaluation of the trophic status in typical coastal waters of China.

Highlights

- *Develop an integrated eutrophication assessment model reflecting both water quality (the pressure part) and ecological effect (the response part).*
- *Scientifically evaluate the eutrophication status of typical coastal waters. The indicators of both human activity-derived pressures and ecological responses are relatively important and should all be taken into consideration.*
- *In typical waters along China's coast, the eutrophication problem in the inner bays and big estuaries were very serious where anthropogenic activities were dense, and the ecological responses were also serious.*

Outlook

This method has been listed as a marine standard for the assessment of coastal eutrophication in China, and it will ultimately be published in the near future.

Representing China in the framework of NOWPAP, six international reports were proposed to UNEP, and such eutrophication detection methods will be continuously involved in the future plans issued by NOWPAP.

The relevant data will be updated continuously, to further contribute to the realization of SDGs through evaluation results and decision support.

↑ Large scale HAB occurrences in a typical eutrophicated coastal area of China

Ecosystem health assessment in Jiaozhou Bay, China

Scale: Local

Study area: Jiaozhou Bay, China

One of the most important approaches to ensuring the protection and sustainable development of marine environments and resources is to establish ecosystem-based management practices that maintain a healthy ocean ecosystem. Marine ecosystem health assessments can be used as important decision support tools to provide direct, high-quality information and to guide sustainable coastal use and development. It can also help to improve an ecologically sound management strategy for sustainable use and development of coastal areas. Industrialization, urbanization, aquaculture, agriculture, tourism, and other human activities, combined with global changes, are compounding pressures on coastal ecosystems. Ecosystem health assessment needs to integrate relevant data sources from different aspects describing ecosystem conditions and impacts of existing pressures. A coordinated way of integrating land and marine data/information is hence necessary to assess current cumulative pressures and impacts. The research is working to develop new approaches based on multi-source data, big data analysis, and machine learning technologies.

Target 14.2: By 2020, sustainably manage and protect marine and coastal ecosystems to avoid significant adverse impacts, including by strengthening their resilience and take action for their restoration, to achieve healthy and productive oceans.

Indicator 14.2.1: Proportion of national exclusive economic zones managed using ecosystem-based approaches.

Method

Taking Jiaozhou Bay as a case study, a primary assessment framework was established based on long-term studies that focused on variations in meteorological, hydrological, chemical, and biological elements and key processes, as well as their impacts on marine ecosystem evolution. With a focus on SDG 14.2, a selection of indicators and guideline settings were reviewed to gain a better understanding of ecosystem structure, services, functions, and ecological disasters and diseases. The present case study uses data mining to improve guidelines, thresholds, and reference settings in existing health assessments using machine learning techniques. The goal is to translate monitoring, observation, and research results into information that can be understood easily by the public and policy makers.

Data used in this case

◎ 2006.01-2015.12, observation data in Jiaozhou Bay, including: phytoplankton, zooplankton, benthos, bacteria, hydrological, physical, and chemical factors.

◎ Aquaculture production, area, and other environmental data from 2006-2015 environmental situation bulletins.

Results and analysis

The 2006-2015 long-term variations in the meteorological, hydrological, chemical, and biological elements at Jiaozhou Bay showed that the marine ecosystem in the bay was experiencing a change. Nutrient concentrations in the bay exhibited a decreasing trend, suggesting that the water quality in the bay has been improving; while the health conditions of the plankton community, as represented by the phytoplankton/zooplankton community compositions and size distributions, exhibited an ascending trend (Figure 5-3). The long-term changes in nutrient concentration and structure led to an increasing number of nutrient limitations in the bay (Figure 5-4), which has potential impacts on phytoplankton communities and water quality.

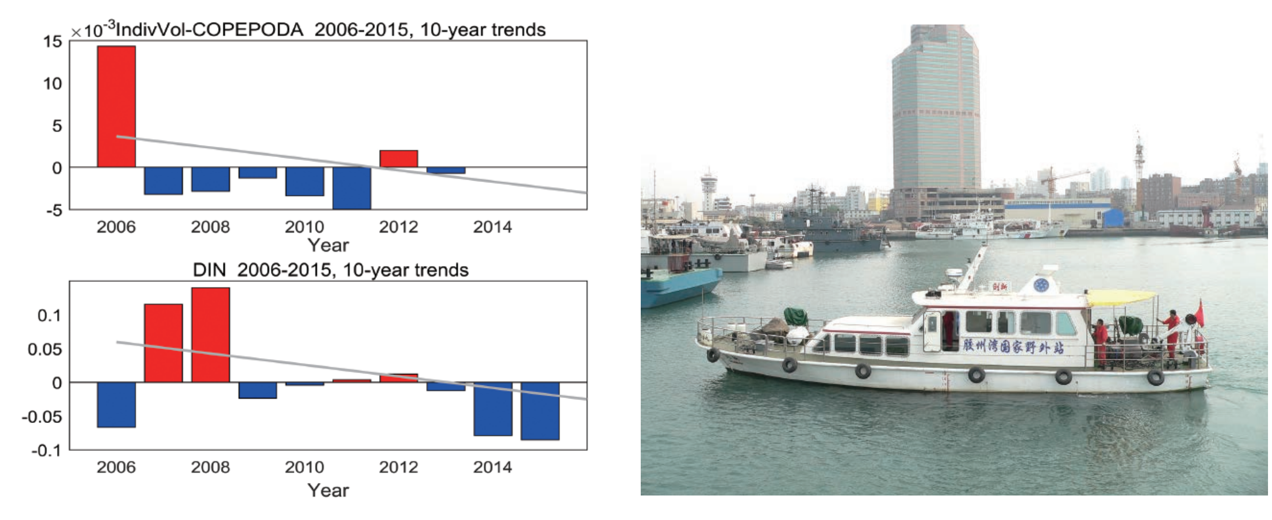


Figure 5-3. Variations in plankton abundance and nutrient concentration in Jiaozhou Bay from 2006 to 2015.

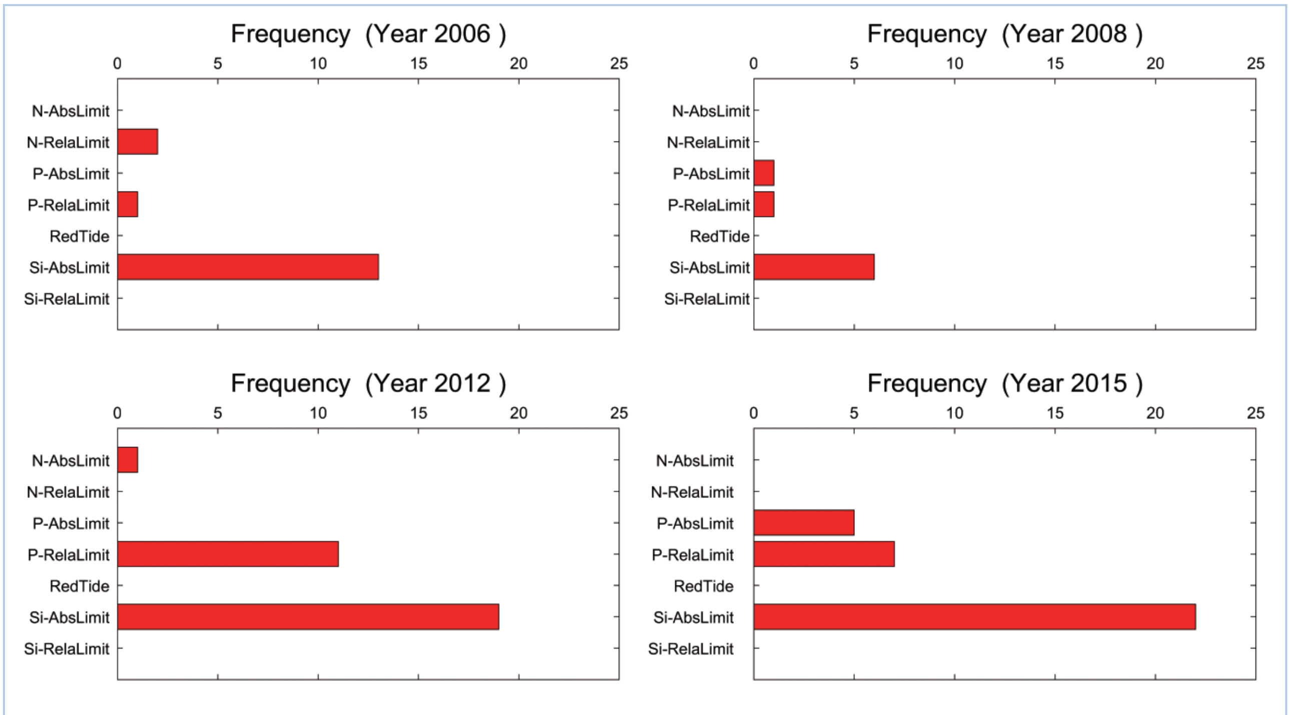


Figure 5-4. Frequencies of nutrient limitations and ecological disasters in Jiaozhou Bay for 2006, 2008, 2012, and 2015.

The results of the pilot health assessment in Jiaozhou Bay show that the health condition of the Jiaozhou Bay ecosystem is classified as grade “B”, which means that the ecosystem is in relatively good condition. Environmental conditions during the study duration show an improving trend, consistent with the varying trend in nutrients. The biota condition in the bay had a slight declining trend, similar to the plankton community condition indicators. The assessment results show nonlinear characteristics in the long-term variations of indicators at different levels, partly consistent with historical trends, with only a few indicators showing a different trend over the past decade.

