

Dear Reviewer,

We are very grateful for your detailed comments and constructive suggestions on our manuscript (essd-2025-107). We revised the manuscript according to your comments and provided a point-by-point reply (in blue color) as follows. Our revisions in the manuscript and supplementary materials are marked in blue.

Comment 1: Please clarify the temporal coverage of the dataset. The title and abstract suggest a continuous 2000–2020 dataset, but results focus on 2000, 2010, and 2020 only. This is misleading if only three years are included. Specify in the title/abstract that data covers decadal intervals. If possible, discuss feasibility of annual data generation or provide suggestions or methods for users to further generate the annual dataset. I recommend making it clear about the spatial resolution of the ES dataset in the title.

Response: Thanks for your detailed consideration. We agree that the previous presentation was misleading, and we have now revised the manuscript. As you suggested, we have revised the title to explicitly state the specific years of data coverage and the spatial resolution. The new title is “A 30-meter spatial resolution dataset of ecosystem services in China for 2000, 2010, and 2020”. We have also amended the abstract and the conclusion sections to clearly state that the dataset provides snapshots for these three decadal intervals (2000, 2010, 2020) and is not a continuous annual time series.

We also added the feasibility of generating an annual dataset in the Limitations and Uncertainties section (**Lines 740-755**), The detailed content is as follows:

In stable climatic conditions, many ecosystem services exhibit slow inter-annual variation. Thus, for numerous policy and management applications - such as evaluating long-term ecological restoration programs - a decadal assessment is often sufficient (Ouyang et al., 2016). However, with the increasing frequency of extreme climate events, which may significantly alter ecosystem services dynamics year-to-year, there is a growing scientific need for annual assessments (Dee et al., 2025). Moreover, improving data availability, particularly the emergence of more detailed annual land cover products, along with advancements in downscaling techniques, will further support the generation of annual ecosystem service datasets (Yang et al., 2021). For users who may wish to interpolate or model annual data, such as using our decadal data as benchmarks and integrating it with annually available coarser-resolution remote sensing indices (e.g., MODIS NDVI) for trend analysis and interpolation. Future research can also focus on other ecosystem services, including biodiversity and habitat quality, pollination, flood regulation, and water quality purification, thereby supporting a more comprehensive assessment. In addition, the biophysical layer can be combined with socio-economic data (such as population density, accessibility and infrastructure, water intake, economic activities, and PES programs) to achieve scenario analysis, trade-off assessment, and fair-oriented decision-making.

Ouyang, Z., Zheng, H., Xiao, Y., Polasky, S., Liu, J., Xu, W., Wang, Q., Zhang, L., Xiao, Y., Rao, E., Jiang, N., Lu, F., Wang, X., Yang, G., Gong, S., Wu, B., Zeng, Y., Yang, W., Daily, G.C.: Improvements in ecosystem services from investments in natural capital, *Sci. Adv.*, 2(2), e1500961, <https://doi.org/10.1126/science.aaf2295>, 2016.

Dee, L., Miller, S., Helmstedt, K., Boersma, K., Polasky, S., Reich, P.: Quantifying disturbance

effects on ecosystem services in a changing climate. *Nat Ecol Evol.*, 9, 436-447, <https://doi.org/10.1038/s41559-024-02626-y>, 2025.

Yang, J., Huang, X.: The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *ESSD.*, 13(8), 3907-3925, <https://doi.org/10.5194/essd-13-3907-2021>, 2021.

Comment 2: Please enrich the detailed processing in terms of the methodologies and model parameters. While the models used (e.g., CASA, RUSLE, RWEQ, InVEST) are well-known, key assumptions, parameterization details, and calibration procedures are insufficiently described. For example, the RUSLE model—designed for plot to watershed scales—may overestimate erosion at 30 m due to neglected deposition processes and micro-topographic effects. It is essential to include a table summarizing input data sources, sample sizes, spatial coverage, and parameter values. Sensitivity or uncertainty analyses for critical parameters (e.g., $\epsilon_{\max}$ in CASA) would greatly strengthen the methodology. Furthermore, please address the suitability of each model for high-resolution applications and provide relevant citations to support their use at 30 m.

Response: Thanks for your detailed consideration. We agree with you that a summary table should be provided to improve clarity for the reader. We have now added the summary table in the ecosystem services assessment parameters to clearly match each model with its corresponding input and factors (Table 1).

