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REVIEW ARTICLE

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Satellites in addressing climate change: Trends, challenges, and future directions

Abstract Addressing climate change has become a global priority, and satellites play an important role. This study provides a bibliometric analysis and review of satellite-based climate change research from the perspectives of mitigation and adaptation strategies from 1994 to 2025. The analysis reveals a shift from early emphases on climate change, atmospheric CO_2, and remote sensing toward emerging topics involving vegetation, land use, air quality, variability, and land-cover dynamics. Existing satellite-based studies on climate change mitigation focus on identifying emission hotspots and quantifying CO_2 and CH_4 emissions from ecosystems and socioeconomic systems, while N_2O and emissions from industrial processes and waste remain underexplored. Satellite-based climate change adaptation has been used to assess water resources, agricultural systems, forest cover, and sea level rise, yet challenges such as uneven water distribution, agricultural instability, forest degradation, and sea-level rise, as well as their impacts on ecosystems and biodiversity, remain insufficiently addressed. The study provides valuable future research directions for satellite-based climate change research.

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1 Introduction

The United Nations Framework Convention on Climate Change defines climate change as "climate change directly or indirectly caused by human activities altering the composition of the global atmosphere and observed natural climate variability within comparable time periods," and distinguishes between climate change caused by human activities and climate variability caused by natural factors (Sands, 1992). The global community has increasingly recognized the considerable threat that climate change poses to human survival and development. There is now a broad consensus on the need for proactive and effective responses. Wang et al. (2023a) reviewed the current state of global climate change and highlighted the urgent need for mitigation and adaptation strategies. Mitigation refers to actions aimed at reducing greenhouse gas (GHG) emissions or enhancing their absorption (IPCC, 2023), while adaptation focuses on adjusting human and natural systems to minimize the damage caused by climate change and to capitalize on emerging opportunities (IPCC, 2023). Both strategies are interdependent and essential for effectively addressing the multifaceted challenges posed by climate change (MEE, 2023).

Since the 1960s, satellite technology has advanced rapidly, with applications in remote sensing, navigation, communication, and scientific research. Satellite remote sensing involves the use of sensors on satellites to gather data about Earth's surface and atmosphere. Compared with other observational methods, satellite remote sensing provides frequent, repetitive, and large-scale coverage (Yang et al., 2014). This capability has enabled the collection of global, long-term, continuous, and objective data on the atmosphere, land, and oceans, offering critical insights into climate change and supporting the validation of climate models and theories. Satellites can monitor

GHG concentrations in the atmosphere and track their sources and distribution patterns (Zhu et al., 2022, Shen et al., 2023). They also measure critical parameters, such as vegetation cover, soil moisture, and surface temperature, to assess climate change impacts on terrestrial ecosystems (Weiland et al., 2023, Aziz et al., 2024). In addition, satellites monitor sea surface temperatures, glacier retreat, and sea level changes, providing valuable data on the effects of climate change on marine ecosystems (Ahmad Affandi et al., 2024, Bij de Vaate et al., 2024, Macdonald et al., 2024). Remote sensing satellites launched and planned globally for addressing climate change are detailed in Appendix A.

Several reviews have already addressed satellite-based climate change research. Yang et al. (2014) conducted a review of satellite remote sensing for climate analysis, revealing insights beyond the reach of traditional climate models, such as the spatial heterogeneity of sea level rise and the cooling effects of stratospheric aerosols. They also identified challenges related to the short duration of satellite observations and emphasized the need for enhanced long-term monitoring. Zhao et al. (2023b) conducted a comprehensive review of the application of satellite remote sensing in monitoring and quantifying atmospheric components such as GHGs, clouds, and aerosols; oceanic components including sea surface temperature, ice melt, sea level rise, ocean currents, mesoscale eddies, phytoplankton, and marine productivity; and terrestrial components such as land use and land cover. Zheng et al. (2023) reviewed the application of nighttime light (NTL) data in urban research, including its use in tracking urban expansion, socioeconomic patterns, environmental change, and human activity, and highlighted its potential in quantifying light pollution. Wang et al. (2025a) reviewed the use of multisource remote sensing data for estimating terrestrial carbon fluxes from satellites, with a focus on global-scale inversion of gross primary productivity (GPP), net biome production, carbon emissions from land-use change and wildfires, and atmospheric CO_2 concentrations. Prentice et al. (2024) presented a perspective on remote-sensing-based numerical models using satellite-borne measurements of light absorption by vegetation to estimate global patterns and trends in GPP, identified the challenge, and explored ways to improve their reliability. Liu et al. (2024a) conducted a bibliometric analysis and review of land-use carbon emission or sink research over 1991–2023, showing that satellite remote sensing and remote-sensing indicators such as the Normalized Difference Vegetation Index (NDVI) are prominent themes for monitoring land-use change and supporting carbon-related assessments.

Existing review studies on satellite-based climate change research are relatively abundant; however, most studies concentrate on either climate change mitigation or adaptation, or focus predominantly on natural ecosystems. Review studies on satellite-based climate change research that integrate bibliometric analysis with systematic or narrative synthesis remain limited and typically emphasize ecological and biophysical processes, while paying insufficient attention to socioeconomic systems and human–environment interactions that are critical for climate-related policy formulation and decision-making. This study systematically summarizes satellite-based climate change research from the perspectives of mitigation and adaptation. It reviews satellite-based climate change research in ecosystems, including terrestrial, marine, and other natural systems, as well as socioeconomic systems, such as urban development, agriculture, and industrial sectors. By combining bibliometric analysis with a structured narrative review, this study provides insights into how satellite-based climate change mitigation and adaptation research has evolved over time, highlighting key areas of research focus and underexplored themes. It clarifies how satellite-based applications contribute to both climate change mitigation and adaptation by revealing their differentiated roles across natural and socioeconomic systems. The main contributions of this study include the following:

(1) A bibliometric analysis revealing the development trends and main issues of satellite-based climate change research is conducted.

(2) A review of satellite-based climate change research is conducted, including the identification of GHG sources and sinks and emission estimation in ecological and socioeconomic systems and the monitoring of key indicators such as precipitation variability, extreme weather, glacier retreat, and sea-level rise.

(3) The research gaps in satellite-based climate change research are summarized. Extant research from the perspective of mitigation lacks the monitoring of carbon flux dynamics, tracking of ecosystem resilience, and capturing of biodiversity and ecosystem services and neglects the monitoring of non-CO_2 emissions from sectors such as agriculture, waste, and industrial processes. Extant research from the perspective of adaptation fails to assess resilience and adaptation strategies to climate change and lacks satellite-based climate risk assessments for infrastructure, health, and livelihoods, especially in terms of vulnerability and dynamic exposure across regions and sectors.

(4) Future research is concluded, including addressing uncertainties in transport models, meteorological fields, initial conditions, and emission inventories; expanding global ecological zones to quantify N_2O and CH_4 emissions; developing high-sensitivity algorithms to detect small-scale emission events; quantifying GHG emissions from poorly monitored sectors; evaluating the impacts of extreme climate events on ecosystem adaptive capacity; developing satellite-based indicators to monitor groundwater, river flow, forest health, coastal degradation, etc.

The structure of this study is as follows: Section 2 presents the bibliometric analysis revealing trends and main areas in satellite-based climate change research; Section 3 reviews the document on satellite-based climate change mitigation; Section 4 reviews the document on satellite-based climate change adaptation; Section 5 provides a conclusion and outlook for future research.

2 Bibliometric analysis

On the basis of data retrieved from the Web of Science Core Collection on December 31, 2025, this study conducts a bibliometric analysis of satellite-based climate change research from 1994 to 2025 using CiteSpace (Donthu et al., 2021). Appendix B provides details on the methodology and data collection. The disciplinary and country distributions, keyword co-occurrence analysis, co-citation network of documents, documents with the strongest citation bursts, author co-citation network, and institutional collaboration network are presented in Appendix C.

The evolution of research clusters based on document co-citation clustering is conducted, which reveals the core thematic structures and developmental trajectories of satellite-based climate change research. As shown in Fig. 1, the network comprises clusters of varying sizes, reflecting heterogeneity in research activity and thematic maturity. The 10 largest clusters, each with at least nine documents, represent areas of sustained academic engagement. As shown in Table 1, all selected clusters exhibit silhouette scores above 0.86, indicating strong internal consistency and clear topical delineation. Cluster labels, generated using the log-likelihood ratio (LLR) algorithm based on the keywords of cited documents, concisely summarize each cluster's intellectual focus. Table 2 classifies satellite-based climate change mitigation and adaptation research based on the climate change reponse strategy classification(IPCC,2023).

Clusters related to satellite-based climate change mitigation focus on GHG monitoring and emission reduction strategies. Cluster #0 focuses on global CO_2 and CH_4 emissions from fossil fuel combustion, particularly in the coal and oil–gas sectors, and extends to regional emission trends and climate policy evaluation in developing economies. Cluster #2 examines CH_4 emissions from high-pollution industries such as steel and waste treatment, assessing the long-term effectiveness of abatement measures. Methodological advances are the core of Clus-

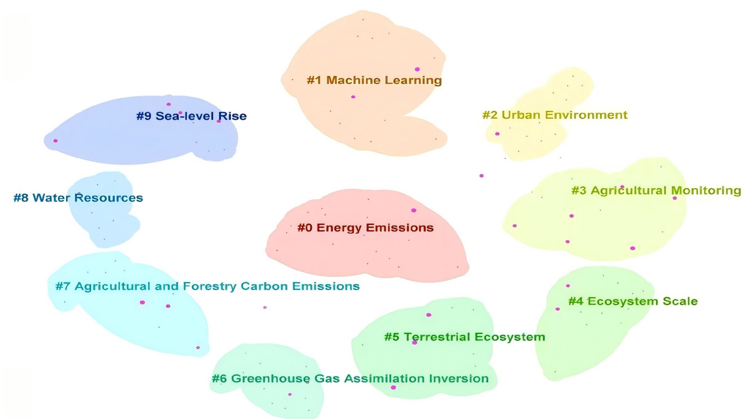

Fig. 1 Clusters and representative studies of article co-citation network.

Table 1 Top 10 clusters in the co-citation network of documents

Cluster ID	Size	Silhouette	Average year	Label (LLR)
0	17	1	2020	Energy Emissions, Fossil Fuels, Global Carbon Cycle
1	14	1	2019	Machine Learning, Carbon Emissions, Data-driven
2	13	0.935	2014	Energy Emissions, Fossil Fuels, Global Carbon Cycle
3	13	0.898	2017	Agricultural Monitoring, Food Security, Food Assurance
4	13	0.959	2018	Urban Environment, Public Health, Climate Adaptation
5	13	1	2014	Terrestrial Ecosystem, Carbon Loss, Vegetation Coverage
6	12	0.863	2007	GHG Assimilation Inversion, Global Carbon Cycle, Source and Sink Balance
7	11	0.977	2010	Agricultural and Forestry Carbon Emissions, Rice Cultivation, Land Use
8	10	0.929	2019	Water Resources, Ecological Hydrological Monitoring, Climate Disasters
9	9	0.909	2020	Sea-level Rise, Coastal Zone Monitoring, Marine Disasters

Table 2 Classification of satellite-based climate change mitigation and adaptation research

Cluster ID	Cluster label	Category by climate change response strategy classification	Category by satellite-based action strategies
0	Energy emissions	Mitigation	Satellite-based emission monitoring in the energy sector
1	Machine learning	Mitigation	Satellite-based GHG source and sink estimation using machine learning
2	Urban environment	Adaptation	Satellite-based urban and human settlement management
3	Agricultural monitoring	Mitigation / Adaptation	Satellite-based emission monitoring in the agriculture, forestry, and other land use sector and agriculture & food security monitoring
4	Ecosystem scale	Adaptation	Satellite-based terrestrial ecosystem management
5	Terrestrial ecosystem	Adaptation	Satellite-based terrestrial ecosystem management
6	Greenhouse gas assimilation inversion	Mitigation	Satellite-based GHG source and sink estimation in Ecosystems & GHG emission monitoring in Socioeconomic systems
7	Agricultural and forestry carbon emissions	Mitigation / Adaptation	Satellite-based emission monitoring in the agriculture, forestry, and other land use sector & agriculture and food security monitoring
8	Water resources	Adaptation	Satellite-based water resource management
9	Sea-level Rise	Adaptation	Satellite-based marine and coastal zone management

ters #1 and #6: Cluster #1 integrates machine learning with satellite observations to improve spatial precision in emission estimates, while Cluster #6 highlights satellite-based monitoring of atmospheric GHG concentrations and source–sink dynamics. Cluster #7 addresses carbon fluxes and sinks in agriculture and forestry, emphasizing the impact of land-use practices.

Clusters related to satellite-based climate change adaptation focus on ecosystem responses and risk management. Cluster #3 traces the evolution of satellite applications in agriculture, from early drought warnings to global yield forecasting and resilience evaluation. Cluster #4 expands the scope of urban adaptation to encompass heat islands, air pollution, and public health risks. Cluster #5 investigates vegetation dynamics and forest health, with growing attention to ecosystem degradation and restoration strategies under climate stress. Cluster #8 focuses on cryospheric and hydrological changes, transitioning from static glacier monitoring to dynamic assessments of drought and water-related hazards. Cluster #9 centers on sea-level rise and coastal risk, progressing toward integrated shoreline management under compound climate stressors.

The clusters express two aspects of the focus: mitigation efforts prioritize emission tracking and technological innovation, and adaptation studies emphasize ecological risk and socioenvironmental resilience.

Figure 1 shows the clusters of the co-citation network, highlighting major research themes and their representative study areas.

3 Satellite-based climate change mitigation research

3.1 Satellite-based GHG source and sink estimation in ecosystems

The ecosystem acts as a source and a sink of GHGs, with fluxes influenced by natural processes and human-induced changes in land use and climate. CO_2 and CH_4 exchange across ecosystems such as forests, wetlands, grasslands, and agricultural areas, offering spatially continuous and temporally consistent data critical for understanding carbon dynamics (Yang et al., 2022).