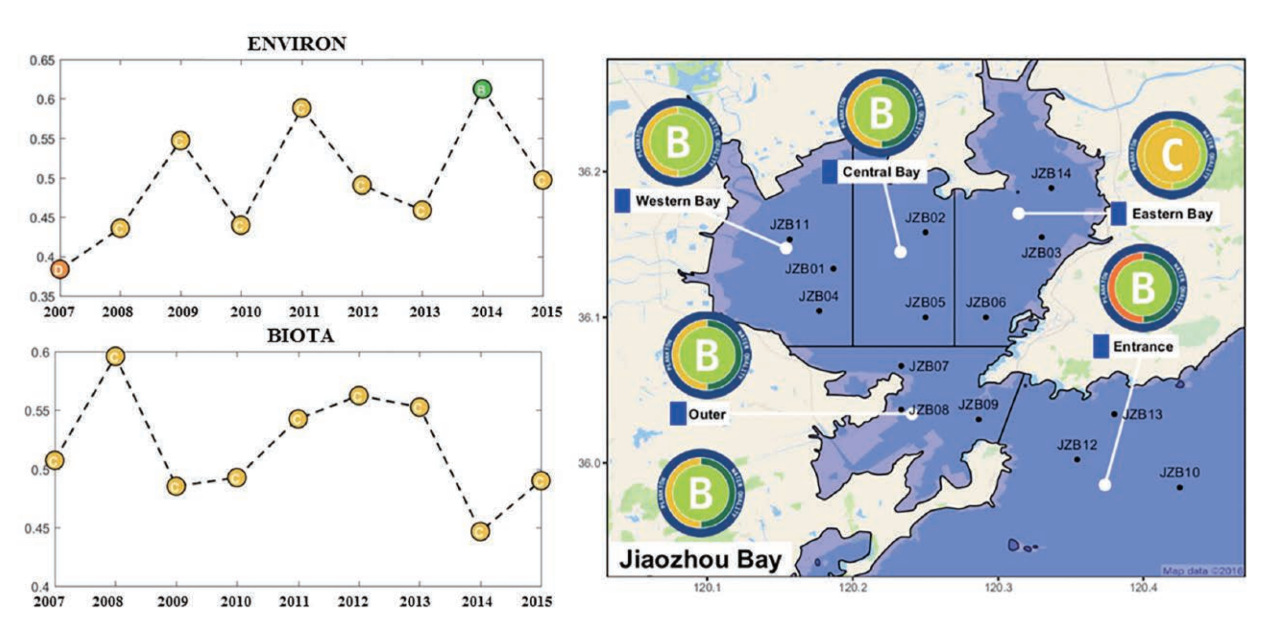


Figure 5-5. Evolution of marine ecosystem conditions from 2007 to 2015, and result of pilot health assessment in Jiaozhou Bay.

Highlights

- *The case study improved ecosystem health assessment research by reviewing a selection of indicators and guideline settings to gain a better understanding of ecosystem structure, services, functions, and ecological disasters and diseases. By applying machine learning-based data mining technology, the guideline, threshold, and reference settings in existing health assessments can be improved. The improved framework was used to conduct a pilot marine ecosystem health assessment in Jiaozhou Bay.*
- *The overall health condition of Jiaozhou Bay is relatively good: environmental conditions during the study duration show an improving trend, and biota conditions in the bay had a slight declining trend.*
- *The assessment results show nonlinear characteristics in the long-term variations of indicators at different levels, partly consistent with historical trends, with only a few indicators showing a different trend over the past decade.*

Outlook

The current case study improves existing coastal ecosystem health assessment research in the following aspects: selecting indicators from ecosystem structure and changes; establishing reference and guideline values for indicators using machine learning technology; and improving assessment methods according to data types and characteristics.

The marine ecosystem health assessment will be further developed, including diagnostic models and scenario simulation models to analyze stress factors on marine health and to diagnose marine ecosystem health. By integrating diagnostic, water quality, ecological, and hydrodynamic modules into a model platform, it will be able to simulate different scenarios and predict possible responses of the marine ecosystem.

This structured research methodology will be repeated to study other coastal regions and improve our model for a wide variety of environments. With collaborating partners such as the Australian Institute of Marine Science and the Indonesian Institute of Sciences, the current research is being considered for application to other areas.

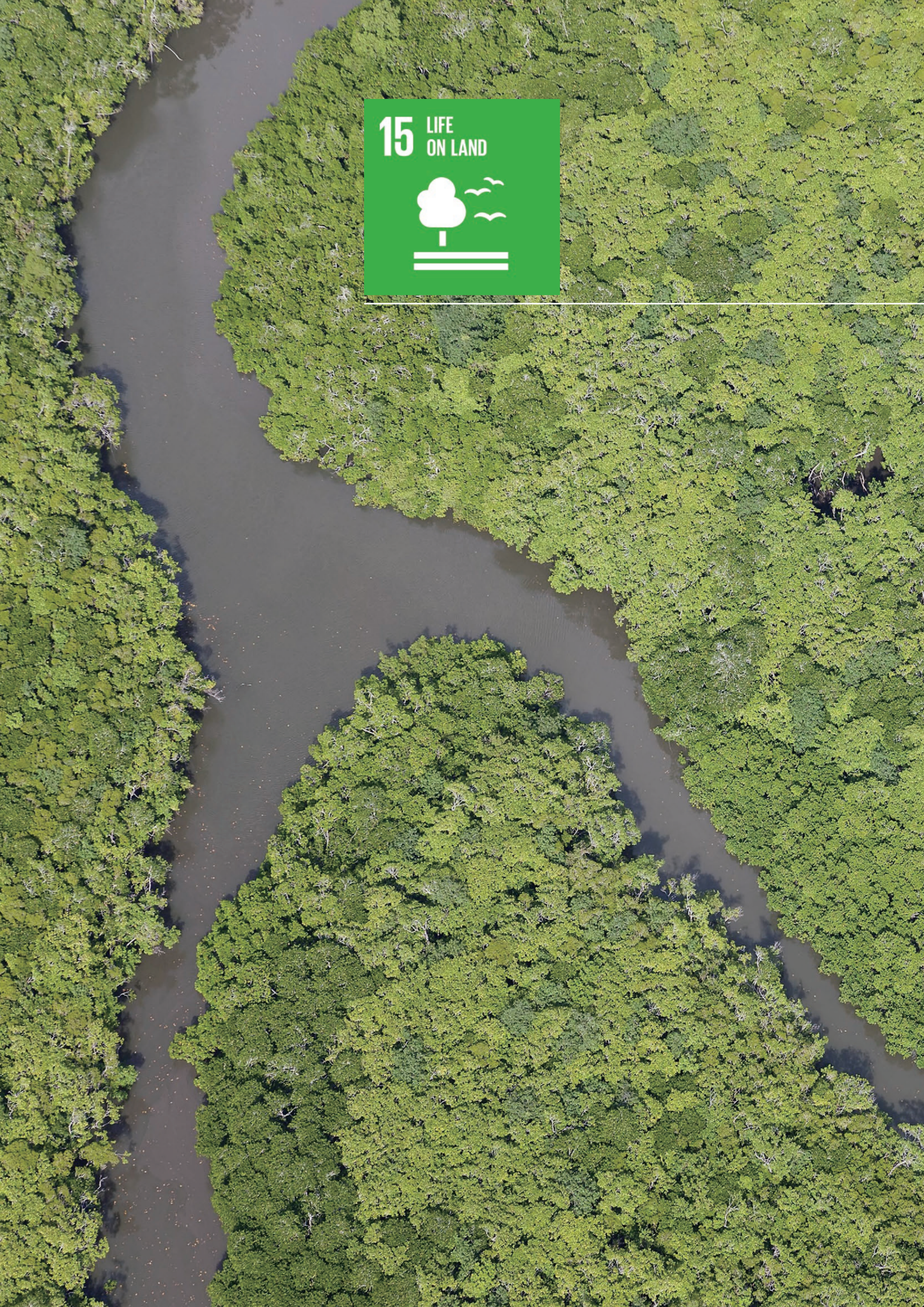
Advisory reports as decision support tools will be developed with the aim to support national strategic objectives and to facilitate targeted end-users towards restoration and protection of coastal and marine environments.

14 LIFE BELOW WATER

Conclusions

Focusing on marine pollution and marine ecosystem health management, an integrated eutrophication assessment model and an experimental evaluation model for marine ecosystems were developed based on data provided through the CAS Big Earth Data Program. Reflecting both water quality and ecological effects, the eutrophication assessment model was applied to evaluate the estuaries and bays along China's coast at multiple scales, and the research reports on eutrophication assessment in China were proposed to UNEP. By participating in the establishment of marine industry standards for coastal eutrophication assessment in China, such models and evaluated results provide scientific and technical support for the management of discharged offshore nutrient pollutants and coastal eutrophication. Experimental evaluation of the ecosystem health of Jiaozhou Bay was also carried out, and a scenario simulation system will be developed to predict possible responses of coastal ecosystems to changes in marine pollution. The operational application of related technologies will be further promoted to provide decision-making support for coastal environmental protection and management, and effectively evaluate the SDG 14.2.1 indicator and realize the SDG 14 target.

Marine aquaculture area in Ningde, Fujian Province of China



15 LIFE ON LAND

SDG 15

Life on Land

Background

Terrestrial ecosystems are important components of the Earth system and provide diverse habitats for humans. The resources and services provided by terrestrial ecosystems have enabled humans to thrive and develop over thousands of years. Unfortunately, excessive exploitation of resources, pollution, and unplanned development have led to land degradation and threatened the sustainability of terrestrial ecosystems. Cropland is currently being lost at rates 30 to 35 times higher compared to the historical record. Drought frequency and desertification extent are also rapidly increasing, resulting in the loss of 12 million hectares of cropland. This development mostly affects poor and vulnerable communities around the world. Additionally, among the 8,300 animal breeds known, 8% are extinct and 22% are at risk of extinction. The impacts of humans on ecosystems over the past 50 years have been more rapid and widespread than at any other time in history, which has led to huge irreversible losses of biodiversity on Earth. Sustainable management of terrestrial ecosystems is now more critical due to the effects of climate change and urgent action is required to mitigate its impact.