We explained the suitability of each model for high-resolution applications and provided relevant citations to support their use at 30 m (**Lines 132-148**). The detailed content is as follows:

The models and input data were based on the following principles: (1) Wide recognition of the models: The selected models (e.g., CASA, RUSLE) are well-established and classic within the field of ecosystem service assessment. Their principles are mature and have been extensively validated in applications at global and regional scales, which facilitates the comparison of our results with existing studies. (2) Data availability and model compatibility: The selected models are compatible with the multi-source remote sensing, meteorological, soil, and topographic data collected for this study, ensuring the feasibility of the assessment. (3) Suitability for spatially explicit assessment: All models are capable of spatially explicit calculation, which allows them to fully utilize the 30-meter high-resolution spatial data to generate detailed distribution maps, meeting the accuracy requirements for refined management and policy formulation. The application of these models at this fine resolution is well-supported by previous studies. The CASA model has been successfully applied to estimate China's land net primary productivity (NPP) data with high accuracy (Sun et al., 2021; Zhang et al., 2023). Similarly, both the RUSLE and RWEQ models have been successfully applied at high resolution for soil erosion and sandstorm prevention mapping, respectively, demonstrating their suitability for high-resolution assessment (Zong et al., 2025; Yang et al., 2025). The InVEST has proved to be suitable for large-scale water yield assessment in China (Yin et al., 2020). This capability meets the accuracy requirements for refined management and policy formulation.

Table 1. Assessment model and input data used in this study.

Ecosystem service	Model	Parameter	Dataset	Resolution	Source
NPP	CASA	NDVI	Landsat 5 (2000 and 2010) and Landsat 8 (2020) Level 2, Collection 2, Tier 1 data	30 m	https://earthexplorer.usgs.gov/
		Temperature	A monthly average temperature dataset with a resolution of 1km in China from 1901 to 2024	1 km	http://www.geodata.cn/data/
		Precipitation	A monthly precipitation dataset with a resolution of 1km in China from 1901 to 2024	1 km	http://www.geodata.cn/data/
		Landcover	GlobeLand 30	30 m	http://globeland30.org/
		Evapotranspiration	MOD16A2	500 m	https://modis.gsfc.nasa.gov/
		Potential evapotranspiration	MOD16A2	500 m	https://modis.gsfc.nasa.gov/
Soil conservation	RUSLE	NDVI	Landsat 5 (2000 and 2010) and Landsat 8 (2020) Level 2, Collection 2, Tier 1 data	30 m	https://earthexplorer.usgs.gov/
		Monthly precipitation	A monthly precipitation dataset with a resolution of 1km in China from 1901 to 2024	1 km	http://www.geodata.cn/data/
		Soil properties	SoilGrids V2.0	250 m	https://soilgrids.org/
		DEM	ASTER Global Digital Elevation Model V003	30 m	https://www.earthdata.nasa.gov/
Sandstorm prevention	RWEQ	Wind speed	ERA5 Hourly Data on Single Levels	0.01°	https://developers.google.com/earthengine/datasets/
		Soil properties	SoilGrids V2.0	250 m	https://soilgrids.org/
		Snow depth	Long-term series of daily snow depth dataset in China (1979-2024)	25 km	https://data.tpdac.cn/
		Potential evapotranspiration	MOD16A2	500 m	https://modis.gsfc.nasa.gov/
		Precipitation	A monthly average temperature dataset with a	1 km	http://www.geodata.cn/data/

Water yield	Invest		resolution of 1km in China from 1901 to 2024 A monthly precipitation dataset with a resolution of 1km in China from 1901 to 2024	1 km	http://www.geodata.cn/data/
		Temperature			
		DEM	ASTER Global Digital Elevation Model V003	30 m	https://www.earthdata.nasa.gov/
		Precipitation	A monthly average temperature dataset with a resolution of 1km in China from 1901 to 2024	1 km	http://www.geodata.cn/data/
		Potential evapotranspi ration	MOD16A2	500 m	https://modis.gsfc.nasa.gov/
		Soil properties	SoilGrids V2.0	250 m	https://soilgrids.org/
		Landcover	GlobeLand 30	30 m	http://globeland30.org/
		Watersheds	/	/	http://www.mwr.gov.cn/

We have also added the uncertainty impact of the models and input data on the assessment results of ecosystem services in the **Limitations and Uncertainties** section (**Lines 721-739**). The detailed content is as follows:

Despite of the high resolution and accuracy of the dataset, our data set still have some limitations. First, some of the ecosystem service modules (e.g., InVEST water yield) simplify hydrological and geomorphic processes and typically do not explicitly simulate groundwater recharge, surface – groundwater interactions, or threshold/nonlinear responses during extreme events (Redhead et al., 2016). Such simplifications can reduce accuracy in arid basins, karst areas, or groundwater-dependent systems. Data scarcity further increases uncertainty in remote regions. In high-elevation and desert areas (e.g., the Tibetan Plateau and arid Northwest), meteorological and hydrological stations are sparse, quality-controlled long time series are limited, and cloud/ice/snow contamination of optical imagery is more frequent (Walther et al., 2025).

Model-based assessments of ecosystem services inevitably involve multiple sources of uncertainty. These uncertainties primarily arise from errors in input data (such as climate variables, land cover types, and soil parameters, etc.), which propagate through the modeling process and have a cumulative effect on the results (Walther et al., 2025). Although cross-validation with existing products and ground-based observations demonstrates the overall robustness of the dataset, this study did not conduct a systematic approach to quantifying uncertainty. Future studies should incorporate quantitative uncertainty analysis, such as sensitivity analysis and error propagation analysis, to provide confidence intervals for key ecosystem service estimates. These potential uncertainties should be carefully considered when applying this dataset to fine-scale ecological planning, ecosystem restoration decision-making, and the design of payment for ecosystem services (PES) schemes.