3.1.1 Satellite-based GHG Concentration Retrieval Using Top-down Approaches

Satellite-based GHG concentration retrieval employs top-down approaches, such as chemical transport models (CTMs), atmospheric inversion techniques, and data assimilation frameworks, which use satellite observations to infer regional and global emissions, which complement bottom-up inventories by providing spatially continuous, global-scale estimates of GHG emissions.

Several studies have applied top-down approaches to estimate carbon fluxes. Wang et al. (2020) estimated Chinese land biosphere CO_2 fluxes by applying an ensemble Kalman Filter framework within the GEOS-Chem atmospheric transport model, assimilating a combination of newly available in situ CO_2 measurements from six Chinese stations, Siberian tower data, and satellite column observations from GOSAT and OCO-2. Schuh et al. (2022) used a comparison of CO_2 flux inversions from the OCO-2 MIP to argue that transport differences between CTMs lead to systematic differences in estimates of the Chinese land carbon sink. Jin et al. (2024) generated a global spatially resolved terrestrial and ocean carbon flux data set by assimilating OCO-2 XCO_2 retrievals using the GONGGA inversion system. Reyes-Muñoz et al. (2024) created global GPP and net primary productivity retrieval models (SCOPE-GPR-TCF) by combining Sentinel-3 OLCI-derived vegetation products with Sentinel-5P TROPOMI solar-induced fluorescence. Wang et al. (2025b) investigated the impact of OCO-3 XCO_2 retrievals on global terrestrial net ecosystem exchange estimates by assimilating them alone and in combination with OCO-2 data using the Global Carbon Assimilation System, version 2. Maasakkers et al. (2019) used observations of atmospheric CH_4 columns from the GOSAT satellite instrument in a global inverse analysis to improve estimates of CH_4 emissions and their trends as well as the global concentration of tropospheric OH and its trend. Ma et al. (2021) tested and refined 42 bottom-up wetland CH_4 emission estimates using satellite-based top-down CH_4 flux estimates derived from GOSAT observations. Zhu et al. (2022) compared decadal CH_4 emission trends from two parallel assimilations of GOSAT proxy XCH_4 retrievals using the Ensemble Kalman Filter with GEOS-Chem at $4° \times 5°$ and $2° \times 2.5°$ resolutions. Shen et al. (2023) used a global ensemble of regional inversions of TROPOMI satellite observations at up to 50-km resolution to quantify national CH_4 emissions from global fossil fuel exploitation. Janardanan et al. (2024) estimated country-level CH_4 emissions and their sectoral trends by high-resolution inversion of GOSAT satellite and surface observations using the NIES-TM–FLEXPART-variational model. Qu et al. (2024) used annual Bayesian analytical inversions of GOSAT satellite observations to attribute the global CH_4 increase to emissions from wet tropical regions.

3.1.2 Satellite-based GHG source and sink estimation using machine learning

Machine learning techniques have been used in satellite-based GHG source and sink estimation, employing algorithms such as support vector machines (SVM), random forest (RF), and deep learning models. These approaches incorporate meteorological variables, land use change, and anthropogenic activity indicators to improve the understanding of CO_2 and CH_4 concentrations and their spatial–temporal patterns.

Machine learning has been applied to satellite-based carbon flux estimation. He et al. (2022) developed a LightGBM model to derive full-coverage and fine-scale midday XCO_2 across China based on OCO-2 satellite retrievals and CarbonTracker output. Zhang and Liu (2023) developed a convolutional neural network (CNN) method to reconstruct contiguous monthly XCO_2 over China using SCIAMACHY, GOSAT, and OCO-2 satellite XCO_2 data alongside emission, vegetation, and meteorological auxiliary data sets. Baccini et al. (2012) improved estimates of carbon dioxide emissions from tropical deforestation by producing a pan-tropical aboveground carbon density map using multi-sensor satellite data (ICESat/GLAS LiDAR, MODIS, and SRTM). Csillik et al. (2019) combined airborne LiDAR measurements with Planet Dove satellite images in a RF regression model to map aboveground carbon stocks and emissions across Peru at 1-ha resolution. Exbrayat et al. (2017) reconstructed annual maps of potential above-ground biomass (AGB) for the Amazon Basin, using a RF machine-learning algorithm trained on climate data and annual AGB maps derived from passive microwave observed vegetation optical depth from a series of satellites including SSM/I, AMSR-E, FY-3B MWRI, and WindSat (Liu et al., 2015). Yan et al. (2023b) evaluated and constructed forest AGB models for the Taiyue Mountain forest, China, using multi-source remote sensing data (including Landsat 8 optical, SAR, and DEM) and machine learning methods (RF, Gradient Boosting Decision Tree, Classification and Regression Trees, and Minimum Distance) on the Google Earth Engine (GEE) platform. Li et al. (2024) explored the coupling relationships among multifaceted driving variables and six machine learning algorithms in AGB upscaling estimates across 18 grassland types in China, using Sentinel-1/2 satellite images and climatic-topographical-soil data. Kang et al. (2024) developed a hybrid geospatial machine learning model combining Ordinary Least Squares and Gradient Boosted Decision Trees (GBDT) to quantify the nonlinear effects of Land Use/Land Cover Change (LULCC) on carbon dynamics, utilizing Sentinel-2 satellite imagery for LULC classification and top-down OCO-2 NCE data. Yu et al. (2023) established the MeSAA-ML-ECS algorithm by combining the semi-mechanistic algorithm and machine learning method to retrieve seawater pCO_2 and air-sea CO_2 fluxes using MODIS/Aqua and AVHRR_OI satellite data. Li et al. (2023b) developed a pCO_2 model based on a RF algorithm using MODIS-Aqua satellite data along with in situ salinity to estimate sea surface pCO_2. Song et al. (2023) developed the MeSAA-ML-SCS algorithm to retrieve sea surface pCO_2 using MODIS-Aqua satellite data.

Machine learning has been applied to satellite-based CH_4 emission detection and quantification. Radman et al. (2023) introduced a deep learning approach based on fine-tuned EfficientNet-V2L for methane source rate quantification using Sentinel-2 satellite imagery. Duan et al. (2023) developed a RF model to estimate diffusive CH_4 emissions from Lake Taihu using MODIS/Aqua satellite imagery. Schuit et al. (2023) designed a two-step machine learning approach using a CNN and a support vector classifier to detect CH_4 super-emitter plumes in TROPOMI satellite data. Ai et al. (2024) combined TROPOMI satellite-based CH_4 concentration data and a RF-based machine learning approach to simulate atmospheric CH_4 enhancements. Rouet-Leduc and Hulbert (2024) developed a deep learning model with a vision transformer encoder to detect CH_4 emissions in Sentinel-2 multispectral satellite imagery.

Several challenges persist in satellite-based GHG concentration retrieval using top-down approaches. Limitations in transport models, meteorological inputs, and uncertainties in initial conditions and emission inventories lead to considerable deviations in atmospheric gas distribution. In regions with complex biodiversity and anthropogenic activity, disentangling natural biospheric fluxes from anthropogenic emissions remains difficult. While satellite observations capture short-term atmospheric variability, robust trend detection requires long-term, continuous data sets. Satellite-based CH_4 emission estimation using machine learning has limitations because most models rely on specific conditions, limiting generalizability. Point source detection accuracy depends on uncertain variables such as wind speed and surface reflectance. Deep learning models often lack interpretability, hindering the understanding of emission dynamics and complicating integration with transport models. Current models also have difficulty characterizing long-term variability or responding to abrupt emission events. The main contributions and limitations of studies on satellite-based GHG source and sink estimation in Ecosystems are concluded in Table D1 in Appendix D.

3.2 Satellite-based GHG emission monitoring in socioeconomic systems

The socioeconomic system is a primary contributor to anthropogenic GHG emissions, encompassing sectors such as energy, agriculture, forestry, industry, and waste. Satellite-based CO_2, CH_4, N_2O, and other GHG detection and quantification from these sectors, providing spatially explicit and temporally consistent insights that complement ground-based inventories.

3.2.1 Satellite-based emission monitoring in the energy sector

The energy sector accounts for around three-quarters of global GHG emissions (IEA, 2025). Satellite-based CO_2, CH_4, and N_2O emission monitoring from fossil fuel combustion and fugitive sources, mainly including coal-fired power plants and oil and gas systems, employs direct plume detection and regional scale inversion methods.

(1) Satellite-based emission monitoring in the coal industry

Satellite-based CO_2 emission monitoring from coal-fired power plants mainly focuses on estimating emissions from combustion processes at regional and facility scales. Direct observation methods integrate high-resolution satellite sensors with plume dispersion models to capture individual emission events. Hanna et al. (2023) classified satellite-based monitoring into two categories: direct retrievals from single overpasses and multitemporal statistical approaches that characterize long-term or regional emission trends. On the basis of direct retrieval methods, Nassar et al. (2017) demonstrated that OCO-2 satellite observations could be used to quantify daily CO_2 emissions from individual coal-fired power plants by fitting the data to a Gaussian plume model. Cusworth et al. (2023) compared satellite-derived CO_2 emission rates quantified using the integrated mass enhancement method and the Gaussian plume model with in situ observations, based on PRISMA and OCO-3 satellite data acquired at over 30 global coal-fired power plants. Guo et al. (2023) estimated CO_2 emissions from coal-fired power plants based on an improved Gaussian plume model and OCO-2/3 satellite observations. Filonchyk and Peterson (2023) applied an integrated approach using terrestrial and satellite data to examine emissions from US coal-fired power plants and their spatial extent, detecting point source emissions with TROPOMI satellite data. Han et al. (2024a) quantified CO_2 emissions from power plants using the EMI-GATE model and XCO_2 observations from the Aerosols and Carbon Dioxide Lidar onboard the DQ-1 satellite. He et al. (2024b) applied three top-down approaches including Gaussian plume model, WRF-Chem inversion, and WRF-FLEXPART inversion to estimate CO_2 emissions from coal-fired power plants using OCO-2 satellite observations. On the basis of statistical and multitemporal approaches, Gray et al. (2018) used satellite imagery from Planet, NASA, and Copernicus and applied a machine learning model based on a pre-trained CNN to estimate the capacity factors of coal-fired power plants. Liu et al. (2020) presented a method to infer CO_2 emissions from coal-fired power plants using OMI satellite observations of co-emitted NO_2, applied to eight large and isolated US power plants.

Satellite-based CH_4 and CO_2 emission monitoring from coal production mainly focuses on estimating emissions from mining activities using regional-scale inversion models and point-source detection approaches. On the basis of regional scale monitoring using atmospheric chemistry models, Peng et al. (2023) estimated coal mine CH_4 emissions by assimilating TROPOMI satellite observations in a high-resolution regional inversion. Shao et al. (2023) evaluated the impact of coal fires on CO_2 and CH_4 emissions by applying a single-channel surface temperature retrieval algorithm and using Landsat 8 and GOSAT satellite data. Trenchev et al. (2023) applied a methodology to determine background concentrations and apply a 3σ filter to Sentinel-5P TROPOMI data to detect emissions of CH_4, NO_2, and CO from coal mines. On the basis of the point-source level, leveraging high-resolution imagery, Madhuanand et al. (2021) used a Very Deep CNN architecture trained with a data set of Sentinel-2 image patches to identify surface coal mines at a global scale. Han et al. (2024b) capitalized on 2 years of hyperspectral observations from the Advanced Hyperspectral Imager onboard the GaoFen-5B satellite to identify and quantify CH_4 point sources.

(2) Satellite-based emission monitoring in oil and gas systems

Satellite-based CH_4 and CO_2 emission monitoring from the oil and gas sector mainly focuses on estimating emissions from extraction and processing activities using regional-scale inversion models and point-source detection approaches. Pandey et al. (2019) quantified the CH_4 emission from a natural gas well blowout using the mass balance approach and cross-sectional flux method based on TROPOMI satellite observations. Varon et al. (2019) estimated CH_4 emissions from anomalously large point sources using the IME and cross-sectional flux methods based on GHGSat-D and TROPOMI satellite observations. Schneising et al. (2020) quantified CH_4 emissions from five major US oil and gas basins and two fields in Turkmenistan using dense daily TROPOMI measurements. Zhang et al. (2020) quantified CH_4 emissions using an atmospheric inverse modeling framework and TROPOMI satellite observations. Ialongo et al. (2021) presented an analysis of NO_X and CH_4 emissions from gas flaring and oil production using a multi-satellite approach with TROPOMI NO_2 and CH_4 products, VIIRS active fire data, and Sentinel-2 imagery. Ehret et al. (2022) presented an automatic quantification process and detection framework for CH_4 plumes using recurrent Sentinel-2 imagery over global oil and gas infrastructures. Wu et al. (2022) applied a thermal anomaly index combined with a framework incorporating GEE cloud computation and local batch processing to monitor gas flaring, using Sentinel-2 MSI and Landsat-8 OLI images, and further linked the detected flaring sites with OCO-2 XCO_2 and Sentinel-5P XCH_4 data to identify GHG emission hotspots. Lu et al. (2022) and Lu et al. (2023) conducted inverse analyses using Gaussian mixture models to quantify sectoral and regional trends in CH_4 emissions, leveraging the complementarity of the in situ GLOBALVIEWplus CH_4 ObsPack and the satellite-based GOSAT CH_4 observations.

(3) Satellite-based emission monitoring in fossil fuel combustion systems

Satellite-based estimation of fossil fuel CO_2 ($ffCO_2$) emissions employs two principal strategies: direct atmospheric inversion of observed CO_2 concentrations, and indirect proxy-based modeling of fuel combustion activities. Ye et al. (2020) evaluated the utility of a Bayesian inversion system coupled with high-resolution transport modeling to constrain whole-city $ffCO_2$ emissions from urban areas, using OCO-2 observations of total XCO_2. Liu et al. (2021) proposed an improved panel data model to estimate spatiotemporal dynamics of county-level fossil fuel consumption based on integrated DMSP-OLS and NPP-VIIRS NTL data.