Table 6-1. Focused SDG 15 indicators

Target	Indicator	Tier
15.1 By 2020, ensure the conservation, restoration, and sustainable use of terrestrial and inland freshwater ecosystems and their services. This refers to forests, wetlands, mountains, and drylands, and is in line with international agreements.	15.1.2 Proportion of sites for terrestrial and freshwater biodiversity that are covered by protected areas.	Tier I
15.5 By 2020, take urgent action to reduce the degradation of natural habitats, halt the loss of biodiversity, and protect and prevent the extinction of threatened species.	15.5.1 Red List Index.	Tier I

Contributions

The research aims to use Big Earth Data approaches to support monitoring and evaluating SDG 15 indicators in China and specific areas. It will provide a platform for linking Chinese expertise and experience in key fields related to SDG 15 with the international community (Table 6-2). The research on Big Earth Data for SDGs has multiple objectives, including developing and improving other related data products, such as the biodiversity dataset, and the species Red List Index in China. In addition, the research results will provide decision support through published reports and assessments, and access to data and information.

Table 6-2. Cases and their contributions to SDG 15

Indicator	Case	Contributions
15.1.2 Proportion of important sites and ecosystems for terrestrial and freshwater biodiversity that are covered by protected areas.	Evaluating the effectiveness of the management of protected areas: An example from Qianjiangyuan National Park in China.	Data product: Qianjiangyuan National Park ecosystem and biodiversity datasets. Decision support: Countermeasures for biodiversity conservation and management in Qianjiangyuan National Park.
15.5.1 Red List Index.	Evaluation of the Red List Index of threatened species in China.	Data product: Chinese species Red List Index data.
	Assessment of giant panda habitat fragmentation.	Data product: The data describes the current distribution and past changes in the giant panda habitat in China over the past 40 years. Decision support: Support is provided to assess evolutionary characteristics and suggestions are offered for protecting giant panda habitats.

15 LIFE ON LAND

Case Study

Evaluating the effectiveness of the management of protected areas: An example from Qianjiangyuan National Park in China

Scale: Local

Study area: Qianjiangyuan National Park, China

Protected areas, including national parks, nature reserves, and other nature parks, represent a primary means for preventing global biodiversity loss. Assessing the effectiveness of protected areas on biodiversity conservation usually involves two dimensions. First, the coverage of Key Biodiversity Areas (KBAs) by protected areas is assessed at global, regional, or national scales to ensure that important biodiversity areas are included in the protected area system. Secondly, the rationality of the spatial planning and management effectiveness are evaluated at the scale of a single protected area. This is required to ensure that the protected area can effectively protect biodiversity after it is established. Significant progress has been made towards expanding the spatial extent of protected areas. For example, 15% of terrestrial and freshwater environments are now covered by protected areas. However, the effectiveness of existing protected areas is constrained by extensive human activities within their boundaries as well as protected area downgrading, downsizing and degazettement (PADDD). Numerous studies have examined the effectiveness of protected areas using different indicators, yet there is a lack of systematic monitoring data and indicators for assessing the effectiveness of management practices.

Qianjiangyuan National Park was one of the first ten pilot national parks in China. The park was established to protect a large area of low lying zonal evergreen broadleaved forests in Eastern China (Figure 6-1). It is home to two China's endemic species, the first-class protected species, black muntjac (*Muntiacus crinifrons*) and Elliot's pheasant (*Syrmaticus ellioti*). The park also provides important ecosystem services relating to water provisions for the developed region in the Yangtze River Delta, Eastern China. Qianjiangyuan National Park was used as an example in this case study, and an indicator system was developed to evaluate the effectiveness of protected area management. A corresponding biodiversity monitoring platform was also established to provide data support for the calculation of indicators. This enables a comparison of management effectiveness between protected areas, and the integration of data from different areas for evaluation at regional and global scales.

Target 15.1: By 2020, ensure the conservation, restoration, and sustainable use of terrestrial and inland freshwater ecosystems and their services. This includes forests, wetlands, mountains, and drylands, and is in line with obligations under international agreements.

Indicator 15.1.2: Proportion of important sites and ecosystems for terrestrial and freshwater biodiversity that are covered by protected areas.

Figure 6-1. A lowland evergreen broadleaved forest in Qianjiangyuan National Park (left). A first-class protected animal known as the black muntjac (above right). Elliot's pheasant (bottom right).

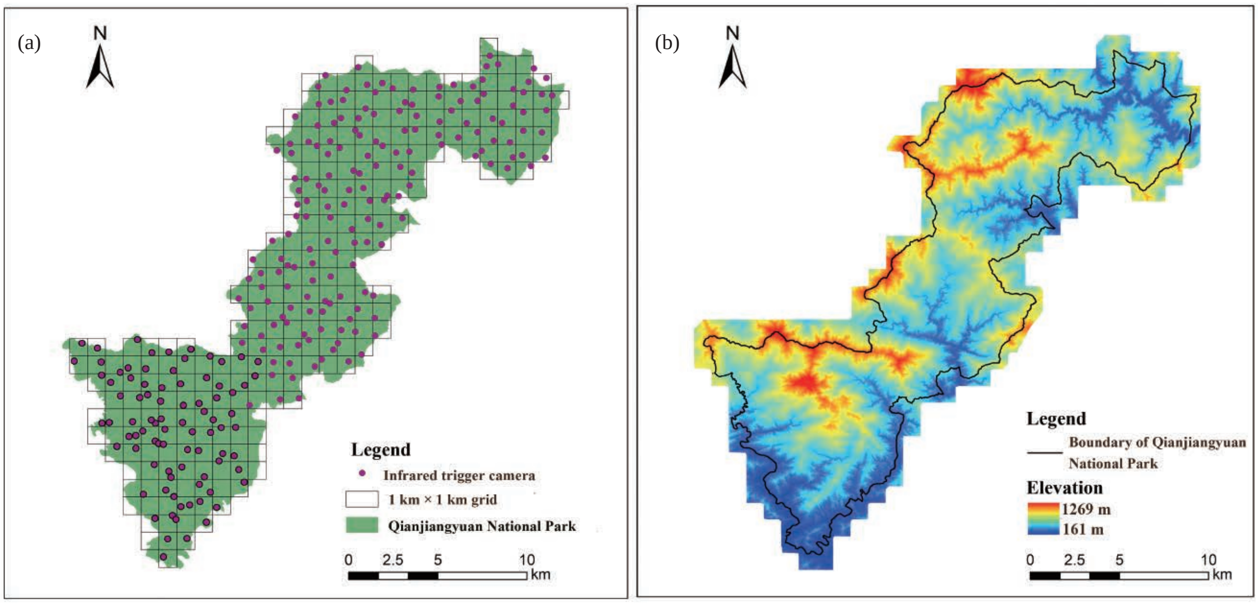


Figure 6-2. (a) National park plant and animal diversity monitoring platforms. Each infrared trigger camera was set up in a forest dynamics plot. (b) Digital surface model (DSM) of the national park remote sensing platform.

Method

The management effectiveness of protected areas was assessed using the following three indicators: (1) the area and degree of fragmentation of key target ecosystems, (2) the change in population size for key protected plants and animals, and (3) ecosystem functions as indicated by above-ground biomass and carbon stock.

Three biodiversity monitoring platforms were established based on the above indicators to obtain data for Qianjiangyuan National Park (Figure 6-2).

(1) The national park plant diversity monitoring platform involved dividing the entire park into a 1×1 km grid and the construction of 641 plots with an area ≥0.04 ha (Figure 6-2a). All freestanding stems that were ≥1 cm in diameter at breast height were censused in each plot. Eight 2×2 m subplots and 1×1

m subplots were established for monitoring shrubs and herbs, respectively.

(2) In the national park animal diversity monitoring platform, an infrared trigger camera was installed in 1×1 km grid cells to monitor animal diversity and population dynamics (Figure 6-2a).

(3) In the national park remote sensing platform, forest canopy structures were obtained for the entire park using light detection and ranging (LiDAR). Moreover, the functional traits of plant leaves were retrieved using hyperspectral remote sensing data (Figure 6-2b).

The data from the three biodiversity monitoring platforms was integrated to evaluate the management effectiveness of Qianjiangyuan National Park. Forest communities were classified using the data from the forest dynamics plots and remote sensing imagery. The area and fragmentation indices for subtropical evergreen broadleaved forests were calculated for the entire national park. The abundance and inter-annual change in population size of the black muntjac and Elliot's pheasant were estimated in the national park using the N-mixture model based on the data from infrared trigger cameras. The above-ground biomass and carbon stock of the forest ecosystem was estimated at the forest plot level using data from forest dynamics plots. These results were scaled up to the level of the entire national park and combined with remote sensing imagery.

Data used in this case

The field survey data included 641 forest dynamics plots with an area of ≥0.04 ha and an infrared trigger camera monitoring network constructed on a 1×1 km grid. The remote sensing datasets included LiDAR and hyperspectral data, and a digital orthophoto map.

Results and analysis

(1) Results revealed that evergreen broadleaved forests covered 5,827.1 ha, or 23.1% of the total area in Qianjiangyuan National Park. The largest patch of evergreen broadleaved forest was 1,178 ha in area. Plantation forests accounted for 26% of the total area in the park. There are still large areas covering old-growth evergreen broadleaved forests in the neighboring areas.