Sun, J., Yue, Y., Niu, H.: Evaluation of NPP using three models compared with MODIS-NPP data over China, PLoS ONE., 16(11), e0252149, <https://doi.org/10.1371/journal.pone.0252149>, 2021.

Zhang, Z., Zhao, W., Liu, Y., Pereira, P.: Impacts of urbanisation on vegetation dynamics in Chinese cities, Environ. Impact Assess. Rev., 103, 107227, <https://doi.org/10.1016/j.eiar.2023.107227>, 2023.

Zong, R., Fang, N., Zeng, Y., Lu, X., Wang, Z., Dai, W., Shi, Z.: Soil Conservation Benefits of Ecological Programs Promote Sustainable Restoration, Earth's Future., 13, e2024EF005287, <https://doi.org/10.1029/2024EF005287>, 2025.

Yang, J., Wang, S., Feng, J., He, H., Wang, L., Sun, Z., Zheng, C.: New 30-m resolution dataset reveals declining soil erosion with regional increases across Chinese mainland (1990-2022), Remote Sens. Environ., 323, 114681, <https://doi.org/10.1016/j.rse.2025.114681>, 2025.

Yin, L., Wang, X., Wang, Y.: Water Yield Product 1-km Grid Yearly Dataset in National Barrier Zone of China, 1-km resolution dataset of water yield in the National Ecological Barrier Zone (2000-2015), Journal of Global Change Data & Discovery., 4(4), 332-337, <https://doi.org/10.3974/geodp.2020.04.03>, 2020.

Redhead, J., Stratford, C., Sharps, K., Jones, L., Ziv, G., Clarke, D., Oliver, T., Bullock, J.: Empirical validation of the InVEST water yield ecosystem service model at a national scale, Sci. Total Environ., (569-570), 1418-1426, <https://doi.org/10.1016/j.scitotenv.2016.06.227>, 2016.

Walther, F., Barton, D., Schwaab, J., Kato-Huerta, J., Immerzeel, B., Adamescu, M., Andersen, E., Coyote, M., Arany, I., Balzan, M., Bruggeman, A., Carvalho-Santos, C., Cazacu, C., Geneletti, D., Giuca, R., Inácio, M., Lagabrielle, E., Lange, S., Le Clec'h, S., Vanessa Lim, Z., Mörtberg, U., Nedkov, S., Portela, A., Porucznik, A., Racoviceanu, T., Rendón, P., Ribeiro, D., Seguin, J., Hribar, M., Stoycheva, V., Vejre, H., Zoumides, C., Grêt-Regamey, A.: Uncertainties in ecosystem services assessments and their implications for decision support – A semi-systematic literature review, Ecosyst. Serv., 73, 101714, <https://doi.org/10.1016/j.ecoser.2025.101714>, 2025.

Comment 3: Currently, only net primary productivity (NPP) is validated through cross-comparison with existing datasets. Other ES outputs lack validation, which limits confidence in their reliability. Where possible, incorporate in situ measurements or site-level observed data for validating additional ES variables (e.g., soil erosion, water yield). Multiple open-source NPP datasets are available and should be utilized for more robust validation. Please provide more comprehensive validation for the published dataset.

Response: Thanks for your insightful consideration. We must acknowledge that a comprehensive validation with existing datasets is lacking for all ecosystem services other than NPP, which limits the assessment of their reliability (**Lines 366-372**). The detailed content is as follows:

In response to this kind of situation, we have developed an indirect cross-validation framework that integrates multiple dataset sources and land cover stratification. The framework systematically leverages diverse, authoritative proxy datasets to triangulate the reliability of the simulations from multiple perspectives, thereby minimizing dependence on any single observational source. Beyond multi-source datasets, we stratify all evaluations by land cover class (e.g., cropland, forest, grassland, shrubland, and barren), enabling class-specific accuracy diagnostics and revealing class-dependent biases that might be masked in aggregate assessments.

The verification results show that the ecosystem services simulated in this study have high accuracy both overall (Fig. 2, Fig. 3, Fig. 4, Fig. 5) and by land cover type (Fig. S1, Fig. S2, Fig. S3, Fig. S4) compared with the published data products (**Lines 365-529**).