3.2.2 Satellite-based emission monitoring in the agriculture, forestry, and other land use sector

Satellite-based GHG emission monitoring in the agriculture, forestry, and other land use sector mainly focuses on land use change, rice cultivation, and biomass burning.

(1) Satellite-based emission monitoring from land use change

Satellite-based carbon emission monitoring in land use change mainly focuses on LULC classification, thermal analysis, and carbon flux modeling. Ghafoor et al. (2022) integrated CA-Markov and InVEST models to assess LULCC impacts on carbon dynamics using Landsat imagery for the Hayat-ul-Mir subtropical scrub forest, Pakistan. Wang et al. (2023b) combined carbon emission modeling and the Tapio decoupling analysis to assess the impact of land use patterns on carbon emissions, using GlobeLand30 land cover data. Weiland et al. (2023) evaluated three empirical models and a RF algorithm for estimating soil respiration using satellite-derived land surface temperature (LST) from MODIS/VIIRS and soil moisture from Soil Moisture Active Passive (SMAP). Kang et al. (2024) developed a geospatial machine learning model combining regression and GBDT to quantify nonlinear LULCC effects on carbon dynamics, using OCO-2 NCE data and Sentinel-2 imagery.

(2) Satellite-based CH_4 emission monitoring from rice cultivation

Satellite-based monitoring of CH_4 emissions from rice cultivation integrates atmospheric inversion, biogeochemical modeling, and land-use proxy data. Zhang et al. (2016) used a coupled biogeochemical model in combination with satellite-derived contemporary inundation area (GIEMS) to quantify the magnitude and spatiotemporal variation of CH_4 emissions from global rice fields. Peters et al. (2017) developed a simple inverse advection model using satellite-derived CH_4 column mixing ratios from AIRS, SCIAMACHY, and GOSAT and satellite-derived inundation area from TRMM-TMI to estimate CH_4 emissions from inundated rice fields and wetlands. Wei et al. (2024) developed a phenology-based identification algorithm using Landsat-7/8 satellite data and employed the DNDC model to evaluate the spatiotemporal expansion of rice-crayfish fields and their effect on CH_4 emissions.

3) Satellite-based GHG monitoring from biomass burning

Satellite-based GHG emission monitoring from biomass burning mainly focuses on quantifying CO_2, CH_4, and N_2O emissions from forest fires, crop residue burning, and peatland combustion. Ito et al. (2019) estimated CH_4 emissions from biomass burning based on burnt area and dry-matter combustion data derived from MODIS images. Shi et al. (2021) implemented a daily inventory of crop residue burning emissions based on fire radiative power data (FRP) from the Himawari-8 satellite and agricultural statistics. Hong et al. (2023) developed a crop residue burning inventory using Himawari-8 Advanced Himawari Imager data, national agricultural statistics, and the fire radiative energy method based on FRP. Deshpande et al. (2023) incorporated agricultural burned area from the MODIS MCD64A1 burned area product into a remote sensing-based approach to estimate crop residue burning emissions.

3.2.3 Satellite-based emission monitoring in industrial processes and product use sector

Satellite-based GHG emission monitoring from industrial processes and product use mainly focuses on identifying emission sources, evaluating industrial activity levels, and supporting inventory compilation. Zhang et al. (2019b) employed a three-sliding window algorithm based on the multifractal theory to detect industrial heat sources, producing a national detection map using daily nighttime VIIRS SDR band I4 images across China. Wu et al. (2023a) examined several deep learning models including U-Net, R2U-Net, Attention U-Net, and DLabv3 + as well as a traditional machine learning model RF for detecting and segmenting industrial smoke plumes in Sentinel-2 satellite imagery over European industrial sites. Yang et al. (2024b) proposed a semi-automatic framework to identify global cement plants, assess their operational status, and evaluate activity levels using time-series Landsat-8 OLI and Sentinel-2 MSI imagery.

3.2.4 Satellite-based emission monitoring in the waste sector

Satellite-based GHG emission monitoring from solid waste and wastewater systems mainly focuses on quantifying CH_4 and CO_2 emissions from landfills, waste combustion, and wastewater treatment processes. Tu et al. (2022) developed a wind-assigned anomaly method to calculate emission strengths from landfill CH_4 plumes, using TROPOMI XCH_4 and combined TROPOMI + IASI $TXCH_4$ data. Susunaga-Miranda et al. (2023) applied the Mexican Biogas Model 2.0 to determine greenhouse gas emissions from the abandoned Veracruz landfill, using waste volume data derived from multi-criteria analysis of Google Earth satellite images. de Foy et al. (2023) estimated CH_4 emissions from 61 urban areas using a two-dimensional Gaussian model and TROPOMI XCH_4 retrievals. Kannankai and Devipriya (2024) quantified GHG emissions using the Landfill Gas Emissions Model (LandGEM) and visualized the dispersion of PM2.5 particles using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model, based on Landsat 8 LST data and VIIRS active fire data.

Satellite-based GHG emission monitoring in economic and social systems still has room for improvement. Emissions from industrial processes, product use, and the waste sector are comparatively underrepresented. The complex, nonlinear nature of multisource satellite data sets, such as atmospheric concentration variability, seasonal fluxes, shifts in ecosystem services, and spatial changes in water availability, has not been fully leveraged in emission estimation models. Furthermore, current satellite systems face challenges in accurately detecting and quantifying small-scale, spatially dispersed biomass burning events, such as agricultural residue fires, which may lead to substantial underestimation of associated GHG emissions. The main contributions and limitations of studies on satellite-based GHG emission monitoring in socioeconomic systems are concluded in Table D2 in Appendix D.

4 Satellite-based climate change adaptation research

4.1 Satellite-based climate change adaptation research in ecosystems

Satellite-based climate change adaptation in ecosystems mainly focuses on water resource management, terrestrial ecosystem monitoring, and marine and coastal zone assessment.

4.1.1 Satellite-based water resource management

Satellite-based water resource management encompasses water body monitoring, groundwater assessment, early warning of extreme climate events, and glacier change analysis.

(1) Satellite-based water body monitoring

Rishikeshan and Ramesh (2018) proposed an automated mathematical morphology driven algorithm for water body extraction from multiple satellite images, including Cartosat-2, Cartosat-1, Resourcesat-1 LISS IV, IRS P6 LISS-III, and Landsat-5 TM. Busker et al. (2019) estimated global lake and reservoir volume variations by establishing area-level regressions between water surface areas from the Landsat-derived JRC Global Surface Water data set and water levels from the DAHITI altimetry database. Olthof and Rainville (2022) applied the automated supervised machine learning methodology of the Emergency Geomatics Service to generate dynamic surface water maps from Landsat imagery. Wu et al. (2023b) developed a novel framework by synergistically using multi-themed, satellite-based observations and employed supervised machine learning classifiers to quantify and attribute global decadal river extent changes from Landsat imagery. Wieland et al. (2023) trained a U-Net CNN with a MobileNet-V3 encoder for semantic segmentation of water and flood water bodies using a globally sampled data set of very high-resolution satellite images from IKONOS, GeoEye-1, WorldView-2, and WorldView-3, and aerial images from four different airborne camera systems. Valman et al. (2024) applied a novel CNN-based model to automate water mask extraction from daily 3 m resolution PlanetScope satellite imagery. Yan et al. (2023a) proposed a Transformer-based network to extract lakes from Sentinel-2 imagery in the endorheic basin of the Qinghai-Xizang Plateau. Kang et al. (2023) proposed a novel network coupled with the Transformer and CNN for waterbody detection from optical high-resolution remotely sensed images, specifically using GF-2, ZY-3, and Google Earth imagery. Wang et al. (2024) proposed a multi-scale nonlinear mixture model framework for the automatic estimation of 500 m daily open water body fraction maps using dense GOES-16 ABI imagery.

(2) Satellite-based groundwater storage monitoring

Ali et al. (2022) applied four machine learning models to downscale Gravity Recovery and Climate Experiment (GRACE) Terrestrial Water Storage and Groundwater Storage data, with XGBoost demonstrating superior performance. Seo and Lee (2023) developed and validated a CNN–long short-term memory (CNN–LSTM) deep learning model using multi-satellite data from TRMM, GLDAS, Landsat, GRACE, and GRACE-FO to predict groundwater storage changes. Li et al. (2023a) developed and employed a blending ensemble learning-based model, integrating multi-source satellite data from GRACE/GRACE-FO RL06 Mascon, GLDAS Noah, MODIS, and Landsat 8, to perform downscaling inversion of groundwater storage anomalies. Zhao et al. (2023a) used GRACE satellite data and HydroSHEDS data sets, combined with the Theil-Sen median slope method and Mann-Kendall test, to quantify the multi-scale spatiotemporal variations of groundwater storage. Zhao et al. (2024) utilized GRACE gravity satellite data and GLDAS model data, employing methods including the generalized three-cornered hat, Augmented Dickey-Fuller test, and wavelet analysis to analyze the spatiotemporal variation of groundwater storage.

(3) Satellite-based extreme climate event monitoring

Zhang et al. (2019a) utilized multiple satellite microwave remote sensing data to process the Microwave Integrated Drought Index aimed at improving meteorological drought monitoring capability over tropical and subtropical water-limited ecosystems. Cao et al. (2022) assessed the performance of the Soil Moisture and Ocean Salinity and SMAP satellite soil moisture products on agricultural drought monitoring, with a comparison between two soil moisture-based drought indices, the Soil Water Deficit Index and the Soil Moisture Condition Index. Wei et al. (2025) evaluated the effectiveness of IMERG-F v07B and GSMaP-G v8 satellite-based precipitation products in detecting extreme drought using the Standardized Precipitation Evapotranspiration Index. Mateo-Garcia et al. (2021) trained CNN models on the WorldFloods data set for flood segmentation and tested their system on the Intel Movidius Myriad2 co-processor aboard the ΦSat-1 satellite, processing HyperScout-2 images. Tuan et al. (2021) analyzed and hybridized time-series SAR images from Sentinel-1 and ALOS-2 PALSAR-2 to optimize flood mapping, utilizing the Hammock Swing Thresholding algorithm. Zhu et al. (2023) proposed a downscaling-calibration scheme based on the XGBoost algorithm for generating high-resolution and high-quality estimates for extreme precipitation events during typhoons, utilizing PERSIANN-CDR satellite precipitation data. Ghanghas et al. (2023) proposed and used a grid-based indicator termed Spatial-Homogeneity to assess the changes in the spatial extent of short-duration extreme precipitation events globally, utilizing the Global Precipitation Measurement (GPM) records. Yang et al. (2024a) analyzed the influence of divergent urban development patterns on extreme rainfall occurrences using the Global Artificial Impervious Areas data set and the Integrated Multi-satellitE Retrievals for GPM product.

(4) Satellite-based glacier change monitoring

Bhattacharya et al. (2021) analyzed multi-temporal geodetic glacier mass budgets using digital elevation models generated from Corona KH-4, Hexagon KH-9, and Pleiades satellite data to characterize glacier response to climate across High Mountain Asia. Wallis and Hogg (2023) used Sentinel-1 satellite data to measure the ice speed of 105 glaciers on the west coast of the Antarctic Peninsula from 2014 to 2021, revealing widespread seasonal speed-up. Fluegel and Walker (2024) used satellite remote sensing data including Landsat 7–9, Sentinel-3, Operation IceBridge ATM, ICESat-2 ATLAS, and ITS_LIVE, along with reanalysis data from the ECCO2 ocean model and ERA5, to characterize changes in Hektoria Glacier. Maslov et al. (2025) proposed Glacier-VisionTransformer-U-Net (GlaVITU), a convolutional-transformer deep learning model for globally scalable glacier mapping using open optical and SAR satellite imagery across diverse regions worldwide.

4.1.2 Satellite-based terrestrial ecosystem management

Satellite-based terrestrial ecosystem monitoring mainly focuses on vegetation dynamics, land cover change, wildfire impacts, and forest pest and disease detection.

(1) Satellite-based vegetation cover monitoring

Bai et al. (2022) analyzed meteorological elements on a seasonal scale and used Lasso regression to identify critical periods affecting vegetation coverage change, based on MODIS-derived vegetation coverage data and ERA-Interim meteorological data. Song et al. (2022) developed an operational framework to estimate fractional vegetation cover (FVC) using Landsat 8 and GF-2 data. Feng et al. (2024) quantified the variability of urban FVC and analyzed its driving factors using the pixel dichotomy model based on Landsat data. Harrison et al. (2025) conducted an accuracy assessment of the RAP by comparing its Landsat-derived cover estimates to field plot data.

(2) Satellite-based land cover change monitoring

Xie et al. (2020) mapped vegetation cover changes by applying a dynamic reference cover method to 30 years of Landsat observations over Queensland rangelands. Zhou et al. (2024) mapped vegetation cover changes using the Dynamic Reference Cover Method based on 36 years of Landsat imagery in the Xilin River Basin. Vera et al. (2024) analyzed vegetation cover and land use changes by employing the RF algorithm on Landsat satellite images. Wu et al. (2024) proposed the COLD-MC method based on dense Landsat time series to track the dynamics of tidal wetlands. Ren et al. (2023) assessed regional thermal environment changes using zoning statistics and spatial autocorrelation analysis based on 10-day geostationary satellite LST Thermal Condition Index products. Liu et al. (2024b) investigated the efficacy of SDGSAT-1 for urban wetland classification using the GBDT algorithm and for LST retrieval using the Radiative Transfer Equation, through a comparative study with Sentinel-2 and Landsat 8 data. Aziz et al. (2024) employed remote sensing techniques leveraging Sentinel-2 satellite imagery and applied ANN and RF machine learning algorithms for forest cover classification.