(2) The mean amount of above-ground carbon stock was estimated to be 86.2 mg/ha, and ranged between 75 and 100 mg/ha. The largest carbon stock (228.5 mg/ha) was found in old-growth evergreen broadleaved forests. Conversely, the lowest

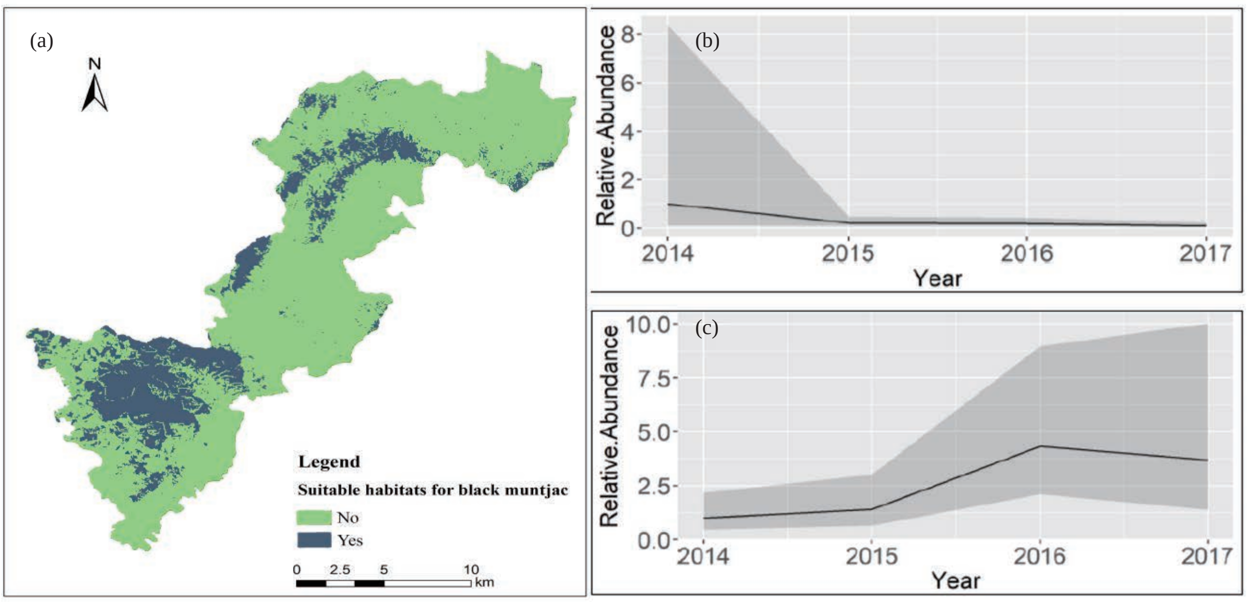


Figure 6-3. Distribution of suitable habitat patches for black muntjac in Qianjiangyuan National Park (a). The variation in relative abundance for black muntjac (b) and Elliot's pheasant (c) during 2014-2017.

carbon stock (18.1 mg/ha) was found in secondary forests 30 years after clear-cut tree harvesting, which accounted for one-twelfth of the carbon stock of old-growth forests.

(3) The total area of suitable habitats for the black muntjac was 4,250 ha and accounted for 16.9% of the park (Figure 6-3a).

(4) The population of black muntjac significantly declined during 2014-2017, and the population of Elliot's pheasant increased during this period (Figure 6-3b, c).

(5) Results demonstrate that the population size of the black muntjac in Qianjiangyuan National Park significantly decreased, requiring further monitoring and conservation. Cross-border cooperation is necessary to protect evergreen broadleaved forests and endangered animal habitats, and to restore plantation forests to improve the effectiveness of national park management.

Highlights

- *Three biodiversity monitoring platforms were developed to collect data to assess the effectiveness of management in Qianjiangyuan National Park. The park conserves a large area of low-lying zonal evergreen broadleaved forest as well as a large area of suitable habitats for the black muntjac, an endangered species. These indicators assess ecosystem integrity in Qianjiangyuan National Park.*
- *In 2014-2017, the population size of Elliot's pheasant was observed to increase, but the population of the black muntjac had significantly declined. Additional monitoring and conservation efforts are necessary to understand the cause of this phenomenon. Furthermore, cross-border cooperation is required to protect evergreen broadleaved forests and endangered animal habitats. Such efforts are also necessary for restoring plantation forests in the park and to improve the effectiveness of park management.*

Outlook

The biodiversity monitoring indicator system established in this study promotes the assessment of management effectiveness in protected areas. Currently, the specific indicator system has only been applied to Qianjiangyuan National Park. Appropriate indicators should be selected based on the type and characteristics of ecosystems. The characteristics of the protected area should be considered when applying the monitoring scheme to other protected areas.

The accuracy and timeliness of the management assessment of protected areas can be improved using various methods. For instance, it is recommended to perform in-depth research on the correlation between ground observation data (e.g., vegetation dynamics plots and infrared camera datasets) and near-surface remote sensing. There is also a need to develop new indices for retrieving biodiversity patterns based on near-surface remote sensing, and to enhance the application of "Space-Air-Ground" integrated biodiversity monitoring platforms.

Evaluation of the Red List Index of threatened species in China

Scale: National

Study area: China

Climate change and human activities are currently threatening global biodiversity. Researchers have proposed a Red List Index based on the red list of species of the International Union for Conservation of Nature (IUCN) to assess changes in biodiversity and the effectiveness of conservation measures. This indicator is one of the most effective means for assessing endangered species and has been listed as one of the evaluation indicators in the UN MDGs. Moreover, the indicator has been widely used in the assessment of conservation progress at global scales. Many countries have conducted a national-scale assessment using the Red List of Species due to availability of detailed and accurate species information. The Red List of Chinese Species was first released by China in 2004 and was updated in 2016-2017. The Red List Index is calculated based on the National Red List of Species and accurately reflects the changing biodiversity trends in the country and guides conservation work at the national level. In this study, the Red List Index in the National Red List of Species was used to assess the threat levels to higher plants, terrestrial mammals, and birds in China from 2004 to 2017. The goal was to provide a basis for the study of biodiversity and the formulation of conservation strategies in China.

Target 15.5: By 2020, take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity, and protect and prevent the extinction of threatened species.

Indicator 15.5.1: Red List Index.

Method

The first assessment of the red lists for higher plants was gathered from *China Species Red List, Vol. 1: Red List*. The second assessment was obtained from the *China Biodiversity Red List—Higher Plants* with some minor revisions from the special issue of Higher Plants of China published in Biodiversity Science. The two assessments of terrestrial mammals and birds were obtained from *China Species Red List, Vol. 2: Vertebrates* and the *Chinese Red List of Vertebrates*.

Species that have been evaluated at least twice can participate in Red List Index calculation. Moreover, species that were first assessed as extinct (EX/EW/RE), and any species that were once assessed as data deficient DD were not used in the calculations. A total of 3,948 higher plants, 568 terrestrial mammals, and 1,213 birds were used in the calculation of the Red List Index.

Data used in this case

The data were derived according to the IUCN classification criteria for threatened factors. These factors referred to the spatial data of human activities, including the population density, the number of highways and waterway entrances, power infrastructure, urban areas, and farmland.

Results and analysis

(1) Changes in the threatened status for species.

From 2004 to 2017, the proportions of higher plants that have declined, remained stable, and improved in status were 7.9%, 37.4%, and 47.8%, respectively, with a few species going extinct. The number of mammal species that are critically endangered (CR) has increased, while the number of species that are endangered (EN) and vulnerable (VU) has declined. The number of threatened bird species (including CR, EN, VU) has also increased.

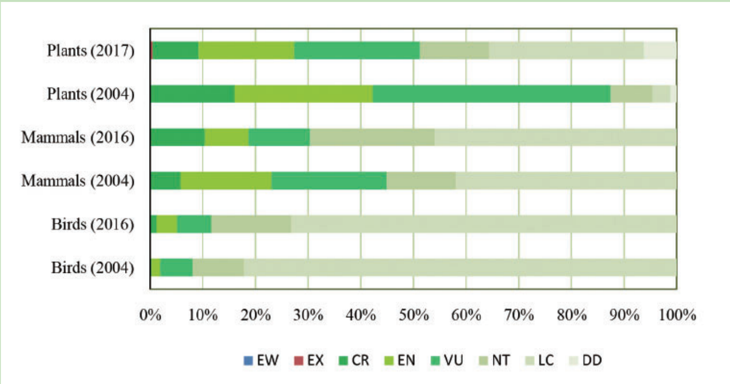


Figure 6-4. Changes in the threatened levels of higher plants, terrestrial mammals, and birds in China.

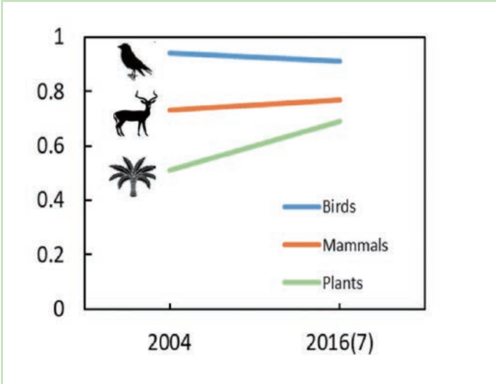


Figure 6-5. Red List Index for higher plants, terrestrial mammals, and birds in China.