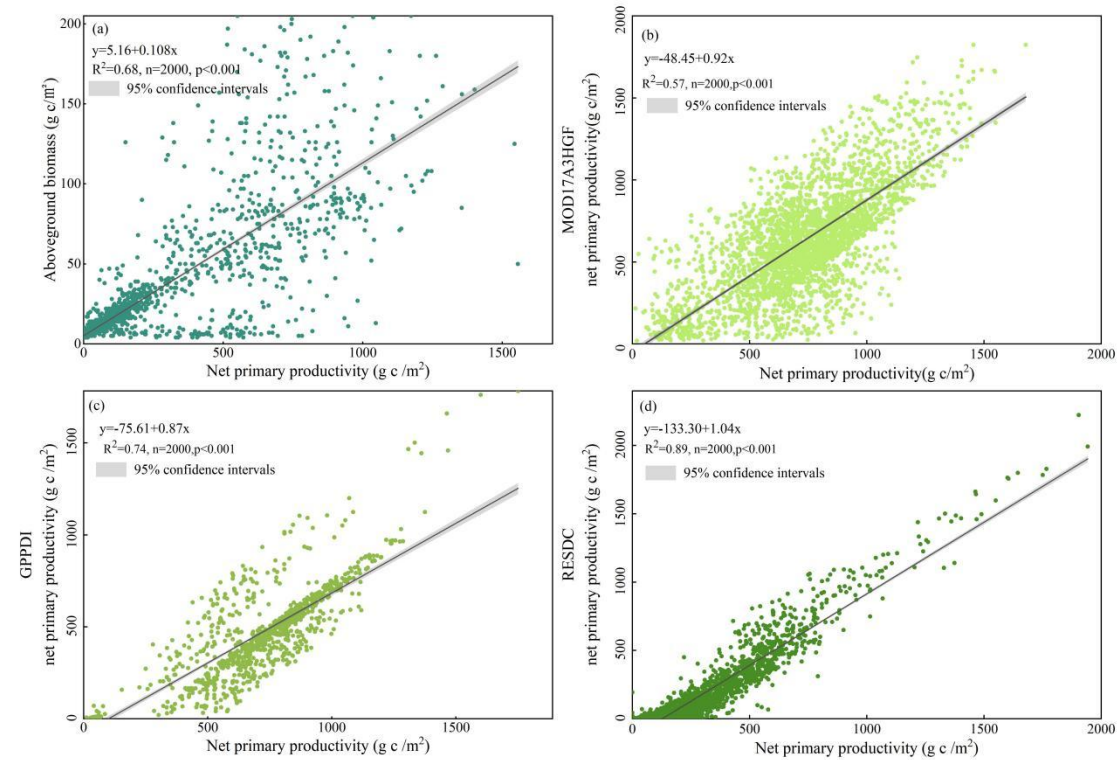


Figure 2: Validation of the NPP in this study, (a) the aboveground biomass and NPP of China in 2010, (b) the NPP estimated in this study and MODIS/Terra Net Primary Production Gap-Filled Yearly L4 (MOD17A3HGF), (c) the NPP estimated in this study and Global Primary Production Data Initiative (GPPDI) NPP data, (d) the NPP estimated in this study and Resource and Environment Science and Data Center (RESDC) NPP data.