(3) Satellite-based wildfire monitoring

Liu et al. (2023) developed the GOES-Observed Fire Event Representation algorithm for deriving the hourly progression of large wildfires, using GOES-East and GOES-West geostationary satellite observations. Khairoun et al. (2024) used the FireCCISFD burned area products generated from Sentinel-2 MSI images at 20 m resolution to analyze fire-related forest loss. Mumma et al. (2024) calculated the differenced normalized burn ratio to define wildfire burns and assess vegetation regrowth using Landsat and Sentinel-2 imagery.

(4) Satellite-based forest disease monitoring

Ye et al. (2022) designed an end-to-end automatic pest detection framework using a multi-scale attention-UNet (MA-UNet) model to detect pine wilt disease using Landsat 8 satellite remote sensing image data. Cai et al. (2023) introduced a novel framework for Pine Wilt Disease (PWD) detection using an improved YOLOv5-PWD model to detect individual plants infected with PWD using high-resolution RGB drone imagery and free-access Sentinel-2 satellite multi-spectral imagery. Nicoletti et al. (2024) analyzed the multispectral data of the Copernicus Sentinel-2 satellite to monitor the health state of the vegetation using Sentinel-2 satellite image.

4.1.3 Satellite-based marine and coastal zone management

Satellite-based marine and coastal zone monitoring mainly focuses on sea level rise analysis and marine hazard detection.

(1) Satellite-based sea level rise monitoring

Varotsos et al. (2024) investigated the scaling properties of the global mean sea level by applying detrended fluctuation analysis (DFA) and multifractal DFA to satellite altimeter data obtained from the TOPEX/Poseidon, Jason-1, Jason-2, and Jason-3 missions and reconstructed data. Ahmad Affandi et al. (2024) employed robust fit regression to estimate sea level rise trends and projections using 26 years of multi-mission satellite altimeter data from TOPEX, Jason-1, Jason-2, Jason-3, ERS-1, ERS-2, Envisat, CryoSat-2, SARAL, and Sentinel-3A, combined with approximately 28 years of tidal data. Bij de Vaate et al. (2024) studied the spatiotemporal variability of global storm surge water levels using a time-dependent generalized extreme value distribution applied to satellite radar altimetry data from eight missions spanning 1993 to 2021, which included TOPEX/Poseidon, Jason-1, Jason-2, and Jason-3. Nie et al. (2025) derived three decades of barystatic sea level change estimates by applying the forward modeling technique to time-variable gravity fields from satellite laser ranging, GRACE, and GRACE-FO. Mu et al. (2025) modeled sea level rise with sterodynamic sea level from the Sample Ocean Data Assimilation and ORAS5, along with sea-level fingerprints, and explored its implications for measurements from tide gauges and satellite altimetry.

(2) Satellite-based marine hazard monitoring

Macdonald et al. (2024) developed and validated a decision tree regression model to retrieve winter sea ice roughness from RADARSAT Constellation Mission backscatter data, based on comparisons with ICESat-2 measurements. Zhang et al. (2024) utilized 72 days of GPS-R and BDS-R delay-Doppler maps from the Jilin-1 Wideband-01B satellite for sea ice detection in the Antarctic region. Li and Xiong (2024) constructed a machine learning model using the RF algorithm to estimate sea ice concentration in the Arctic under summer conditions, based on SSM/I-SSMIS microwave brightness temperature data and MODIS SIC reference data. Park et al. (2024) introduced a semi-empirical C-band model for dark spot detection by analyzing microwave backscatter of the ocean surface using 193 global oil spill data from Sentinel-1 C-band SAR satellites.

Satellite-based climate change adaptation research in ecosystems still faces several challenges. Transboundary water and ecosystem monitoring is often hindered by fragmented policy, regulatory, and jurisdictional frameworks. Many regional hydrological studies fail to account for fine-scale geographic heterogeneity and lack standardized protocols for data processing, integration, and evaluation, thus limiting robust cost–benefit analysis. In forest research, satellite-based applications have mainly focused on land cover classification and vegetation dynamics, with less attention paid to the physiologic impacts of extreme events, such as droughts. In marine research, satellite-based monitoring has largely concentrated on surface and nearshore environments, with limited coverage of deep-sea or polar regions, and minimal exploration of emerging issues such as marine microplastic pollution. The main contributions and limitations of studies satellite-based climate change adaptation research in ecosystems are concluded in Table D3 in Appendix D.

4.2 Satellite-based climate change adaptation research in socioeconomic systems

Satellite-based climate change adaptation research in socioeconomic systems encompasses agriculture and food security, public and environmental health, infrastructure and major engineering projects, urban development and human settlements, and financial services.

4.2.1 Satellite-based agriculture and food security monitoring

Satellite-based agricultural and food security monitoring mainly includes crop type classification, growth condition assessment, yield anomaly forecasting, and evaluation of disaster-induced impacts.

(1) Satellite-based agricultural monitoring and crop yield assessment

Qu and Hao (2018) analyzed Vegetation Health Index data derived from NASA MODIS satellite products for assessment of crop health and food security. Salomão et al. (2024) used spectral-temporal metrics from Landsat 5 TM, 7 ETM +, and 8 OLI data to map land use and land cover changes associated with hydropower expansion and cash crop dynamics. Panek-Chwastyk et al. (2024) employed the XGBoost algorithm to forecast crop yield anomalies, based on Copernicus Sentinel-1 and Sentinel-3 satellite data and ERA-5 agrometeorological indicators.

(2) Satellite-based Agricultural Disaster Monitoring. Fu et al. (2022) researched a quantitative monitoring model combining the derivative of ratio spectroscopy algorithm and the RF algorithm to monitor cotton aphid infestation severity based on Sentinel-2 multispectral imagery. Ballaran et al. (2024) ascertained the correlation between unmanned aerial vehicle and Sentinel-2 NDVI measurements and employed a combination of Sentinel-2 NDVI and Synthetic Aperture Radar NDVI to estimate rice crop damage.

4.2.2 Satellite-based public and environmental health monitoring

Satellite-based public and environmental health monitoring encompasses disease surveillance, risk forecasting, and monitoring of environmental exposures driven by climate variability.

(1) Satellite-based disease monitoring and risk prediction

Mukherjee et al. (2019) evaluated the suitability of satellite-derived NTL data from the DMSP-OLS sensors as a predictor for sanitation-driven improvements in groundwater fecal pollution and human health across major parts of India. Rahman et al. (2021) utilized Advanced Very High-Resolution Radiometer-derived vegetation health indices, together with GIS and artificial neural network (ANN), to develop a malaria early warning system in Bangladesh aimed at predicting and mitigating outbreak risks. He et al. (2024a) used a probabilistic approach to study 30 East Asian cities from 1980 to 2020 and found significant associations between respiratory deaths and extreme rainfall events, using ERA5-Land reanalysis data derived from a combination of satellite observations and ground-based measurements.

(2) Satellite-based environmental health monitoring

Fadadu et al. (2020) employed the Jonckheere-Terpstra test to analyze differences in ground-level $PM_{2.5}$ concentrations across ordered smoke plume density categories derived from NOAA Hazard Mapping System satellite imagery for the San Francisco Bay Area during the 2017–2018 wildfire seasons. O'Dell et al. (2024) developed a methodology to quantify the health benefits of improved identification of severe $PM_{2.5}$ pollution events using 24hr mean $PM_{2.5}$ estimates derived from the ABI sensor on GOES-16/GOES-17 geostationary satellites over the contiguous United States for the year 2020. Yadav et al. (2024) proposed DeepAQ, a two-step deep transfer learning approach for air quality estimation in data-poor LMIC cities, using MAXAR WorldView-2 satellite imagery in experiments conducted over Accra, Ghana, Los Angeles, and New York City.

4.2.3 Satellite-based urban and human settlement management

Satellite-based urban and human settlement management encompasses urban lifeline systems, green infrastructure, and the assessment of overall living environment quality.

(1) Satellite-based urban lifeline system monitoring

Paulik et al. (2019) estimated the co-seismic vertical displacement field from SAR data of the Sentinel-1 satellite to support the calculation of tsunami runup heights in Palu City. Tanim et al. (2022) combined ground observed data from road closure reports with Sentinel 1 satellite imagery to develop and train machine-learning models for flood detection for the City of San Diego.

(2) Satellite-based green infrastructure monitoring

Kranjčić et al. (2019) analyzed four machine learning methods (SVM, RF, ANN, and the naive Bayes classifier) for the classification of the green infrastructure in city areas using satellite imagery from the Sentinel-2 multispectral instrument. Cheng et al. (2022) evaluated the carbon sink performance of aggregated green infrastructure using a spatial autocorrelation analysis method based on Sentinel-2A satellite imagery in the central urban area of Nanjing, China. Kim and Kim (2024) employed a difference-in-differences framework to assess changes in green space coverage, using land cover data from Terra and Aqua combined Moderate Resolution Imaging Spectroradiometer sensors.

(3) Satellite-based living environment quality monitoring

Ramsay et al. (2023) used Generalized Additive Mixed Models to estimate spatial and temporal trends in surface temperature based on 29 years of Landsat satellite data for Makassar, Indonesia. Kursah (2023) used the thermal field variance index to evaluate the ecological evaluation index and thermal comfort using Landsat-derived LST data from January 2020 for Winneba, Ghana. Lin et al. (2024) applied a human-computer interaction annotation process and data enhancement techniques to construct the Construction Waste Landfill Data set using Google Earth and GF-2 high-resolution satellite images for Changping and Daxing districts in Beijing, China.

4.2.4 Satellite-based financial management

Satellite-based financial management encompasses disaster assessment, risk evaluation, and claims processing. Shofiyati et al. (2021) applied satellite-based drought monitoring methods, including the calculation of the SPI from GSMaP data, KBDI from MTSAT data, and vegetation indices (VCI, TCI, VHI) from MODIS Terra data, to analyze meteorological and agricultural drought in Java, Indonesia, for supporting rice crop insurance claims. Using a synthetic index method, Murthy et al. (2022) introduced a satellite-based composite index, the Crop Health Factor, to replace yield data for loss assessment and payout in paddy crop insurance, using Sentinel-1, Sentinel-2, and Copernicus Global Land Service FAPAR data along with weather data. Nordmeyer and Musshoff (2023) surveyed 127 German farmers and applied a modified Transtheoretical Model of Perceived Usefulness to analyze farmers' perceived usefulness of satellite-based index insurance in general, using a hypothetical insurance product example based on satellite-retrieved soil moisture data. Nordmeyer et al. (2023) investigated farmers' preferences for drought insurance based on a satellite-retrieved volumetric soil moisture index derived from radar radiation measurements, using a discrete choice experiment.

Satellite-based climate change adaptation research in socioeconomic systems still has some limitations. Most studies focus on crop monitoring under normal conditions, with limited attention to dynamic resource changes during crises such as conflicts and insufficient assessment of the spatial distribution and reuse potential of agricultural waste. Satellite-derived environmental data are rarely integrated into infectious disease transmission models, particularly for spatial risk assessments linking environmental exposure to health outcomes. Satellite-based monitoring mainly addresses spatial patterns, short-term dynamics, and disaster vulnerability, but long-term assessments of infrastructure performance, especially in the Global South, remain underdeveloped. The integration of spatial data with behavioral or demographic factors is limited; urban heat island studies often neglect variables such as humidity and wind, and comparative analyses across cities of different types and scales are lacking. Although satellites contribute to disaster monitoring, their integration with economic models for loss estimation, insurance pricing, and asset valuation remains in its infancy. The main contributions and limitations of studies Satellite-based Climate Change Adaptation Research in Socioeconomic Systems are concluded in Table D4 in Appendix D.

5 Conclusions and future direction

5.1 Conclusions

This study provides a bibliometric analysis and document review of satellite-based climate change research from 1994 to 2025, from the perspectives of mitigation and adaptation strategies, which systematically outline the development trends of satellite-based climate change research. The study shows that since 2010, satellite-based climate change research has grown rapidly, with increasing emphasis on GHG monitoring and modeling, ecosystem responses such as vegetation cover and water distribution, and the quantification of urban environmental changes and adaptation policies.

In satellite-based climate change mitigation research, satellites are mainly used to monitor CO_2 and CH_4, identify major emission sources such as energy and power production, and quantify their spatial and temporal dynamics. However, satellite-based non-CO_2 GHG emission monitoring and quantification remain limited, especially regarding N_2O emissions from agriculture, waste treatment, and industrial processes such as fertilizer use, livestock farming, landfill decomposition, and chemical manufacturing. Small-scale, spatially diffused, and informal emission sources, such as crop residue burning and scattered industrial sites, are often excluded from global inventories. Satellite-based emission monitoring and quantification has yet to be fully utilized to capture spatiotemporal emission variations across regions and sectors, constraining the identification of major emission drivers and undermining mitigation strategies in socioeconomic systems.

In satellite-based climate change adaptation research, satellites are mainly used to monitor global water resources, vegetation dynamics, and coastal changes to assess the impacts of climate change on agriculture, hydrology, forests, and sea-level rise. However, satellite-based groundwater availability monitoring, forest ecosystem health tracking, and coastal ecosystem degradation capturing still struggle with accuracy, spatial resolution, and fine-scale detection, particularly in capturing cross-regional variability and long-term trends. Comparative analyses across climate zones and temporal scales are limited. Assessments of climate risks to infrastructure, public health, and livelihoods are underdeveloped, especially in high-risk and data-scarce regions. Environmental exposures, such as heatwaves, air pollution, and water scarcity, are rarely integrated into spatial health impact assessments. Mapping of agricultural waste distribution and reuse potential remains limited. Long-term evaluations of infrastructure resilience and asset-level climate risks in the financial sector are also lacking. Satellite-based climate change adaptation research remains in its early stage, with incomplete coverage and insufficient integration across ecological and socioeconomic systems.