(2) Red List Index

The results of the Red List Index evaluation show that (Figure 6-5), Red List Index of birds declined slightly, while mammal index was on the rise. For higher plants, the Red List Index was 0.51 in 2004 and increased to 0.69 in 2017. This suggested that their overall endangered status of higher plants and terrestrial mammals in China has been improved. After the first assessment of threatened species in 2004, many conservation measures have been taken by national and local biodiversity conservation organizations and units, and even many protected areas have been established and conserved for some species. Therefore, many endangered species have been effectively protected since 2004, alleviating their endangered status to a certain extent, and making their Red List Index show an upward trend.

(3) Threats to biodiversity loss

Among the 12 categories of threats leading to biodiversity loss, the use of biological resources and agriculture/aquaculture development are the main threats to China's terrestrial mammals and birds. Higher plants are mostly threatened by natural system modifications and the use of biological resources. Controlling these threats is an effective means for stopping the decline of threatened species and curbing biodiversity loss.

These findings reveal that several changes in the threatened status of higher plants, terrestrial mammals, and birds have occurred in China over the past decade. Results suggest that conservation actions have mostly improved the threatened status of higher plants and terrestrial mammals. However, some groups such as bird species have been declining in threatened status, suggesting that urgent action is needed to reverse their decline. This study provides scientific information to guide species conservation in China and demonstrates the potential of using a national species red list for biodiversity conservation.

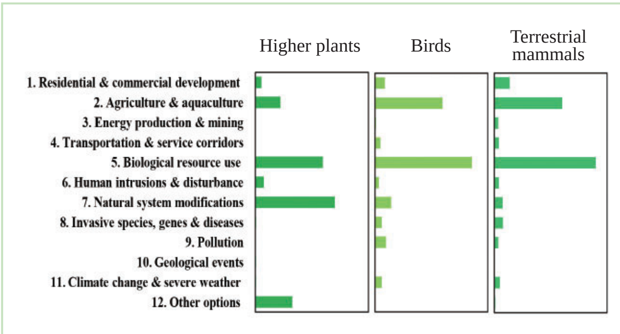


Figure 6-6. Composition and proportion of threatening factors faced by higher plants, terrestrial mammals, and birds in China.

Highlights

- *Results reveal that the Red List Index for higher plants and land mammals in China was on the rise from 2004 to 2017, and their endangered status has been improved.*
- *Bioresource use and agriculture/fishery development are the main threats faced by terrestrial mammals and birds in China. Higher plants are more exposed to direct threats from ecosystem changes and over-exploitation. These threats can be controlled to reverse population decline and curb biodiversity loss.*

Outlook

Establishing dynamic monitoring of threatened species or species of conservation concern in China, so as to find and eliminate species threat factors and promote species conservation will be an effective way and an important work for biodiversity conservation in the future.

The overall situation of conservation of terrestrial mammal and bird diversity in China is still very serious, and some species groups need to be paid more attention because of differences in anthropogenic threats.

The next step is to strengthen the analysis of threats to species and their spatial patterns to provide targeted support for protection and management. This will assist in slowing the rate of biodiversity decline and reversing biodiversity loss.

Assessment of giant panda habitat fragmentation

Scale: Local

Study area: Giant Panda Habitat, China

The fourth national giant panda survey report indicates that China has 1,864 wild giant pandas (*Ailuropoda melanoleuca*). The adult giant panda populations have increased since past surveys. As a result, the IUCN downgraded the status of the giant panda from "endangered" to "vulnerable" in 2016. However, many domestic and foreign conservationists have doubts about the validity of this downgrade. Currently, the determination of whether a species is endangered depends on its population size but neglects changes in habitat quality and quantity.

Target 15.5: By 2020, take urgent action to reduce the degradation of natural habitats, halt the loss of biodiversity, and protect and prevent the extinction of threatened species.

Indicator 15.5.1: Red List Index.

Method

Data collection methods, analyses, and the sample area for the four national giant panda surveys are inconsistent, which makes comparisons difficult. This method attempts to provide comparable estimates for different surveys by using the same geographical area. The area contains 56 counties in Sichuan, Shaanxi, and Gansu provinces. The method is consistent for habitat extent and quality determination in conjunction with years of field investigations, and GIS and remote sensing data. This method is intended to produce a comprehensive analysis of giant panda habitats.

The giant panda habitats were evaluated using a model that combines elevation, slope, and forest cover. Elevation and slope data were obtained from a DEM with a 90-meter pixel resolution. Forest cover was assessed using 52 Landsat Multispectral Scanner (MSS)/TM images from the CAS scientific database (http:// www.csdb.cn/) and the China Remote Sensing Satellite Ground Station.

The fragmentation of panda habitats was evaluated using Fragstats 3.3 to estimate the number of isolated habitat units and the mean patch size. The number of isolated habitat units reflects the integrated effects of isolation by natural processes and human activities. The panda habitats were overlaid with isolation factors (e.g., major rivers, permanent snow cover, and major roads) to analyze the variation for habitat isolation in different periods. These factors represent major barriers to panda migration.

Several metrics were used to assess the effects of different biophysical and socioeconomic drivers. These include wetness indexes, elevation, human population, road density, and the number of nature reserves at the county level. These variables were then used to develop multiple general linear regression models to analyze the contribution of relevant factors.

Data used in this case

The remote sensing dataset consisted of Landsat MSS/TM images from 1976, 1988, 2001, and 2013. Other data included DEM data from SRTM, river data from the national geographic information center, road data from the transportation department, population data, economic data, and nature reserve boundary data.

Results and analysis

Results from the assessment of giant panda habitats revealed that the habitat area had increased by 0.4% between 2001 and 2013. Moreover, the mean patch size of each habitat also increased by 1.8%, despite the devastating 2008 Wenchuan earthquake. This indicates that the implementation of ecological protection and restoration projects had resulted in an increase in

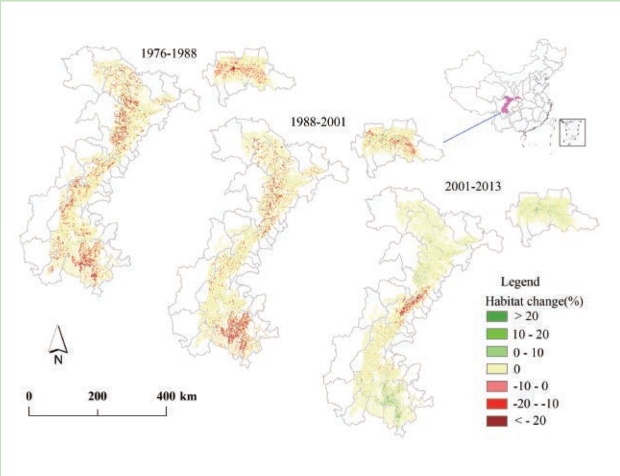


Figure 6-7. Change in giant panda habitats between 1976 and 2013.

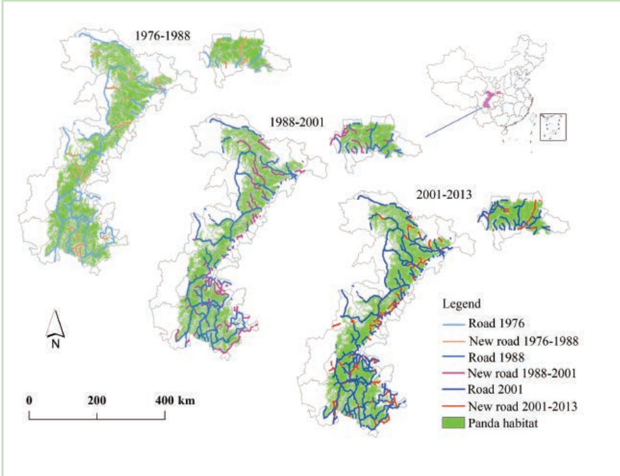


Figure 6-8. Change in road networks and panda habitat areas from 2001 to 2013.

giant panda habitat area since 2001 (Figure 6-7). These projects included the construction of nature reserves, natural forest conservation programs, and the Grain-to-Green program.

However, the past 40 years have witnessed long-term commercial logging, rapid road construction, and natural disasters such as earthquakes and debris flows. Consequently, panda habitats have shrunk in area and become more fragmented in 2013 than when the giant pandas were still listed as endangered in 1976 and 1988. The amount of isolated panda habitats in 2013 was three times higher than in 1976 (Figure 6-8), implying that communication barriers between panda populations have greatly increased.

Research suggests that the downgrade of giant pandas from endangered to vulnerable is reasonable in terms of population size. However, this change is not valid in terms of habitat change. Giant panda habitats may have increased in size since 2001. However, these habitats shrank and were more fragmented in 2013 than in 1988 when the species was listed as endangered. Currently, giant pandas are still facing many threats and challenges, and the downgrade is unreasonable. Future assessment of a species' endangered level should consider both their population and habitat.

Figure 6-9. Panda habitat in Sichuan Wolong Nature Reserve.

Highlights

- *Although the panda population increased from 1976 to 2013, the habitat area was observed to be smaller and more fragmented in 2013 than in 1988. It is unreasonable to reduce the panda's status from endangered to vulnerable solely based on the population. An assessment of a species' endangered level requires considering both their population and habitat.*

Outlook

The method presented in this case enables a more reasonable evaluation of panda habitat dynamics, and provides a powerful tool and data support for future conservation work.

This case approach can be applied to assess the habitats of other endangered species around the world, and analyze fragmentation status and other influential factors. Furthermore, this case study supports the implementation of SDG 15.5, which represents the need to "take urgent action to reduce the degradation of natural habitats, halt the loss of biodiversity, and protect and prevent the extinction of threatened species by 2020".