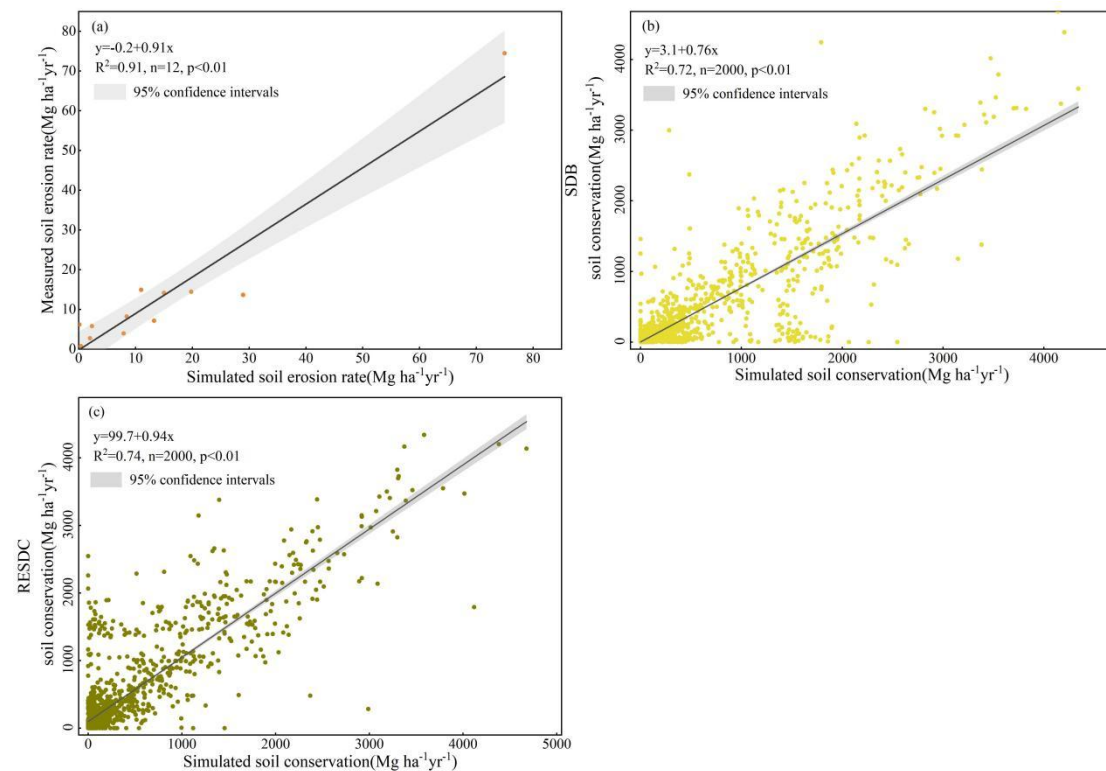


Figure 3: Validation of the soil conservation in this study, (a) the simulations and measurement of annual soil erosion rates for six river basins, including those of the Yangtze, Yellow, Haihe, Huaihe, Pearl, and Songhua and Liaohe in 2000 and 2010, (b) the soil conservation simulated in this study and Science Data Bank (SDB) soil conservation data in 2010, (c) the soil conservation simulated in this study and Resource and Environment Science and Data Center (RESDC) soil conservation data.

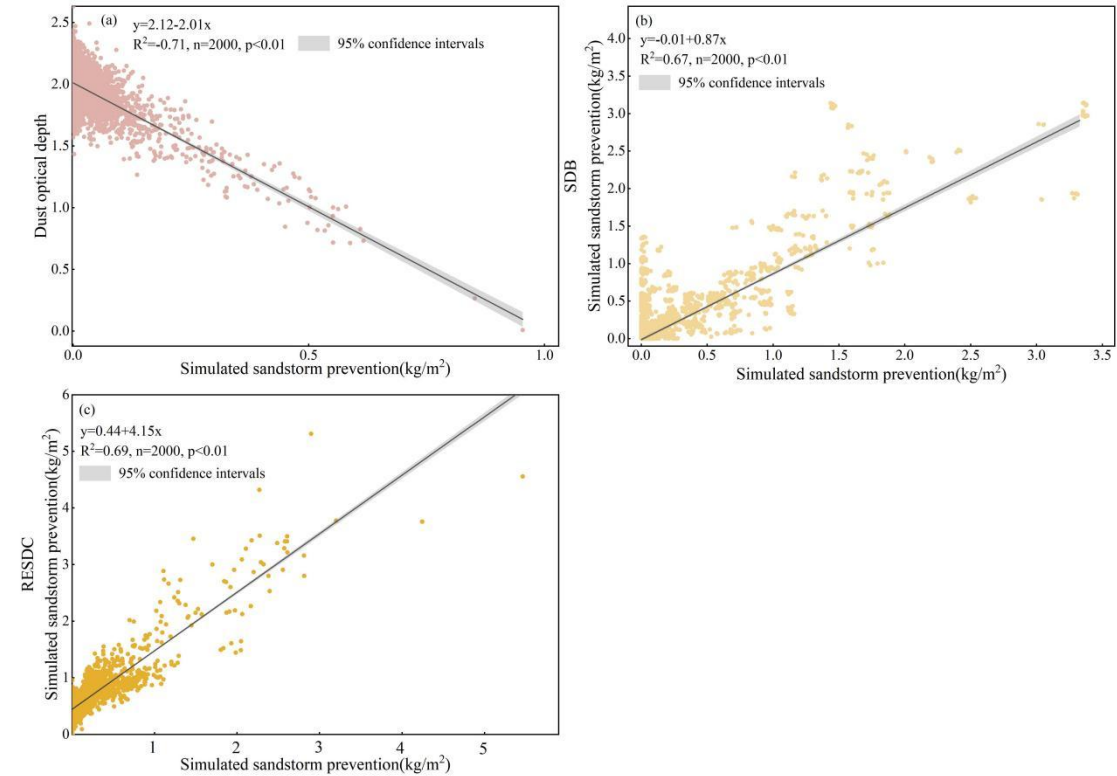


Figure 4: Validation of the sandstorm prevention in this study, (a) the simulated sandstorm prevention and dust optical depth of China in 2010, (b) the sandstorm prevention simulated in this study and Science Data Bank (SDB) soil conservation data in 2010, (c) the sandstorm prevention simulated in this study and Resource and Environment Science and Data Center (RESDC) soil conservation data.