5.2 Future directions

By analyzing the extant studies in satellite-based climate change research, future research can be advanced in the following aspects:

Satellite-based Climate Change Mitigation in Ecosystems: Future work can address uncertainties in transport models, meteorological fields, initial conditions, and emission inventories to improve the accuracy of GHG retrieval, especially by enhancing the capacity to distinguish biogenic and anthropogenic sources in ecologically complex regions. Focus can be placed on global ecological zones such as peatlands, savannas, and arid grasslands to quantify N_2O and CH_4 emissions using satellite-based approaches. High-sensitivity algorithms are needed to detect small-scale, intermittent emission events such as biomass burning. High-frequency, temporally resolved source–sink inversion models based on sparse ground observations can improve attribution of fluxes. Advances in atmospheric correction, cloud filtering, and data fusion can be integrated with CTMs to generate high-resolution and stable CO_2 distribution maps. Particular attention can be given to identifying long-term carbon storage trends in ecosystems vulnerable to land degradation, frequent fires, and droughts to assess potential tipping points in carbon sink capacity. Future work can also integrate multi-sensor data to improve the temporal and spatial resolution of satellite-based monitoring; combine satellite data with ground-based measurements and socioeconomic factors to refine emission estimation and source attribution; and develop high-sensitivity sensors and integrate them with global climate models to improve carbon flux tracking and uncertainty characterization.

Satellite-based climate change mitigation in socioeconomic systems: Future work can quantify GHG emissions from globally distributed but poorly monitored sectors, including cement production, chemical industries, landfill waste decomposition, and informal burning practices. It can analyze the emission profiles of these sectors across countries and their contributions to national inventories, particularly in regions lacking ground-based monitoring infrastructure. Future work can also explore spatial disparities in emission intensities across continents and evaluate how economic transitions, energy structure shifts, and urbanization influence global emission trends. A key focus is identifying high-emission hotspots in developing regions and understanding their drivers under varying development pathways. Future work can also explore satellite-based monitoring to verify national greenhouse gas and non-greenhouse gas emission inventories to obtain more accurate and comprehensive emission data, and integrate satellite-based data with corporate carbon disclosure frameworks to enhance the transparency and credibility of carbon trading and other market mechanisms.

Satellite-based Climate Change Adaptation in Ecosystems: Future work can systematically evaluate the impacts of extreme climate events, such as droughts, wildfires, and marine heatwaves, on the adaptive capacity of global ecosystems, with a focus on identifying the vulnerability of key systems, such as tropical rainforests, alpine zones, and coral reefs, under multiple climate stressors. Comparative studies across continents can be conducted to explore global ecological adaptation thresholds and potential tipping points. Efforts can prioritize the development of satellite-based indicators to monitor groundwater recharge, river flow variability, forest health including pest outbreaks and species migration, and coastal ecosystem degradation. Standardizing regional-scale assessments of water availability and long-term trends will improve the robustness of cost–benefit analyses. Coupled model–data approaches can be used to reveal forest ecosystem responses to climate extremes, and the establishment of long-term ecological monitoring data sets can support resilience assessments across diverse biomes.

Satellite-based Climate Change Adaptation in Socioeconomic Systems: Future work can expand satellite use in assessing crop losses, water allocation stress, infrastructure vulnerability, and health impacts. Focus can be placed on exposure and recovery pathways during extreme events such as floods, droughts, and heatwaves and on the mechanisms linking climate risks with socioeconomic inequality. The spatial distribution and reuse potential of agricultural waste can be evaluated to improve regional management. Drought monitoring can be enhanced through unified classification and assessment protocols. Satellite-based systems can be developed to track disease transmission by integrating environmental variables such as air quality and climate with geospatial epidemiological data. Urban adaptation research can link satellite-derived spatial data with behavioral and demographic information to anticipate infrastructure and health needs. Satellite monitoring of infrastructure, particularly in the Global South, can inform resilience planning, identifying vulnerabilities in roads, bridges, and buildings over time. Satellite data can be used to evaluate climate risks to assets and investments, track extreme events, and support insurance pricing and payout optimization. Future work can also construct high-resolution spatial risk maps to analyze the correlations among infrastructure exposure, population distribution characteristics, and the severity of climate hazards.

Appendix A Remote sensing satellites launched and planned globally for addressing climate change

Satellite remote sensing has played an important role in addressing climate change, evolving from early meteorological observations to the current monitoring of GHGs, extreme weather forecasting, ecological protection, and water resource management. Numerous remote sensing satellites have been launched worldwide, including the United States' TIROS-1, the world's first meteorological satellite, which ushered in the era of meteorological satellites. Other notable examples include Europe's Meteosat First Generation, Japan's GHGs Observing Satellite (GOSAT), and China's TanSat (Carbon Satellite), all contributing to the gradual establishment of a global climate change monitoring system. As shown in Table A1, current operational remote sensing satellite systems, such as the Sentinel series and the Fengyun-3 (FY-3) series, enable coordinated observations of atmospheric components, GHG concentrations, and oceanic and terrestrial parameters, providing essential scientific data for climate change research and policy formulation.

Major countries around the world are planning to enhance remote sensing satellite systems with higher spatial and temporal resolution and improved detection capabilities to strengthen climate change mitigation efforts. For instance, the CH_4 Remote Sensing LiDAR Mission (MERLIN) enhances CH_4 detection precision using LiDAR technology, and the Copernicus Carbon Dioxide Monitoring Mission (CO2M) enables coordinated monitoring of CO_2, CH_4, and NO_2. These remote sensing satellites, as shown in Table A2, promote international climate cooperation through a global remote sensing

Table A1 Overview of remote sensing satellites launched globally for addressing climate change

Satellite name	Country/Organization	Launch year / period	Main mission
TIROS-1	USA	1960	First weather satellite; meteorological observations
Nimbus series	USA	1964–1978	Meteorology, ozone, radiation balance, and Earth-system observations
NOAA series	USA	1970–present	Operational weather and environmental monitoring
Landsat series	USA	1972–present	Land-use, land-cover, and ecosystem monitoring
TRMM	USA/Japan	1997	Tropical and subtropical precipitation monitoring for water-cycle and climate studies
Meteosat First Generation	Europe	1977–2017	Geostationary meteorological observations
TOPEX/Poseidon	USA/France	1992	Ocean topography and sea-level monitoring
FY-2 series	China	1997–2018	Geostationary meteorological observation; support disaster monitoring and climate-change response
Terra	USA	1999	Global observations of atmosphere, land, oceans, and Earth's energy balance
Jason-1	USA/France	2001	Sea-level, wave-height, and ocean-circulation monitoring
Envisat (carrying SCIAMACHY)	Europe	2002	Atmospheric composition and ozone monitoring
HY-1 series	China	2002–present	Ocean color and coastal/ocean observation
GRACE	USA/Germany	2002	Tracking mass change in water, land ice, oceans, and solid Earth
Aqua	USA	2002	Water-cycle and environmental monitoring
ICESat	USA	2003	Ice-sheet elevation and surface-altimetry monitoring
Aura	USA	2004	Atmospheric chemistry, ozone, aerosols, and trace-gas monitoring
CloudSat	USA	2006	Cloud vertical structure and climate-role observations
CALIPSO	USA/France	2006	Cloud and aerosol profiling for climate and weather studies
Jason-2	USA/France	2008	Ocean topography and sea-level-rise monitoring
FY-3 series	China	2008–present	Polar-orbiting meteorological satellites supporting climate monitoring, global change studies, atmospheric, ocean, ice, and environmental observations
GOSAT	Japan	2009	Atmospheric greenhouse-gas monitoring
SMOS	Europe	2009	Soil moisture and ocean salinity monitoring
CryoSat-2	Europe	2010	Ice-sheet, sea-ice, and polar-climate monitoring

(*Continued*)

Satellite name	Country/Organization	Launch year / period	Main mission
HY-2 series	China	2011–present	Ocean dynamic-variable observation, including sea level, wind, waves, sea-surface temperature and sea-ice-related variables
GCOM-W	Japan	2012	Observing water circulation changes
OCO-2	USA	2014	Global CO_2 source–sink observations
GPM Core Observatory	USA/Japan	2014	Global precipitation measurement supporting water-cycle and climate studies
SMAP	USA	2015	Soil moisture, freeze–thaw state, and water/carbon/energy-cycle monitoring
Sentinel-2 series	Europe	2015–present	High-resolution optical land monitoring, including land cover, vegetation, forests, inland waters, coastal areas, and emergency services
Sentinel-1 series	Europe	2014–present	C-band radar imaging for land, ocean, disaster, and cryosphere monitoring
TanSat	China	2016	Global atmospheric CO_2 monitoring
FY-4 series	China	2016–present	Geostationary meteorological satellites supporting climate applications, environmental monitoring, and disaster monitoring
Jason-3	USA/France	2016	Sea-level, ocean circulation, and climate-change monitoring
GHGSat series	Canada	2016–present	High-resolution point-source greenhouse-gas monitoring
Sentinel-3 series	Europe	2016–present	Ocean, land, ice, and atmosphere monitoring
Sentinel-5P	Europe	2017	Atmospheric composition and air-quality monitoring
GCOM-C	Japan	2017	Observing climate changes
GOSAT-2	Japan	2018	Greenhouse-gas monitoring
GRACE-FO	USA/Germany	2018	Tracking water movement, ice sheets, glaciers, groundwater, and sea level
ICESat-2	USA	2018	Ice-sheet, sea-ice, and surface-height monitoring
GF-5	China	2018	Atmospheric and environmental monitoring
CFOSAT	China/France	2018	Global sea-surface wind and wave observations; support marine research and global climate-change studies
Sentinel-6 Michael Freilich	USA/Europe	2020	High-precision sea-level monitoring
HJ-2A/B	China	2020	Land observation and disaster/environment monitoring
GF-5-02	China	2021	Atmospheric chemistry, aerosol, and environmental monitoring
DQ-1	China	2022	Atmospheric aerosol and CO_2 monitoring
Terrestrial Ecosystem Carbon Monitoring Satellite ("Jumang")	China	2022	Land-ecosystem carbon monitoring and forest carbon-sink observation
GF-5-01A	China	2022	Environmental monitoring, atmospheric-element detection, and climate change studies
SWOT	USA/France/Canada/UK	2022	Surface water, ocean topography, and climate-related hydrology/coastal observations
MethaneSAT	USA / New Zealand	2024	Methane monitoring, especially major emission regions and oil-and-gas sources
Tanager-1	USA (Carbon Mapper Coalition)	2024	High-resolution methane and CO_2 point-source detection
PACE	USA	2024	Ocean–atmosphere observations for ocean health, carbon pathways, and climate change
Ocean-4 01 (HY-4A)	China	2024	Ocean salinity observation for water-cycle monitoring and global climate-change research
EarthCARE	Europe / Japan	2024	Cloud, aerosol, and radiation monitoring
Biomass	Europe	2025	Forest biomass and carbon-stock assessment
MicroCarb	France	2025	High-precision atmospheric CO_2 monitoring
GOSAT-GW	Japan	2025	GHG and water-cycle monitoring
NISAR	USA/India	2025	Monitoring ecosystems, ice masses, groundwater, sea level rise, and Earth-surface change
Sentinel-6B	USA/Europe	2025	High-precision sea-level monitoring
MTG-S1 (carrying Sentinel-4)	Europe	2025	Geostationary atmospheric composition monitoring; supports air-quality, pollution, and climate monitoring
MetOp-SG A1 (carrying Sentinel-5)	Europe	2025	Polar meteorology and atmospheric composition monitoring

Table A2 Overview of remote sensing satellites planned globally for addressing climate change

Satellite name	Country/Organization	Planned launch year	Main mission
Sentinel-3C	Europe	2026	Continuity of ocean, land, ice, and atmosphere monitoring
FLEX	Europe	2026	Global measurements of vegetation fluorescence and photosynthetic activity; improves understanding of carbon exchange between plants and the atmosphere, and of photosynthesis in the carbon and water cycles
HY-2E	China	⩾2026	Observation of ocean dynamic variables
HY-2F	China	⩾2026	Observation of ocean dynamic variables
DQ-2	China	⩾2026	Atmospheric aerosol and CO_2 monitoring
TanSat-2	China	⩾2026	Measurement of CO_2, CH_4, NO_2 and solar-induced chlorophyll fluorescence
FORUM	Europe	2027	Far-infrared outgoing-radiation monitoring for climate science
CO2M-A	Europe	2027	Anthropogenic CO_2 monitoring; also CH_4 and NO_2 observations for emission verification
CRISTAL	Europe	2027	Sea-ice thickness, snow depth, and ice-sheet elevation monitoring
HY-1F	China	⩾2028	Ocean observation
GRACE-Continuity	USA/Germany	2028	Tracking water movement and surface-mass change, including ice sheets, glaciers, groundwater, soil moisture, and sea levels
CO2M-B	Europe	2028	Anthropogenic CO_2 monitoring; also CH_4 and NO_2 observations for emission verification
MERLIN	France/Germany	2029	Lidar-based methane monitoring
CO2M-C	Europe	2029	Anthropogenic CO_2 monitoring; also CH_4 and NO_2 observations for emission verification
CIMR-A	Europe	2029	Sea-ice concentration, sea-surface temperature, sea-surface salinity, and broader polar/ocean monitoring
Harmony	Europe	2029	Ocean, ice, and land-dynamics monitoring; contributes to climate research and risk monitoring
ROSE-L	Europe	⩾2029	L-band radar monitoring for soil moisture, crop conditions, forests, cryosphere, maritime surveillance, and natural and human-induced hazards
LSTM	Europe	⩾2029	Land-surface temperature and evapotranspiration monitoring; supports agriculture, water resources, drought monitoring, and climate-variability studies

network and provide enhanced data support for global climate change mitigation and adaptation efforts.