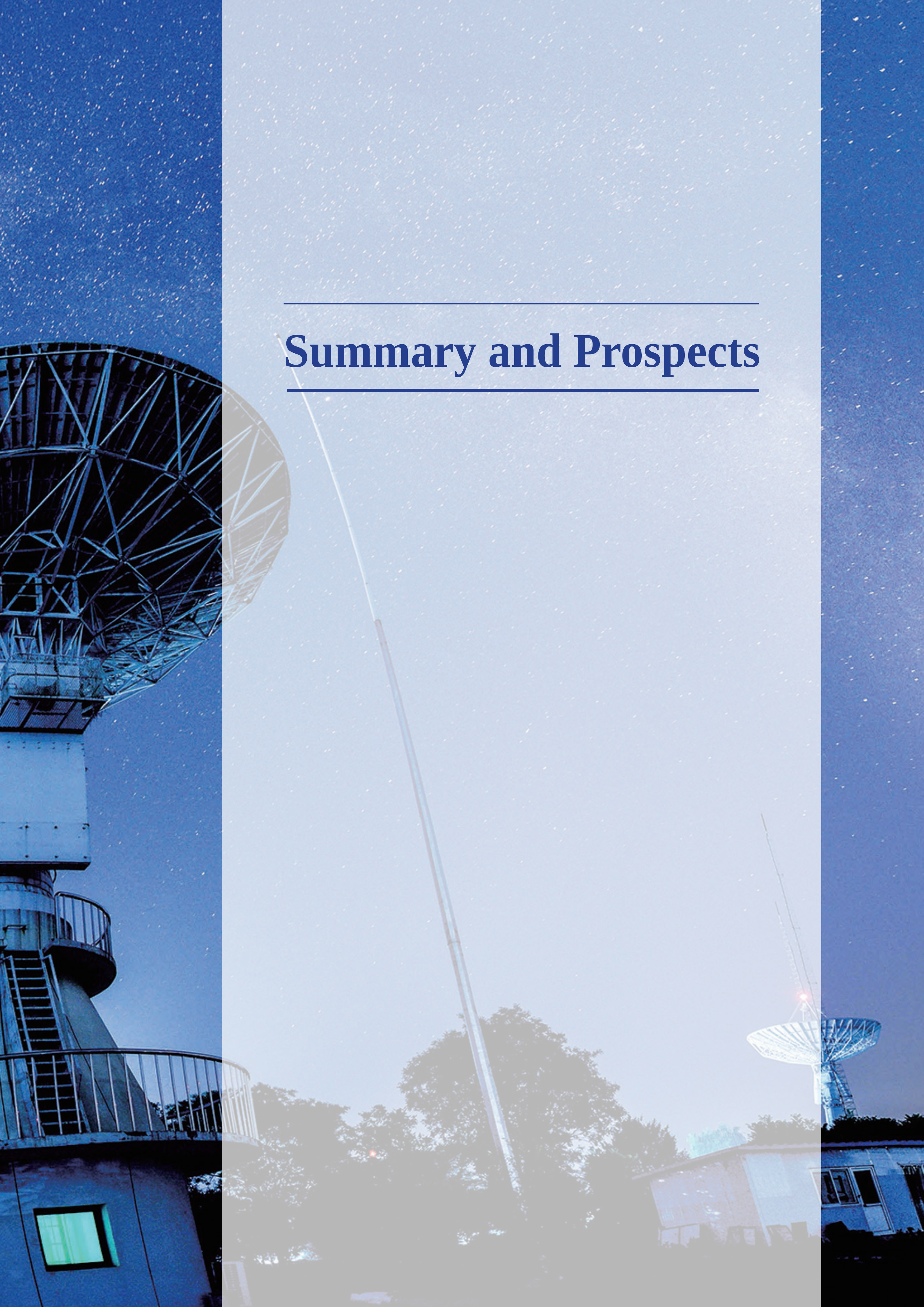
Conclusions

This report provides an evaluation of the practices for fulfilling SDG 15 through examples that are applied using Big Earth Data technologies and methods. These data products, models, and methods provide the ability for frequent, dynamic, quantitative, and objective evaluation of sustainability and spatial refinement for SDG 15 indicators. This report also provides support for comprehensive evaluation of global and regional sustainable development. The following indicators and factors will be investigated in future work.

(1) SDG 15.1.2: The integration models for habitats, human activities, environmental impacts, and climate change will be assessed. This is required to promote the coordination of three types of indicators, including: natural resource protection, the rational use of resources, and social sustainable development. The methods and data will be further improved to support the accurate assessment of forest ecosystem protection efforts. A comprehensive monitoring platform and evaluation index will be developed and applied to protected areas. This will enable the development of protection and management plans for other protected areas.

(2) SDG 15.5.1: The composition and spatial distribution of factors threatening China's endangered species will be assessed to fulfill the objectives outlined by SDG 15.5.1. Moreover, the goal will be to provide information support for targeted conservation and management of endangered species, and to reverse losses in biodiversity. Lastly, global endangered species' habitats will be analyzed in terms of habitat fragmentation and other influencing factors.

Summary and Prospects



Summary and Prospects

The 2030 Agenda for Sustainable Development emphasizes that the implementation of policies and the decision-making process should be based on scientific evidence. Continuous, timely data relevant to SDGs needs to be collected and analyzed to generate reliable, high-quality information to assist UN member states in making informed policies and decisions.

This report presents case studies highlighting the use of Big Earth Data to evaluate 11 indicators in five SDGs, focusing on challenges in aspects of data, methodological models, and the decision-making process. Below is a summary of the five SDGs addressed in the report.

(1) This report puts forward a method to calculate indicator SDG 2.4.1, using diverse datasets including remote sensing data, statistical data, and ground survey data. The result shows that between 1987 and 2015, the environmental intensity of four indicators—land use, irrigation water consumption, nitrogen excess, and phosphorus excess—dropped in approximately 26% of Chinese farmlands, and these farmlands have become more sustainable across all of the four indicators.

(2) For indicators SDG 6.3.2, the case study develops datasets of the proportion of good ambient water quality at provincial levels in China providing new sources of data and methods for evaluating the indicators of SDG 6.

(3) For indicators SDG 11.2.1, SDG 11.3.1, SDG 11.4.1, SDG 11.6.2, and SDG 11.7.1, the report presents cases that monitor and evaluate these indicators. The evaluation methods for the SDG 11 indicators include methods for extracting information on public transport, populations, and global urban impervious surfaces. The report suggests a new overview of the connotation of SDG 11.4.1: “increasing capital investment per unit area to preserve and protect world cultural and natural heritage”. The report also provides data for evaluating the SDG 11 indicators including spatial distribution of global urban impervious surfaces with 10-meter resolution.

(4) For SDG 14.1.1 and SDG 14.2.1, the report presents case studies that establish a system for comprehensive evaluation of eutrophication in coastal waters of China based on the “Pressure-State-Response” framework, and proposes a method for evaluating the typical marine ecosystems in China’s coastal waters. The evaluation, which employs machine learning techniques, is based on the characteristics of the structure of marine ecological systems, service functions, and ecological disasters/diseases. These cases provide new methods to evaluate SDG 14 indicators at the local scale.

(5) For SDG 15.1.2, and SDG 15.5.1, two indicators related to life on land, this report takes proportion of important sites for terrestrial and freshwater diversity as research objects. The report provides new data related to evaluating SDG 15, such as the China Red List Index and Qianjiangyuan National Park, and proposes suggestions to assess a species' endangered level by comprehensivly considering both the numbers and the habitat environment of the giant panda.

The cases presented in this report aim to improve scientific methods and explore new and innovative technologies to support sustainable development. By relying on Big Earth Data technology and analytical tools, researchers can collect and analyze data more efficiently, make up for the data gaps in current SDG indicator evaluations, increase the spatiotemporal resolution and accuracy of data, and provide new ways to evaluate and monitor Tier III indicators.

The world must achieve the SDGs by 2030, which is extremely challenging in reality. We still face many challenges in leveraging Big Earth Data to support SDGs.

The global SDG indicators are divided into three main categories, and the global indicator framework provides a basis for all countries to evaluate the indicators. However, due to the differences in innovative capabilities of information and network technologies as well as Big Earth Data, there are method gaps for SDG evaluation between different countries and regions. Many countries, particularly developing countries, have no roadmap for effectively carrying out scientific evaluation of SDGs. By studying and developing a methodological system of Big Earth Data for SDG evaluation, which would be capable of being utilized at multiple spatial scales, it can assist member states of the UN at different developmental stages in reducing the differences in capabilities for SDG evaluation.

Evaluation of SDG indicators requires a variety of data, including data related to land, transport, population, sanitation, economy, environment, and ecology, at different spatial and temporal scales, over long time intervals. Collecting this data is not an easy task for either developed or developing countries. Traditional ways of data acquisition must be reformed and efforts need to be intensified to develop Big Earth Data infrastructure in all member states of the UN. Data sharing and access through online channels and platforms need to be expanded to open up the information and data needed for SDG evaluation.

Globally, many organizations are committed to building data and information platforms. The UN is using information platforms such as the Sustainable Development Knowledge Platform and the TFM online platform to promote the sharing of information on SDGs. However, it lacks a formal policy and uniform standards involving data structure and data security among other important issues related to data access and privacy. A Big Earth Data framework could promote collaborative data sharing, and strengthen multi-divisional and multidisciplinary cooperation among government agencies, international organizations, and international science programs. Joint research can be promoted through sharing of information, methods, and data, which will help to develop technical standards and promote cooperation towards global and regional sustainable development.