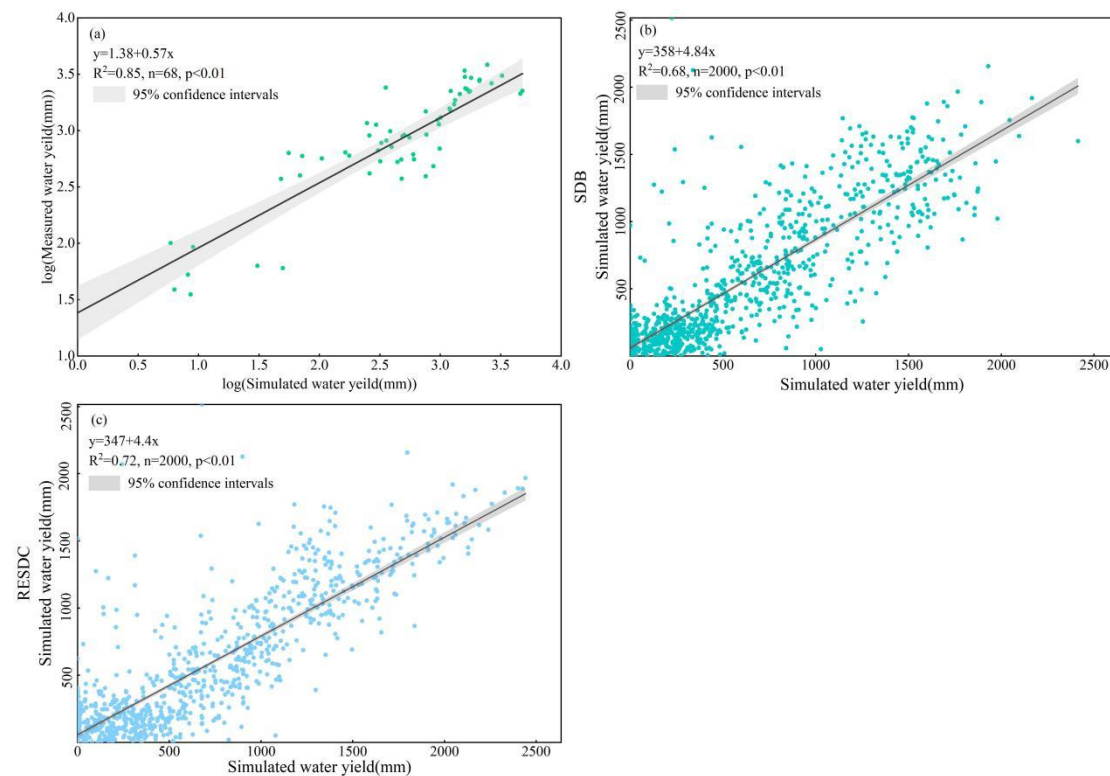


Figure 5: Validation of the water yield in this study, (a) the simulations and measurements of water yield for 34 provinces in 2000 and 2020. (b) the water yield simulated in this study and Science Data Bank (SDB) water yield data in 2010, (c) the water yield simulated in this study and Resource and Environment Science and Data Center (RESDC) water yield data.

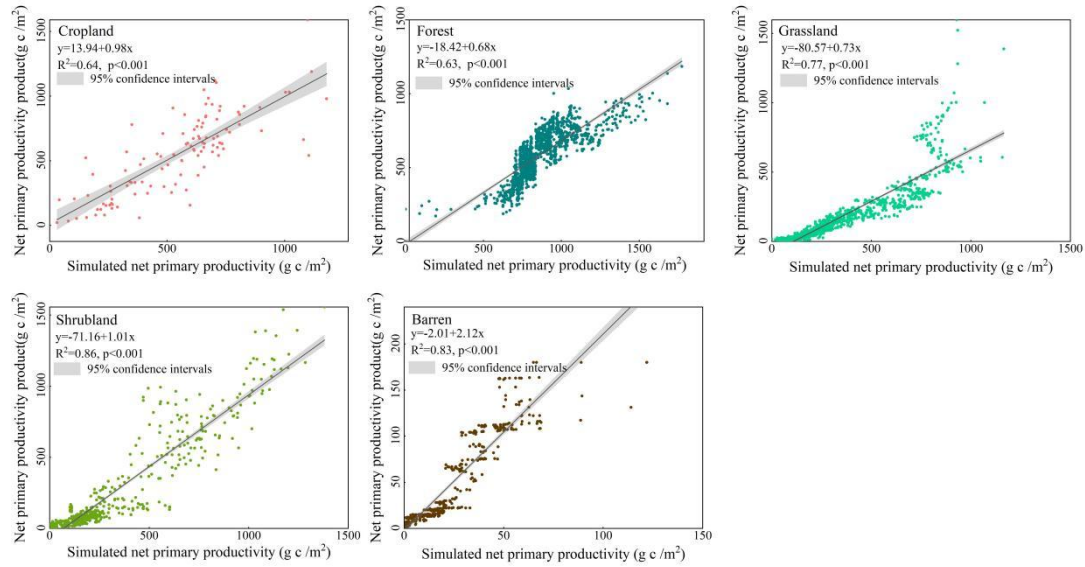


Figure S1: The verification map of the land cover type of NPP simulated by the CASA model and the published NPP products.