Despite remarkable advancements in improving observation accuracy, resolution, and coverage, satellite remote sensing still faces several challenges in addressing climate change. These challenges include insufficient accuracy in concentration inversion and emission estimation, a focus on monitoring CO_2 and CH_4 with limited remote sensing of other important gases such as N_2O, weak ground-based validation capabilities, a lack of synergy in observing GHGs and aerosols, and insufficient satellite data resolution and accuracy to capture small-scale or rapidly changing details. Long satellite revisit cycles also limit monitoring capabilities for fast-changing ecological and socioeconomic processes. Additionally, satellite data may not fully capture the impact of human activities on the environment or reflect biodiversity and ecosystem complexity. Furthermore, satellite remote sensing mainly provides surface-level information, while interactions between the surface and water bodies in socioeconomic systems, such as urban drainage systems and rivers, may not be directly captured.

Appendix B Methodology and data collection

B1 Methodology

This study presents a bibliometric analysis of satellite-based climate change research from 1994 to 2025 using CiteSpace, based on bibliographic records retrieved from the Web of Science Core Collection as of 31 December 2025. Bibliometric analysis is a well-established quantitative approach for mapping the intellectual structure, research fronts, and evolutionary dynamics of a scientific field (Donthu et al., 2021), which consisting of descriptive statistics and network- and structure-based analyses.

B2 Data collection

A comprehensive search query was formulated for literature on satellite-based climate change research. The query used key terms such as “Satellite,” “Remote sensing,” “Night lighting,” “Space information,” and “Space observations” to cover studies related to satellite observations. Climate-related terms such as “Carbon emissions,” “Climate change,” “Greenhouse gases,” and “Global warming," along with specific terms like "Carbon neutrality," "Carbon peaking," and "CH_4," were included. Socioeconomic terms like "Sustainable," "Policy," "Risk," and "Health" were also part of the query. The search focused on documents published between 1994 and 2025, and the data was accessed on December 31, 2025, including articles, reviews, early access publications, proceedings papers, book chapters, and letters.

Only academic documents, such as peer-reviewed articles, reviews, and book chapters, directly related to satellite observations, remote sensing, and climate change/carbon emissions were included. Data were sourced from the Web of Science Core Collection (SCI-EXPANDED, SSCI), ensuring complete bibliographic details (title, abstract, keywords).

Non-English publications, non-scholarly documents (e.g., meeting abstracts, news articles), and documents with incomplete metadata (e.g., missing authors, affiliations, keywords) were excluded. Studies with weak or irrelevant connections to the core research focus were also discarded.

Raw records (authors, keywords, abstracts) were exported from Web of Science, duplicates were removed, and keywords were standardized (e.g., "carbon neutrality" and "carbon neutral"). A manual verification process randomly checked 5% of the data set to ensure relevance and consistency.

The final literature collection consists of 17,363 documents, which were used for our subsequent bibliometric analysis and literature review.

Appendix C Supplementary bibliometric analyses

C1 Disciplinary and country distributions

Statistical analysis of the 17,363 records from the WOS database reveals considerable interdisciplinary diversity in satellite-based climate change research, as shown in Fig. C1. Environmental Sciences leads with 7,897 documents (45.48%), reflecting its central role in this field. Geosciences Multidisciplinary (4,020; 23.15%) integrates geophysical and environmental knowledge to understand Earth system responses. Remote Sensing (3,295; 18.98%) provides the core methodological foundation for satellite observation. Meteorology and Atmospheric Sciences (2,837; 16.34%) focuses on atmospheric monitoring, while Imaging Science and Photographic Technology (2,722; 15.68%) supports the development of imaging systems crucial to environmental observation. Disciplines such as Water Resources (1,721; 9.91%), Ecology (1,455; 8.38%), Environmental Studies (1,074; 6.19%), Geography Physical (893; 5.14%), and Forestry (832; 4.79%), demonstrate the widely applications of satellites in resource management, ecological conservation, and sustainable development. These findings reflect the interdisciplinary contributions of satellite-based climate change research and highlight their critical role in addressing global challenges.

Figure C1 displays the disciplinary distribution of the documents included in the review.

Table C1 shows the distribution of journals in satellite-based climate change research, with Remote Sensing leading at 9.083%, followed by Science of the Total

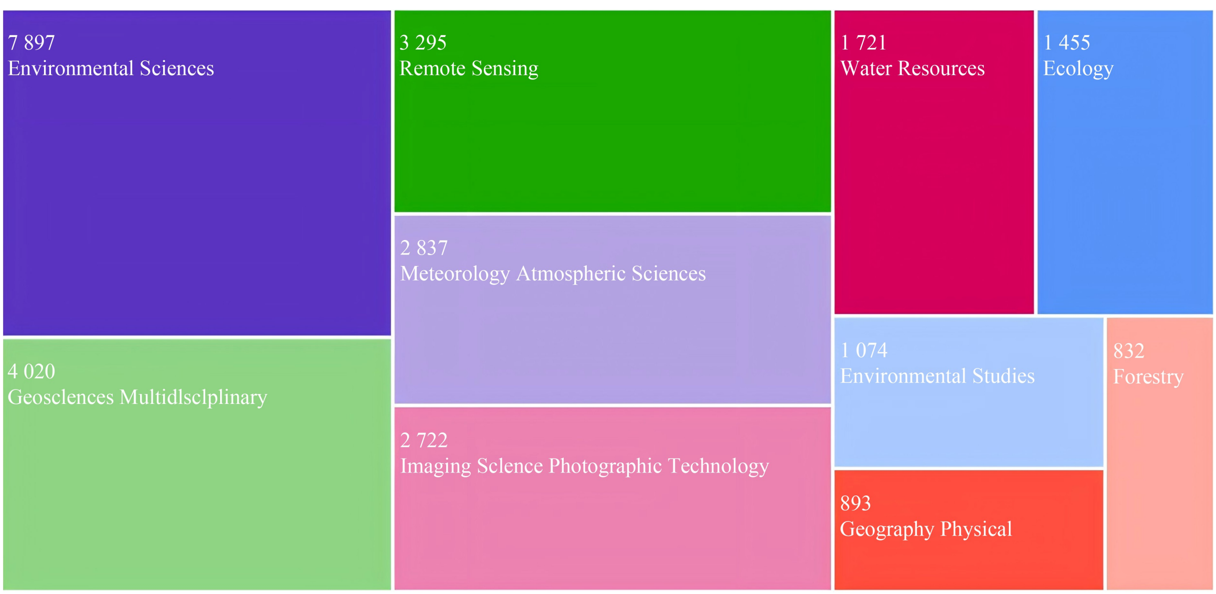

Fig. C1 Disciplinary distribution of the records.

Table C1 Journal distribution of satellite-based climate change research (Top 25)

Rank	Journal titles	Record count	% of 17,363
1	Remote Sensing	1577	9.083
2	Science of The Total Environment	446	2.569
3	Sustainability	434	2.5
4	Remote Sensing of Environment	373	2.148
5	Water	310	1.785
6	Ecological Indicators	298	1.716
7	Journal of Hydrology	255	1.469
8	Environmental Research Letters	249	1.434
9	Land	248	1.428
10	Atmospheric Chemistry and Physics	234	1.348
11	Forests	226	1.302
12	Scientific Reports	208	1.198
13	Journal of Geophysical Research Atmospheres	201	1.158
14	Environmental Monitoring and Assessment	198	1.14
15	Atmosphere	193	1.112
16	Journal Of Environmental Management	184	1.06
17	International Journal of Applied Earth Observation And Geoinformation	170	0.979
18	International Journal of Remote Sensing	170	0.979
19	Agricultural and Forest Meteorology	166	0.956
20	Atmospheric Environment	156	0.898
21	Global Change Biology	150	0.864
22	IEEE Journal of Selected Topics In Applied Earth Observations and Remote Sensing	141	0.812
23	Geophysical Research Letters	130	0.749
24	Isprs Journal of Photogrammetry and Remote Sensing	125	0.72
25	Atmospheric Measurement Techniques	115	0.662

Environment (2.569%), Sustainability (2.5%), and Remote Sensing of Environment (2.148%). These journals focus on remote sensing, environmental science, and climate dynamics, with an emphasis on satellite-based climate change research, such as water resource management, air quality monitoring, and ecosystem health assessments.

C2 Keyword co-occurrence analysis

Analysis of keyword co-occurrence identifies key research trends, as shown in Fig. C2. Top keywords as “climate change,” “remote sensing,” “model,” “variability,” “vegetation,” “satellite,” “climate,” “temperature,” “impact,” and “dynamics”, highlight the themes of satellite-based climate change research.

Figure C2 shows major research themes and their interrelationships.

The temporal evolution of satellite-based climate change research shows a gradual shift in thematic priorities. In the timeline visualization, the horizontal axis indicates when each theme is active, colors distinguish thematic clusters, node sizes reflect their prominence, and connecting curves reveal how topics emerge and evolve over time. As shown in Fig. C3, early studies (1994–2005) primarily emphasized foundational topics, as reflected in the red cluster (#0: climate change) and the pink cluster (#8: remote sensing), which demonstrate the field’s initial focus on satellite observations and climate diagnostics. Between 2007 and 2015, research gradually diversified toward Earth system modeling and land–atmosphere interactions, as shown by the expansion of the yellow cluster (#1: model) and the green–yellow cluster (#2: land surface temperature). After 2016, methodological advances contributed to the rapid growth of the light-green cluster (#3: machine learning) and the blue–green cluster (#4: Google Earth Engine), indicating increasing integration of large-scale satellite data sets with data-driven analytical approaches. At the same time, socioenvironmental applications became more prominent. The teal cluster (#5: air quality) illustrates the rising use of satellite observations for pollution and exposure assessment, while the blue cluster (#6: variability) and the purple cluster (#7: dynamics) represent the growing

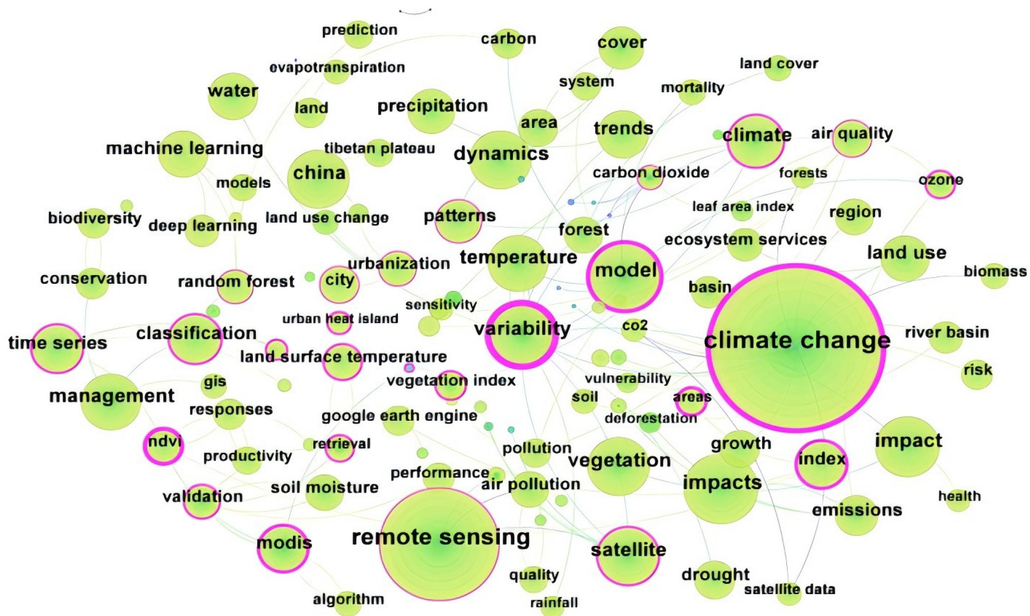

Fig. C2 Co-occurrence network of keywords.

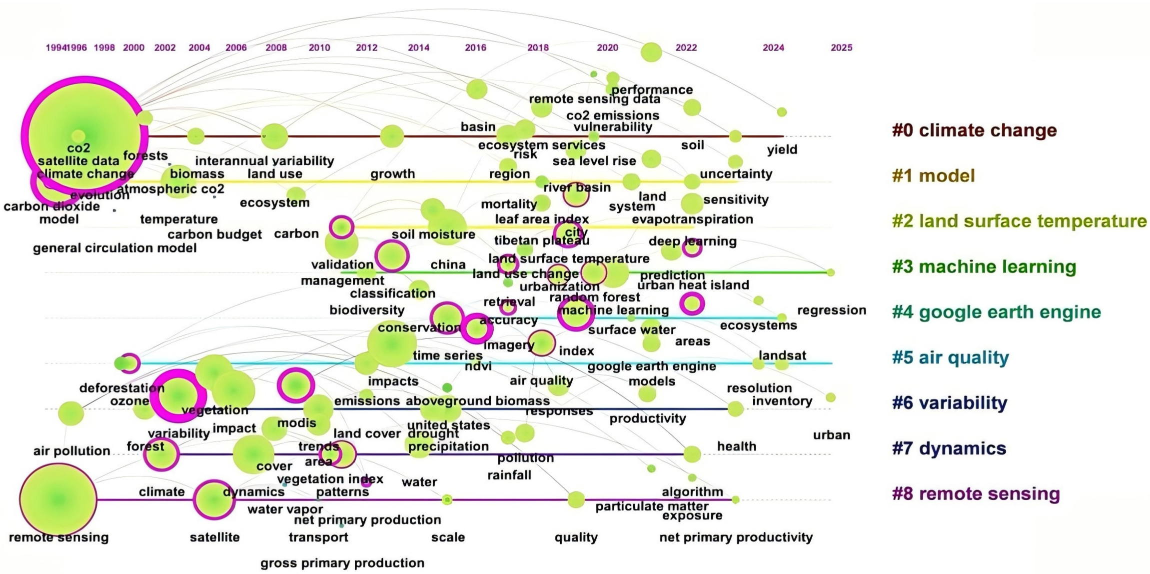

Fig. C3 Timeline of keywords.

interest in ecosystem responses, hydrological variability, and land-cover dynamics. The analysis reveals a shift from early emphases on climate change, atmospheric CO_2, and remote sensing toward emerging topics involving vegetation, land use, air quality, variability, and land-cover dynamics.