Over the past year, researchers have carried out pilot studies to develop Big Earth Data in support of SDGs. However, there are several actions that need to be taken:

(1) Strengthen case studies on Big Earth Data supporting SDG indicators

Data is a prominent bottleneck problem restricting accuracy of SDG evaluation. Among over 230 indicators of SDGs, 39% have specific methods but lack data for evaluation (Tier II). Meanwhile, 16% of the indicators have neither specific methods nor data for evaluation (Tier III). The evaluation of Tier II and Tier III indicators based on Big Earth Data has great potential. The 11 SDG indicators in this report consist of three Tier I indicators, five Tier II indicators, and three Tier III indicators. In the future, the research will focus more on the Tier III indicators. It is necessary to study evaluation models based on Big Earth Data; give full consideration to the integration of satellite remote sensing data, network data, and ground station data (e.g., $PM_{2.5}$ monitoring, water quality monitoring); develop new applicable models and methods on a global scale; carry out more comprehensive evaluations of SDG indicators; and create a series of cases for evaluating Big Earth Data SDG indicators that can be promoted and shared.

(2) Carry out comprehensive evaluation research on SDG indicators

The 2030 Agenda for Sustainable Development emphasizes the comprehensiveness and inseparability of sustainable development goals and their indicators, and the goals and indicators are interrelated and act on each other. SDGs, especially the goals closely related to the environment and resources of the Earth surface system, are characterized by large-scale, periodic changes. The macro, dynamic monitoring capabilities of Big Earth Data provide an important method for analyzing the interrelations and interactions between SDG indicators. In this report, research on monitoring multiple SDG indicators is presented. Going forward, Big Earth Data will be used to strengthen research on the interactions between sustainable development goals and indicators, explore new tools and methods, comprehensively quantify the degree of interactions between the goals and indicators, and provide more relevant information for decision support.

(3) Strengthen collaboration with relevant governmental departments

The SDGs are mainly guided and practiced by UN member states. In the process of achieving the SDGs, governmental departments have abundant policy-making consulting needs. Big Earth Data could assist all departments in making relevant policies in an efficient and targeted way, and it is an important component of the research to strengthen contacts with relevant governmental departments; narrow the "scientific data divide" between scientists and decision makers; ensure that scientific data is acquired, understood, evaluated, and applied; and enhance the credibility of science in serving decision making. Under the TFM, the sharing of the SDG indicator monitoring data and results will be a good way to establish contacts with relevant governmental departments, and present an opportunity for creating a long-term and efficient mechanism for Big Earth Data serving governmental decision making.

(4) Strengthen collaborative research on SDGs with relevant organizations of the UN

The UN has established a complicated governance system under the global indicator framework of SDGs, and the UN and all of its member states involve many stakeholders. Over the past year since its implementation, CAS has cooperated with UNEP and UNCCD to promote the TFM with Big Earth Data at its core. In the future, the research will expand cooperation with more SDG-related UN organizations, sharing the data, methods, and decision support cases related to SDGs with relevant organizations to support member countries, particularly developing countries. The research will also increase the scientific and technological capacity of member countries to use Big Earth Data for their sustainable development policies.

References

Acuto, M., Parnell, S. and Seto, K. C. (2018). Building a global urban science[J]. *Nature Sustainability* 1: 2–4. https://doi: 10.1038/s41893-017-0013-9.

Andries, A., Morse, S., Murphy, R. *et al.* (2019). Translation of earth observation data into sustainable development indicators: An analytical framework[J]. *Sustainable Development* 27: 366–376. http://doi: 10.1002/sd.1908.

Anwar, M. R., Liu, D. L., Macadam, I., *et al.* (2013). Adapting agriculture to climate change: A review[J]. *Theoretical and applied climatology* 113(1–2): 225–245. https://doi:10.1007/s00704-012-0780-1.

Bao, Q., Xu, X. F., Li, J. X., *et al.* (2018). Outlook for El Nino and the Indian Ocean Dipole in autumn-winter 2018–2019[J]. *Chinese Science Bulletin* 64(1): 73–78. https://doi.org/10.1360/N972018-00913.

Behnke, R.H. and Mortimore, M. (2016). The End of Desertification?[M]. Springer-Verlag, Berlin.

Bricker, S. B., Ferreira, J. G., Simas, T. (2003). An integrated methodology for assessment of estuarine trophic status[J]. *Ecological Modelling* 169 (1):39–60. https://doi:10.1016/S0304-3800(03)00199-6.

Butler, J. H. and Montzka, S. A. (2016). The NOAA annual greenhouse gas index (AGGI). http://www.esrl.noaa.gov/gmd/aggi/aggi. html.

Chen, C., Park, T., Wang, X. H., *et al.* (2019). China and India lead in greening of the world through land-use management[J]. *Nature Sustainability* 2:122–129. http://dx.doi.org/10.1038/s41893-019- 0220-7.

Cloern, J. E. (2001). Our evolving conceptual model of the coastal eutrophication problem[J]. *Marine Ecology Progress Series* 210: 223–253. https://doi: 10.3354/meps210223.

Cooper, P. J. M., Dimes, J., Rao, K. P. C., *et al.* (2008). Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change[J]. *Agriculture, Ecosystems & Environment* 126(1–2): 24–35. https://doi: 10.1016/j.agee. 2008.01.007.

Deng, W., Li, A. N., Nan, X., *et al.* (2015). China Digital Mountain Map[M]. Beijing: China Map Press.

Devlin, M., Bricker, S., Painting, S. (2011). Comparison of five methods for assessing impacts of nutrient enrichment using estuarine case studies[J]. *Biogeochemistry* 106:177–205. https://doi:10.1007/ s10533-011-9588-9.

Dinerstein, E., Olson, D., Joshi, A., *et al.* (2017). An ecoregion-based approach to protecting half the terrestrial realm[J]. *Bioscience* 67(6): 534–545. https://doi: 10.1093/biosci/bix014.

Grimm, N. B., Faeth, S. H., Golubiewski, N. E., *et al.* (2008). Global change and the ecology of cities[J]. *Science* 319(5864): 756–760. https://doi: 10.1126/science.1150195.

Guo, H. D. (2017). Big Earth Data: A new frontier in Earth and information sciences[J]. *Big Earth Data* 1: 4–20.

Guo, H. D. (2018). A project on Big Earth Data Science Engineering[J]. *Bulletin of the Chinese Academy of Sciences* 33(8): 818–824.

Guo, H. D. (2018). Scientific Big Data–A footstone of national strategy for Big Data[J]. *Bulletin of the Chinses Academy of Sciences* 33(8): 768–773.

Guo, H. D. (2018). Steps to the digital Silk Road[J]. *Nature* 554: 25–27. https://doi:10.1038/ d41586-018-01303-y.

Guo, H. D. (2018). Using Big Earth Data in support of sustanabile development. People's Daily, 30 July 2018. http://paper.people.com.cn/rmrb/html/2018-07/30/nw.D110000renmrb20180730_2-07.htm.

Halpern, B. S., Walbridge, S., Selkoe, K. A., *et al.* (2008). A global map of human impact on marine ecosystems[J]. *Science* 319 (5865): 948–952. https://doi:10.1126/science.1149345.

Halpern, B. S., Longo, C., Hardy, D., *et al.* (2012). An index to assess the health and benefits of the global ocean[J]. *Nature* 488 (7413): 615–620. https://doi:10.1038/nature11397.

He, L. F. (2017). National Report on New Urbanization[M]. Beijing: China Planning Press.

He, Z., Zeng, Z. C., Lei, L., *et al.* (2017). A data-driven assessment of biosphere-atmosphere interaction impact on seasonal cycle patterns of XCO_2 using GOSAT and MODIS observations[J]. *Remote Sensing* 9(3): 251. https://doi: 10.3390/rs9030251.

Hsu, N. C., Tsay, S. C., King, M. D., *et al.* (2006). Deep blue retrievals of asian aerosol properties during ACE-Asia[J]. *IEEE Transactions on Geoscience and Remote Sensing* 44(11): 3180–3195. https://doi: 10.1109/TGRS.2006.879540.

IUCN. (2016). A Global Standard for the Identification of Key Biodiversity Areas,Version 1.0. First edition. Gland, Swizerland: IUCN.

Jiang, L. L., Jiapaer, G., Bao, A. M., *et al*. (2019). Monitoring the long-term desertification process and assessing the relative roles of its drivers in Central Asia[J]. *Ecological Indicators* 104:195–208. https://doi: 10.1016/j.ecolind.2019.04.067.

Johnson, S., Logan, M., Fox, D., *et al*. (2016). Environmental decision-making using bayesian networks: Creating an environmental report card[J]. *Applied Stochastic Models in Business and Industry* 33(4): 335–347. https://doi: 10.1002/asmb.2190.

Kaufman, Y. J., Tanré, D., Remer, L. A., *et al*. (1997). Operational remote sensing of tropospheric aerosol over land from EOS moderate resolution imaging spectroradiometer[J]. *Journal of Geophysical Research-Atmospheres* 102(D14): 17051–17067. https://doi: 10.1029/96JD03988.

Kosmas, C., Kirkby, M. and Geeson, N. (1999). Manual on key indicators of desertification and mapping environmentally sensitive areas to desertification. *European Commission*, 87.

Kroner, R.E.G., Qin, S. Y., Cook, C. N., *et al*. (2019). The uncertain future of protected lands and waters[J]. *Science* 364(6443): 881. https://doi: 10.1126/science.aau5525.

Levy, R. C., Remer, L. A., Kleidman, R. G., *et al*. (2010). Global evaluation of the Collection 5 MODIS dark-target aerosol products over land[J]. *Atmospheric Chemistry and Physics* 10(21): 10399–10420. https://doi:10.5194/acp-10-10399-2010.

Liu, J., Bowman, K. W., Schimel, D. S., *et al*. (2017). Contrasting carbon cycle responses of the tropical continents to the 2015-2016 El Nino[J]. *Science* 358: 6360. https://doi: 10.1126/science.aam5690.