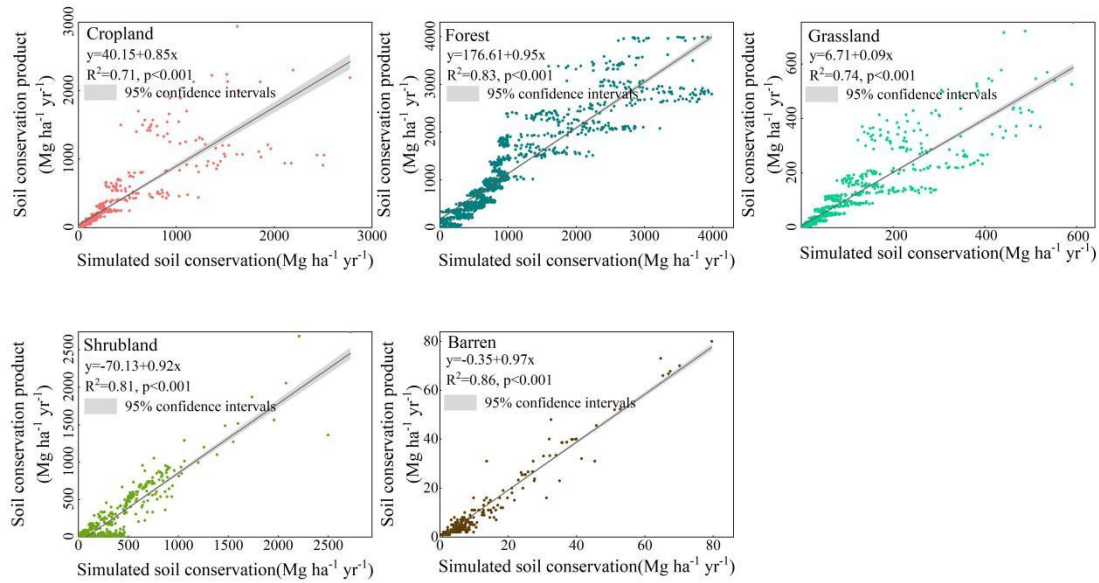


Figure S2: The verification map of the land cover type of soil conservation simulated by the RUSLE model and the published soil conservation products.

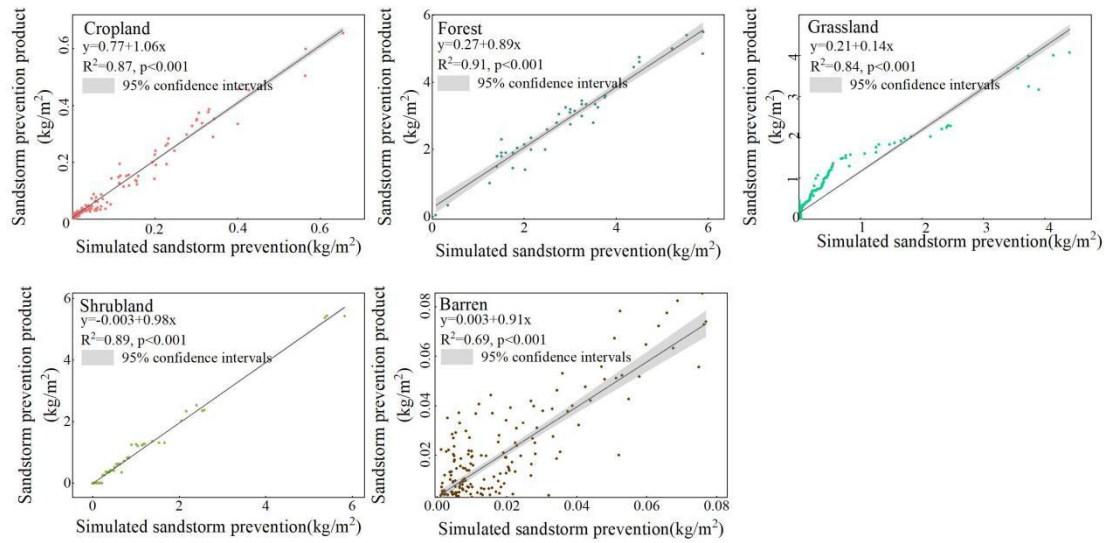


Figure S3: The verification map of the land cover type of sandstorm prevention simulated by the RWEQ model and the published sandstorm prevention products.