Figure C3 presents a timeline visualization of keyword co-occurrence, illustrating the evolution of research themes from 1994 to 2025.

C3 Co-citation network of documents

By using CiteSpace, published documents are treated as network nodes, and a dynamic co-citation network is constructed across successive yearly time slices. Nodes represent cited documents, and a connection between two nodes indicates that they are co-cited by the same citing documents. The analysis spans 1994–2025 with one-year time slices. Figure C4 presents the co-citation network of documents in satellite-based climate change research.

Figure C4 shows the co-citation network of documents, highlighting influential studies and their citation relationships in satellite-based climate change research.

Based on the co-citation analysis, as shown in Table C2, Hersbach et al. (2020) describe the ERA5 global reanalysis, which is based on the IFS Cy41r2 and

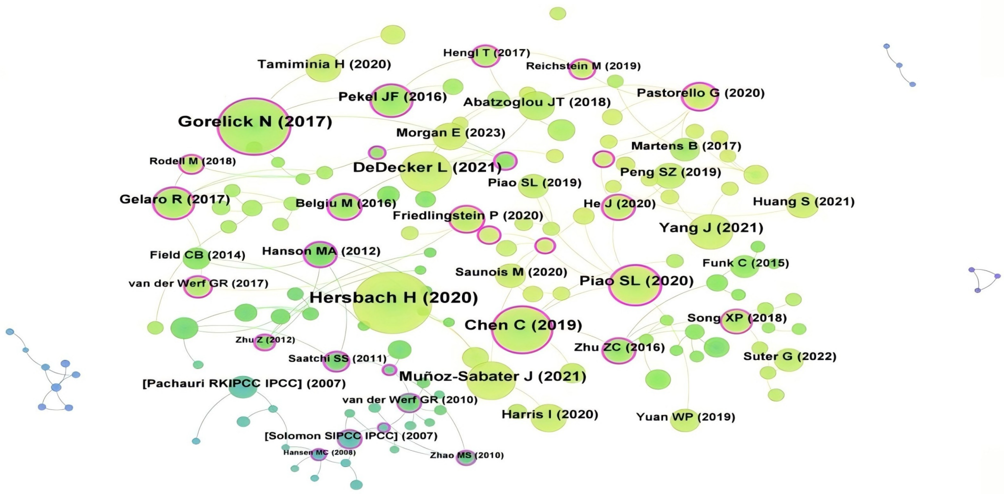

Fig. C4 Co-citation network of the documents.

Table C2 Top 10 co-cited documents

Rank	Citation counts	Silhouette	Year	Node name
1	399	0.02	2020	Hersbach H et al. (2020)
2	315	0.35	2017	Gorelick et al (2017)
3	225	0.35	2019	Chen C et al (2019)
4	156	0.55	2020	Piao S L et al. (2019)
5	152	0.07	2021	Muñoz-Sabater J et al. (2021)
6	133	0.02	2021	Yang and Huang (2021)
7	96	0.34	2017	Gelaro R et al. (2017)
8	86	0.1	2018	Abatzoglou et al. (2018)
9	86	0.02	2020	Tamiminia H et al. (2020)
10	82	0.02	2020	Harris I et al. (2020)

replaces ERA-Interim, with enhanced 31 km resolution, hourly output, and ensemble uncertainty estimates, and provide a basic evaluation of its set-up, characteristics, and performance. Gorelick et al. (2017) introduced GEE, a cloud-based platform for planetary-scale geospatial analysis that leverages Google's computational infrastructure to address high-impact societal challenges. Chen et al. (2019) showed that human land-use management is an important driver of the "Greening Earth", contributing to over one-third of the observed net increase in global leaf area, based on an analysis of MODIS satellite data from 2000 to 2017. Piao et al. (2019) reviewed global greening, including its detection, causes, impacts on carbon cycling and land-atmosphere fluxes, and proposed ways for further understanding. Muñoz-Sabater et al. (2021) released ERA5-Land, a global high-resolution land reanalysis data set. Yang and Huang (2021) developed a RF classifier combined with a spatial-temporal post-processing method to produce the first Landsat-derived annual China land cover dataset at 30 m resolution from 1990 to 2019 using all available Landsat TM/ETM+/OLI imagery. Gelaro et al. (2017) presented the MERRA-2 atmospheric reanalysis system, providing a comprehensive overview of its data assimilation framework, satellite observation integration, and performance evaluation, and showing its value as a key data resource for climate research and monitoring. Abatzoglou et al. (2018) constructed high-resolution climate grids for environmental modeling. Tamiminia et al. (2020) conducted a meta-analysis on 349 peer-reviewed GEE articles from 2010 to October 2019 to show its status and trends. Harris et al. (2020) constructed a new CRU TS v4 climate data set with an updated time span of 1901-2018.

C4 Documents with the strongest citation bursts

Citation burst analysis, as shown in Fig. C5, identifies key contributions that shaped satellite-based climate change research. Foundational works include the Intergovernmental Panel on Climate Change (IPCC) 2023 report, which formalized international climate policy baselines, and Dee et al. (2011), which introduced the ERA-Interim reanalysis data set. Pan et al. (2011) estimated the global forest carbon sink using forest inventory data and long-term ecosystem carbon studies, with forest area estimates derived from the FAO Forest Resources Assessment. Baccini et al. (2012) improved estimates of carbon dioxide emissions from tropical deforestation by producing a pan-tropical aboveground carbon density map using multi-sensor satellite data (ICESat/GLAS LiDAR, MODIS, and SRTM). Hansen et al. (2013) mapped global forest cover change using Landsat time series. Pekel et al. (2016) developed high-resolution global surface water dynamics data sets. Funk et al. (2015) advanced hydrological modeling with the CHIRPS precipitation data set. Gorelick et al. (2017) introduced GEE, a cloud-based platform for planetary-scale geospatial analysis that leverages Google's computational infras-

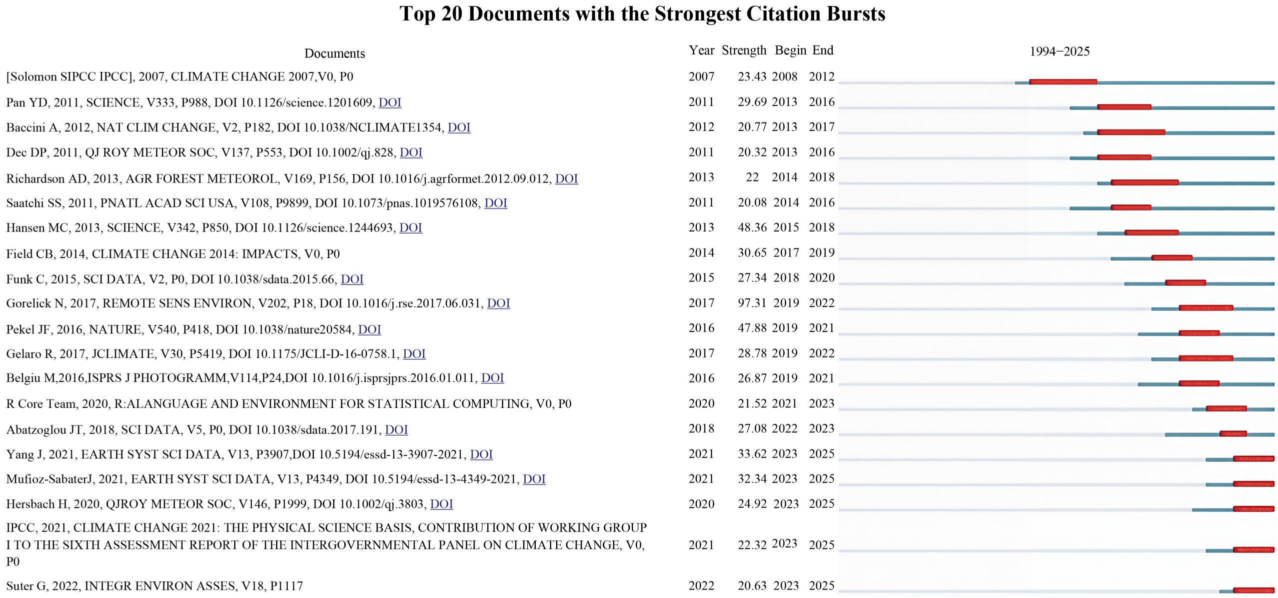

Fig. C5 Documents with the strongest citation bursts.

tructure to address high-impact societal challenges. Gelaro et al. (2017) presented the MERRA-2 atmospheric reanalysis system, providing a comprehensive overview of its data assimilation framework, satellite observation integration, and performance evaluation, and showing its value as a key data resource for climate research and monitoring. Abatzoglou et al. (2018) constructed high-resolution climate grids for environmental modeling. Belgiu and Drăguţ (2016) reviewed the application of the RF classifier in remote sensing, highlighting its ability to handle high data dimensionality and multicolinearity, its extensive use of variable importance measures for feature selection, and its sensitivity to sampling design. Muñoz-Sabater et al. (2021) released ERA5-Land, a global high-resolution land reanalysis data set. Yang and Huang (2021) developed a random forest classifier combined with a spatial-temporal post-processing method to produce the first Landsat-derived annual China land cover dataset at 30 m resolution from 1990 to 2019 using all available Landsat TM/ETM+/OLI imagery.

This figure presents the top 20 documents with the strongest citation bursts in satellite-based climate change research, illustrating the most influential publications and their citation trends over time from 1994 to 2025.

C5 Author co-citation network

Figure C6 shows the author co-citation network. Philippe

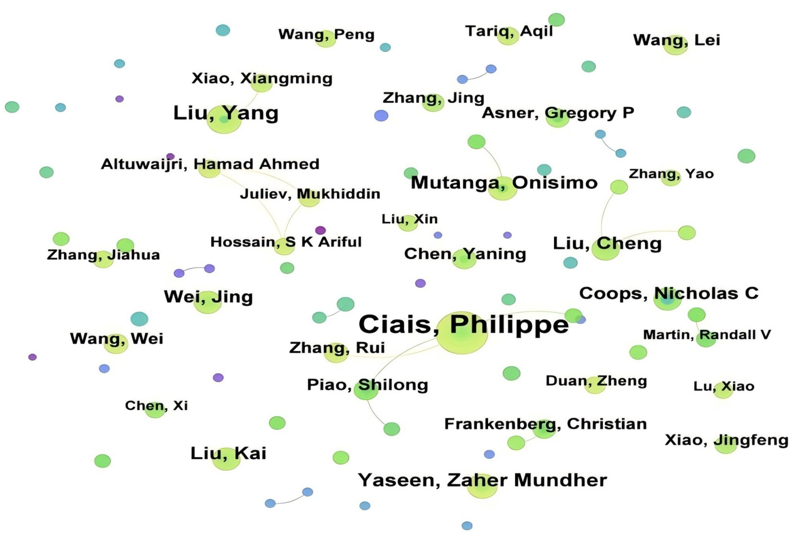

Fig. C6 Author co-citation network.

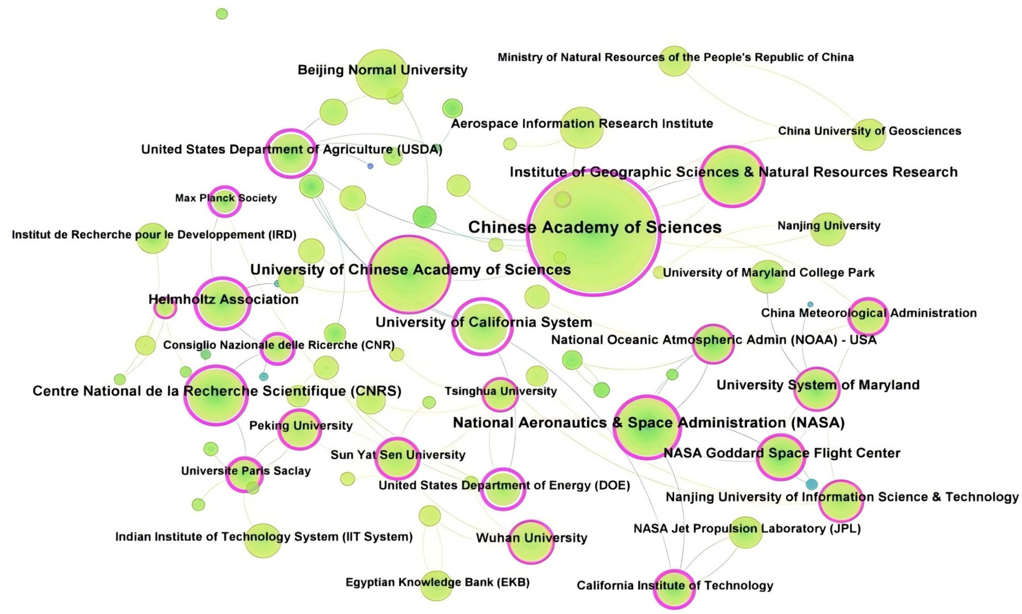

Fig. C7 Collaboration network of institution.

Ciais (51 co-citations) is frequently cited by research on the global carbon cycle and its links to climate change and terrestrial ecosystems. Zaher Mundher Yaseen (15 co-citations) is commonly cited by studies applying artificial intelligence and machine learning to water-related problems. Onisimo Mutanga (14 co-citations) is often cited by work on hyperspectral remote sensing for vegetation and ecosystem applications, including vegetation characterization and monitoring.

Figure C6 displays the author co-citation network in satellite-based climate change research, highlighting key researchers and their interconnections.

C6 Institutional collaboration network

Figure C7 shows the collaboration network between institutions, with node size representing an institution's frequency, reflecting its academic influence. The Chinese Academy of Sciences serves as the largest central node, forming a collaboration network with numerous global institutions through dense connections. Agencies such as the National Aeronautics and Space Administration, the United States Department of Agriculture, and the University of California System demonstrate distinct international collaboration clusters. Although Chinese universities like Beijing Normal University and Nanjing University maintain close ties with research institutes, their node sizes and connection scopes are smaller than those of the Chinese Academy of Sciences. The presence of institutions related to geographic sciences, space technology, meteorological administration (e.g., China Meteorological Administration), and agriculture explicitly reflects interdisciplinary collaboration dominated by Earth sciences.