Lu, S. L., Ma, J., Ma, X.Q., *et al*. (2019). Time series of Inland Surface Water Dataset in China (ISWDC) for 2000-2016 derived from MODIS archives[J]. *Earth System Science Data* 11(3):1099–1108. https://doi.org/10.5194/essd-11-1-2019.

Masó, J., Serral, I., Domingo-Marimon, C., *et al*. (2019). Earth observations for sustainable development goals monitoring based on essential variables and driver-pressure-state-impact -response indicators[J]. *International Journal of Digital Earth*, Online, http://doi:10.1080/17538947. 2019. 1576787.

Micklin, P., Aladin, N. V. and Plotnikov, I. (2016). *The Aral Sea*. Springer.

Monfreda, C., Ramankutty, N. and Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000[J]. *Global Biogeochemical Cycles* 22: 89–102. https://doi:10.1029/2007GB002947.

Nicolai, S., Hoy, C., Berliner T, *et al*. (2016). Projecting progress: Reaching the SDGs by 2030. Overseas Development Institute, London.

Niu, Z. G., Zhang, H. Y., Gong, P. (2011). More protection for China's wetlands[J]. *Nature* 471(7338): 305. https://doi:10.1038/471305c.

NOWPAP CEARAC. (2011). Integrated Report on Eutrophication Assessment in Selected Sea Areas in the NOWPAP Region: Evaluation of the NOWPAP Common Procedure. NOWPAP CEARAC, Toyama, Japan.

Ouyang, Z. Y., Xu, W. H., Xiao, Y., *et al*. (2017). The pattern, quality, service and evolution of Chinese ecosystem[M]. Beijing: Science Press.

Pekel, J. F., Cottam, A., Gorelick, N., *et al*. (2016). High-resolution mapping of global surface water and its long-term changes[J]. *Nature* 540(7633): 418–422. https://doi:10.1038/nature20584.

Poulter, B., Frank, D., Ciais, P., *et al*. (2014). Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle[J]. *Nature* 509(7502): 600. https://doi: 10.1038/nature13376.

Rapport, D. J. (1995). Ecosystem health: Exploring the territory[J]. *Ecosystem Health* 1(1): 5–13.

Sachs, J. S. T., Kroll, C. (2016). SDG Index and Dashboards-Global Report. Bertelsmann Stiftung and Sustainable Development Solutions Network (SDSN), New York.

Siebert, S. and Döll, P. (2010). Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation[J]. *Journal of Hydrology* 384(3–4): 198–217. https://doi:10.1016/j.jhydrol.2009.07.031.

Sun, Z. C., Xu, R., Du, W. J., *et al*. (2019). High-resolution urban land mapping in China from Sentinel 1A/2 imagery based on Google Earth Engine[J]. *Remote Sensing* 11(7): 752. https://doi:10.3390/ rs11070752.

Tang, X. Y., Zhang, Y. H., Shao, M. (2006). Atmospheric Environmental Chemistry(second edition)[M]. Beijing: Higher Education Press.

Thomas, E., Erik, A., Niki, F., *et al*. 2019. Sustainability and resilience for transformation in the urban century[J]. *Nature Sustainability* 2: 267–273. https://doi.org/10.1038/s41893-019-0250-1.

Thornton, P. K., Jones, P. G., Alagarswamy, G., *et al*. (2009). Spatial variation of crop yield response to climate change in East Africa[J]. *Global Environmental Change* 19(1): 54–65. https://doi:10.1016/j.gloenvcha. 2008.08.005.

Tulbure, M.G., Broich, M., Stehman, S.V., *et al*. (2016). Surface water extent dynamics from three decades of seasonally continuous Landsat time series at subcontinental scale in a semi-arid region[J]. *Remote Sensing Environment* 178: 142–157. https://doi: 10.1016/j.rse.2016.02.034.

UNDESA. (2014). World urbanization prospects the 2014 revision. New York: United Nations.

UNESCO. (1972). Convention Concerning the Protection of the World Cultural and Natural Heritage. United nations Education, Cultural and Science Organization, Paris.

UN-Habitat. (2019). A guide to assist national and local governments to monitor and report on SDG goal 11+ indicators, Online Edition.

United Nations. (2015). Transforming Our World: The 2030 Agenda for Sustainable Development. United Nations, New York.

United Nations. (2018). Tracking Progress Towards Inclusive, Safe, Resilient and Sustainable Cities and Human Settlements.

United Nations. (2019). The Sustainable Development Goals Report 2019, Online Edition. https://unstats.un.org/sdgs/report/2019/.

Wei, H. S., Wang, J. L., Cheng, K., *et al*. (2018). Desertification information extraction based on feature space combinations on the Mongolian plateau[J]. *Remote Sensing* 10(10): 1614. https://doi:10.3390/rs10101614.

Xu, W. H., Viña, A., Kong, L. Q., *et al*. (2017). Reassessing the conservation status of the giant panda using remote sensing[J]. *Nature Ecology & Evolution* 1(11): 1635–1638. https://doi:10.10138/s41559-017-0317-1.

Yu, Z. M., Shen, Z. L., *et al*. (2011). Esturification of Yangtze Estuary Waters[M]. Beijing: Science Press.

Zeng, Z. C., Lei, L. P., Hou, S. S., *et al*. (2014). A regional gap-filling method based on spatiotemporal variogram model of columns[J]. *IEEE Transactions on Geoscience and Remote Sensing* 52(6): 3594–3603. https://doi:10.1109/TGRS.2013.2273807.

Zeng, Z. C., Lei, L. P., Strong, K., *et al*. (2017). Global land mapping of satellite-observed CO_2 total columns using spatio-temporal geostatistics[J]. *International Journal of Digital Earth* 10(4): 426–456. https://doi: 10.1080/17538947.2016.1156777.

Zhao, L. N., Yang, Y. C., Liu, H. Y., *et al*. (2019). Spatial knowledge deficiencies drive taxonomic and geographic selectivity in data deficiency[J]. *Biological Conservation* 231: 174–180. https://doi:10.1016/j.biocon.2018.12.009.

Zhao, L. N., Li, J. Y., Liu, H. Y., *et al*. (2016). Distribution, congruence, and hotspots of higher plants in China[J]. *Scientific Reports* 6: 19080. https://doi:10.1038/srep19080.

Zheng, Y. M., Zhang, H.Y., Niu, Z. G., *et al*. (2012). Protection efficacy of national wetland reserves in China[J]. *Chinese Science Bulletin* 57(10): 1116–1134. https://doi:10.1007/s11434-011-4942-9.

Zheng, Y. M., Niu, Z. G., Gong, P., *et al*. (2015). A database of global wetland validation samples for wetland mapping[J]. *Science Bulletin* 60(4): 428–434. https://doi:10.1007/s11434-014-0717-4.

Zheng, Y. M., Niu, Z. G., Gong, P., *et al*. (2017). A method for alpine wetland delineation and features of border: Zoige Plateau, China[J] . *Chinese Geographical Science* 27(5): 784–799. https://doi:10.1007/s11769-017-0897-3.

Zhu, J. A. (2005). Transitional institution for the emerging land market in urban China[J]. *Urban Studies* 42(8):1369–1390. https://doi:10.1080/00420980500150714.

Zscheischler, J., Mahecha, M. D., Harmeling, S., *et al*. (2013). Detection and attribution of large spatiotemporal extreme events in Earth observation data[J]. *Ecological Informatics* 15: 66–73. https://doi:10.1016/j.ecoinf.2013.03.004.

Zuo, L. J., Wang, X., Liu, F., *et al*. (2013). Spatial exploration of multiple cropping efficiency in china based on time series remote sensing data and econometric model[J]. *Journal of Integrative Agriculture* 12(5): 903–913. https://doi:10.1016/S2095-3119(13)60308-1.

Zuo, L. J., Zhang, Z. X., Carlson, K. M., *et al*. (2018). Progress towards sustainable intensification in China challenged by land-use change[J]. *Nature Sustainability* 1: 304–313. https://doi:10.1038/s41893-018-0076-2.

Acronyms

AOD	Aerosol Optical Depth
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CAS	Chinese Academy of Sciences
CLC	CORINE Land Cover
DEM	Digital Elevation Model
DMSP	Defense Meteorological Satellite Program
DSM	Digital Surface Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ETM+	Enhanced Thematic Mapper Plus
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
GHSL	Global Human Settlement Layer
GIS	Geographic Information System
IUCN	International Union for Conservation of Nature
KBAs	Key Biodiversity Areas
LCR	Land Consumption Rate
LCRPGR	Ratio of Land Consumption Rate to Population Growth Rate
LiDAR	Light Detection and Ranging
LST	Land Surface Temperature
MDGs	Millennium Development Goals
MODIS	Moderate Resolution Imaging Spectroradiometer
MSS	Multispectral Scanner
NASA	National Aeronautics and Space Administration
NDSI	Normalized Difference Soil Index
NDVI	Normalized Difference Vegetation Index
NLCD	National Land Cover Database
OLS	Operational Linescan System
PADDD	Protected Areas Downgraded, Downsizing and Degazettement
PGR	Population Growth Rate
$PM_{2.5}$	Particulate matters with dynamic diameter less than 2.5 micrometers

PM_{10}	Particulate matters with dynamic diameter less than 10 micrometers
RSEI	Remote Sensing Ecological Index
SAR	Synthetic Aperture Radar
SDGs	Sustainable Development Goals
SRTM	Shuttle Radar Topography Mission
STI	Science, Technology, and Innovation
TFM	Technology Facilitation Mechanism
TM	Thematic Mapper
UN	United Nations
UNCCD	United Nations Convention to Combat Desertification
UNEP	United Nations Environment Programme
UNICEF	United Nations International Children's Emergency Fund
WHO	World Health Organization

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