Figure C7 illustrates the collaboration network of institutions in satellite-based climate change research, highlighting major global research entities and their connections.

Appendix D Main contributions and limitations of satellite-based climate change research

The main contributions and limitations of satellite-based climate change research are systematically summarized. Table D1 summarizes the main contributions and limitations of studies on satellite-based GHG source and sink

Table D1 Main contributions and limitations in satellite-based GHG source and sink estimation in ecosystems

Subsection	Literatures	Main contributions	Limitations
Satellite-based GHG Concentration Retrieval Using Top-down Approaches	Maasakkers et al. (2019); Wang et al. (2020); Ma et al. (2021); Schuh et al. (2022); Zhu et al. (2022); Shen et al. (2023); Janardanan et al. (2024); Jin et al. (2024); Qu et al. (2024); Reyes-Muñoz et al. (2024); Wang et al. (2025b)	Use GOSAT, OCO-2, TROPOMI and related CTMs, Bayesian inversion, ensemble Kalman filter, and data assimilation frameworks to infer regional and global CO_2 and CH_4 emissions; estimate carbon sinks; analyze emission trends; attribute CH_4 surges; generate global CO_2 surface flux data sets; quantify GPP and NPP.	Limitations in transport models, meteorological inputs, and uncertainties in initial conditions and emission inventories lead to considerable deviations; difficult to disentangle natural biospheric fluxes from anthropogenic emissions; robust trend detection requires long-term, continuous data sets; model resolution affects emission trend estimation.

(*Continued*)

Subsection	Literatures	Main contributions	Limitations
Satellite-based GHG Source and Sink Estimation Using Machine Learning	Baccini et al. (2012); Exbrayat et al. (2017); Csillik et al. (2019); He et al. (2022); Duan et al. (2023); Li et al. (2023b); Radman et al. (2023); Schuit et al. (2023); Song et al. (2023); Yan et al. (2023b); Yu et al. (2023); Zhang and Liu (2023); Ai et al. (2024); Kang et al. (2024); Li et al. (2024); Rouet-Leduc and Hulbert (2024)	Apply CNNs, RF, gradient boosting, deep learning, and hybrid machine learning models with satellite data (e.g., OCO-2, GOSAT, Sentinel-1/2, MODIS, LiDAR) to generate XCO_2 products, map carbon density, estimate AGB, reconstruct carbon fluxes, analyze pCO_2 and air–sea CO_2 exchange, and detect CH_4 point sources and superemitters.	Machine-learning CH_4 estimation relies on specific conditions, limiting generalizability; point source detection depends on uncertain variables such as wind speed and surface reflectance; deep learning models lack interpretability; difficulty characterizing long-term variability or abrupt emission events.

Table D2 Main Contributions and Limitations in Satellite-based GHG Emission Monitoring in Socioeconomic Systems.

Subsection	Literatures	Main Contributions	Limitations
Satellite-based Emission Monitoring in the Energy Sector	Nassar et al. (2017); Gray et al. (2018); Pandey et al. (2019); Varon et al. (2019); Liu et al. (2020); Schneising et al. (2020); Ye et al. (2020); Zhang et al. (2020); Ialongo et al. (2021); Liu et al. (2021); Madhuanand et al. (2021); Ehret et al. (2022); Lu et al. (2022); Wu et al. (2022); Cusworth et al. (2023); Filonchyk and Peterson (2023); Guo et al. (2023); Hanna et al. (2023); Lu et al. (2023); Peng et al. (2023); Shao et al. (2023); Trenchev et al. (2023); Han et al. (2024a); Han et al. (2024b); He et al. (2024b)	Focused on estimating CO_2, CH_4, and NO_2 emissions from coal-fired power plants, coal mining, and oil and gas systems using direct retrievals, multitemporal statistical approaches, regional-scale inversion models, atmospheric chemistry models, mass balance, and deep learning. Developed methods for plume detection, facility-level quantification, regional emission estimation, and urban fossil-fuel CO_2 assessment.	Emission estimates are affected by uncertainties in atmospheric transport models, wind fields, plume dispersion, retrieval algorithms, and background conditions; point-source detection depends on sensor resolution and surface reflectance; multitemporal approaches are limited by data availability and model biases.
Satellite-based Emission Monitoring in the Agriculture, Forestry, and Other Land Use Sector	Zhang et al. (2016); Peters et al. (2017); Ito et al. (2019); Shi et al. (2021); Ghafoor et al. (2022); Deshpande et al. (2023); Hong et al. (2023); Wang et al. (2023b); Weiland et al. (2023); Kang et al. (2024); Wei et al. (2024)	Focused on LULC classification, carbon storage assessment, soil respiration estimation, simulation of LULCC impacts on carbon flux, and CH_4 emission estimation from rice fields and wetlands using multisensor data sets, inverse diffusion models, phenology-based algorithms, fire radiative power, and emission inventories.	Monitoring accuracy is constrained by uncertainties in LULC classification, environmental drivers, combustion efficiency, biomass parameters, and model simulations; small agricultural fires and spatially dispersed biomass burning may be underestimated.
Satellite-based Emission Monitoring in the Industrial Processes and Product Use Sector	Zhang et al. (2019b); Wu et al. (2023a); Yang et al. (2024b)	Focused on identifying industrial emission sources, detecting cement production facilities, mapping radiative flux of industrial heat sources, and automatically segmenting industrial smoke plumes using Landsat, Sentinel-2, VIIRS infrared data, and deep learning models.	Detection performance is limited by thermal signature variability, spatial resolution constraints, false positives in plume segmentation, and dependence on facility characteristics and spectral features.
Satellite-based Emission Monitoring in the Waste Sector	Tu et al. (2022); Susunaga-Miranda et al. (2023); de Foy et al. (2023); Kannankai and Devipriya (2024)	Quantified CH_4 emissions from landfills using TROPOMI, IASI, Gaussian plume dispersion, biogas models, multicriteria evaluation, and Landsat-derived surface temperature; detected landfill fire events and linked high CH_4 emissions with untreated wastewater discharge.	Emission estimation remains limited by wind field anomalies, background concentration variability, spatial heterogeneity of waste sites, and challenges in detecting small or low-temperature combustion events.

Table D3 Main contributions and limitations in satellite-based climate change adaptation research in ecosystems

Subsection	Literatures	Main contributions	Limitations
Satellite-based Water Resource Management	Rishikeshan and Ramesh (2018); Busker et al. (2019); Zhang et al. (2019a); Bhattacharya et al. (2021); Mateo-Garcia et al. (2021); Tuan et al. (2021); Ali et al. (2022); Cao et al. (2022); Olthof and Rainville (2022); Ghanghas et al. (2023); Kang et al. (2023); Li et al. (2023a); Seo and Lee (2023); Wallis and Hogg (2023); Wieland et al. (2023); Wu et al. (2023b); Yan et al. (2023a); Zhao et al. (2023a); Zhu et al. (2023); Fluegel and Walker (2024); Valman et al. (2024); Wang et al. (2024); Yang et al. (2024a); Zhao et al. (2024); Maslov et al. (2025); Wei et al. (2025)	Developed automated extraction algorithms, deep learning networks, and CNN–Transformer models; estimated lake and reservoir volume changes; mapped water body frequency and trends; assessed model adaptability; addressed radiometric and computational challenges; classified river change types; enabled real-time monitoring; downscaled GRACE outputs; assessed droughts; analyzed groundwater trends; enhanced meteorological drought detection; corrected drought index biases; assessed extreme drought events; generated flood masks; enhanced flood mapping; developed downscaling–calibration frameworks; linked precipitation with temperature and water vapor; evaluated heat island effects; constructed digital elevation models; analyzed glacier flow velocities; investigated glacier retreat; developed deep glacier mapping models	Transboundary water and ecosystem monitoring is hindered by fragmented policy, regulatory, and jurisdictional frameworks; regional hydrological studies fail to account for fine-scale geographic heterogeneity and lack standardized protocols for data processing, integration, and evaluation

(*Continued*)

Subsection	Literatures	Main contributions	Limitations
Satellite-based Terrestrial Ecosystem Management	Xie et al. (2020); Bai et al. (2022); Song et al. (2022); Ye et al. (2022); Ren et al. (2023); Liu et al. (2023); Cai et al. (2023); Feng et al. (2024); Aziz et al. (2024); Zhou et al. (2024); Vera et al. (2024); Wu et al. (2024); Liu et al. (2024b); Khairoun et al. (2024); Mumma et al. (2024); Nicoletti et al. (2024); Harrison et al. (2025)	Examined vegetation cover changes; developed high-resolution vegetation cover estimation frameworks; assessed urban vegetation cover; evaluated rangeland vegetation cover; mapped forest cover; detected vegetation loss and degradation; analyzed vegetation change; examined cropland expansion and recovery; monitored tidal wetland change; evaluated satellite thermal infrared performance; assessed urban thermal environment; assessed forest loss from wildfires; modeled postfire vegetation recovery; tracked active fire characteristics; detected pine wilt disease; enhanced tree-level pest detection; monitored pine mortality	In forest research, satellite-based applications have mainly focused on land cover classification and vegetation dynamics, with less attention paid to physiologic impacts of extreme events such as droughts
Satellite-based Marine and Coastal Zone Management	Varotsos et al. (2024); Ahmad Affandi et al. (2024); Bij de Vaate et al. (2024); Macdonald et al. (2024); Zhang et al. (2024); Li and Xiong (2024); Park et al. (2024); Nie et al. (2025); Mu et al. (2025)	Characterized temporal dynamics and scaling behavior of global mean sea level; analyzed sea-level trends and projected changes; investigated storm surge variability; reconstructed historical sea-level changes; estimated sea ice roughness; developed high-accuracy sea ice detection; estimated Arctic summer sea ice concentration; detected marine oil spills	Satellite-based monitoring has concentrated on surface and nearshore environments, with limited coverage of deep-sea or polar regions and minimal exploration of marine microplastic pollution

Table D4 Main contributions and limitations in satellite-based climate change adaptation research in socioeconomic systems

Subsection	Literatures	Main contributions	Limitations
Satellite-based Agriculture and Food Security Monitoring	Qu and Hao (2018); Fu et al. (2022); Salomão et al. (2024); Panek-Chwastyk et al. (2024); Ballaran et al. (2024)	Assessed agricultural drought impacts using MODIS NDVI, VCI, TCI, VHI, surface reflectance, and LST; examined LULC changes linked to hydroelectric dam development; forecasted yield anomalies with Sentinel-1/3 and ERA5 using XGBoost; developed a regional model for cotton aphid damage with Sentinel-2 and RF; estimated flood-induced rice crop damage using Sentinel-2, UAV data, NDVI, and SAR-based features.	Most studies focus on crop monitoring under normal conditions, with limited attention to dynamic resource changes during crises and insufficient assessment of agricultural waste distribution and reuse potential.
Satellite-based Public and Environmental Health Monitoring	Mukherjee et al. (2019); Fadadu et al. (2020); Rahman et al. (2021); He et al. (2024a); Yadav et al. (2024); O'Dell et al. (2024)	Assessed public health impacts using DMSP NTL data with long-term trend analysis; developed a malaria early warning system using AVHRR-derived vegetation health indices, GIS, and ANN; examined extreme rainfall and respiratory mortality using GPM data; estimated urban air quality with WorldView-2 and deep transfer learning; evaluated wildfire-related $PM_{2.5}$ using NOAA smoke density and ground data; estimated $PM_{2.5}$ with GOES aerosol optical depth for air pollution alerts.	Satellite-derived environmental data are rarely integrated into infectious disease transmission models, especially for spatial risk assessments linking environmental exposure to health outcomes.
Satellite-based Urban and Human Settlement Management	Paulik et al. (2019); Kranjčić et al. (2019); Tanim et al. (2022); Cheng et al. (2022); Ramsay et al. (2023); Kursah (2023); Kim and Kim (2024); Lin et al. (2024)	Analyzed earthquake- and tsunami-induced infrastructure destruction using Sentinel-1 and high-resolution imagery; detected urban flooding with SAR and supervised/unsupervised learning; classified urban green infrastructure using Sentinel-2 and ML methods; assessed carbon sequestration potential of clustered green infrastructure; analyzed green space change under aging demographics; examined UHI variation using Landsat and GAMMs; assessed thermal comfort using LST, NDVI, and NDBI; identified construction waste landfills using CNNs and DeepLabV3 +.	Monitoring mainly addresses spatial patterns, short-term dynamics, and disaster vulnerability, while long-term assessments of infrastructure performance remain underdeveloped; integration of spatial data with behavioral or demographic factors is limited; UHI studies often neglect humidity and wind and lack comparative analyses across cities.
Satellite-based Financial Management	Shofiyati et al. (2021); Murthy et al. (2022); Nordmeyer and Musshoff (2023); Nordmeyer et al. (2023)	Monitored meteorological and agricultural droughts using TRMM, GSMaP, MTSAT, MODIS, and Himawari-8, accelerating insurance claims; proposed a "crop health factor" for drought loss assessment using Sentinel and field data; analyzed farmers' perceptions of satellite-based index insurance; examined preferences for satellite-based versus precipitation-based insurance using discrete choice experiments.	Integration of satellite-based monitoring with economic models for loss estimation, insurance pricing, and asset valuation remains in its infancy.

estimation in ecosystems. Table D2 summarizes the main contributions and limitations of satellite-based GHG emission monitoring in socioeconomic systems. Table D3 summarizes the main contributions and limitations of satellite-based climate change adaptation research in ecosystems. Table D4 summarizes the main contributions and limitations of satellite-based climate change adaptation research in socioeconomic systems.

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interests.

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