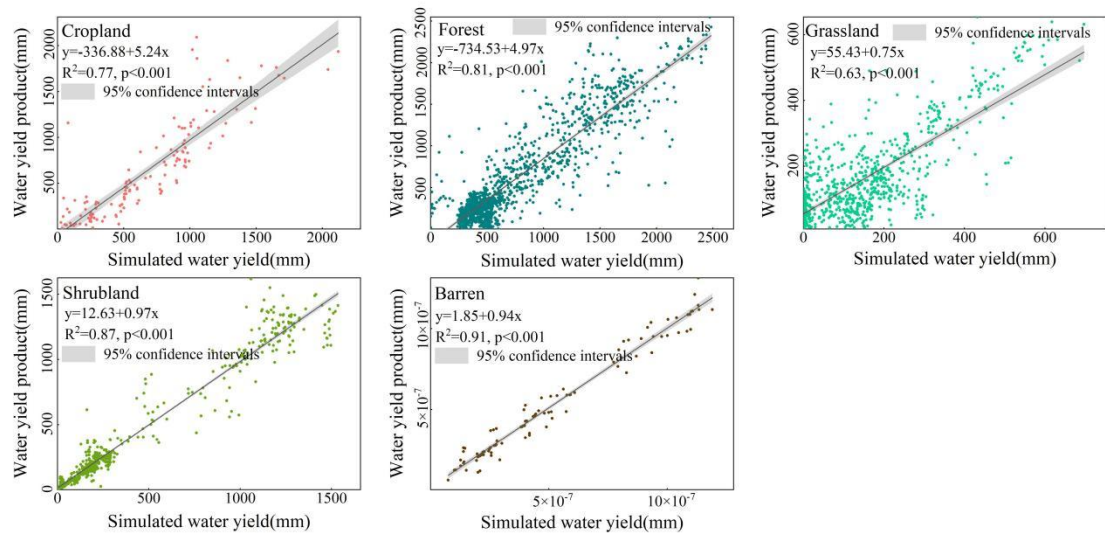


Figure S4: The verification map of the land cover type of water yield simulated by the InVEST model and the published water yield products.

Comment 4: The spatial patterns of ES are well illustrated, but the drivers behind temporal changes (e.g., increased NPP due to afforestation, CO₂ fertilization, or climate influences) are not adequately discussed. Similarly, changes in water yield should be explicitly linked to potential drivers such as urbanization or climate variability. The figures currently rely on qualitative descriptions; adding quantitative summaries—such as provincial averages, standard deviations, and statistical significance tests for change maps—would greatly enhance interpretability.

Response: Thanks for your detailed consideration. The reviewer has correctly pointed out the importance of delving into the drivers of time changes in ecosystem services (ES) and increasing quantitative analysis. We have now revised th

e Ecosystem services dynamics section to add discussions on drivers of ES dynamics and to include quantitative summaries (**Lines 618-667**). Specifically, Table S7 (Supplementary material) reports

province-level absolute changes and percentage changes of all four ES (NPP, soil conservation, sandstorm prevention, and water yield) over 2000 - 2020. The detailed content is as follows:

The provincial differences in ecosystem services are mainly affected by area, terrain, climate, and land cover. Yunnan, Sichuan, Guangdong, Guangxi, and Heilongjiang have good hydrothermal conditions and vegetation growth. Ecological initiatives, such as the Natural Forest Protection Project and Shelterbelt Project in the Upper-middle Reaches of the Yangtze River, have positively impacted net primary productivity (NPP). Meanwhile, negative human activities such as deforestation have relatively low interference, resulting in higher net primary productivity in these regions (Lu et al., 2018). Beyond land-cover change, interannual NPP gains are also consistent with broader climate influences (warmer springs, adequate precipitation, increased radiation) and a background rise in atmospheric CO₂ that may enhance photosynthetic capacity (CO₂ fertilization), especially where water is not limiting (Li et al., 2021). Sichuan, Xinjiang, Tibet, and Qinghai have more soil retention due to their extensive administrative areas. These provinces have rugged terrain, and most of the land cover is barren, which easily leads to soil erosion (Rao et al., 2023). Inner Mongolia, Xinjiang, Gansu, and Qinghai belong to arid or semi-arid climates, with relatively low precipitation and dry soil, making them prone to wind erosion and sandstorms due to high wind speeds and extensive barren (Piao et al., 2020). Yunnan, Sichuan, Guangdong, Guangxi, Jiangxi, Hunan, Hubei, and Heilongjiang have greater water yield due to abundant rainfall, complex terrain with various landforms such as mountains, plateaus, and hills, which facilitates the formation and accumulation of precipitation. Moreover, these regions are mostly covered by rich vegetation, and the transpiration effect of vegetation promotes precipitation formation and circulation (Yang et al., 2023). The interplay of climate and urbanization drives water yield dynamics. Climatically, yield is primarily a function of net water supply (precipitation minus PET), where warming-induced PET increases can negate the benefits of higher precipitation (Zhou et al., 2015). In parallel, urbanization alters the hydrological partitioning: impervious surfaces generate more rapid runoff, but this comes at the cost of reduced infiltration, ultimately diminishing groundwater recharge and baseflow in river basins (Huang et al., 2024).

In recent decades, China has implemented ambitious ecological projects, such as the Natural Forest Protection Project (NFPP), the Grain for Green Program (GFGP), the Three-north Shelter Forest Project (TSFP), and the Project for Preventing and Controlling Desertification (PPCD). The

implementation of these projects has changed the land cover, effectively increasing vegetation coverage and improving ecosystem stability (Cai et al., 2022). Concurrently, warming temperatures in recent years have also supported the vegetation growth (Song et al., 2021), contributing to a general increase in net primary productivity (NPP). Our province-level summaries indicate widespread positive NPP trends in regions targeted by NFPP and GFPP, consistent with afforestation effects and climate co-benefits. The enhanced NPP reflects improved photosynthetic capacity driven by vegetation recovery, particularly in areas targeted by national restoration projects. The expansion of forests, shrubs, and grasslands under these ecological programs has strengthened vegetation and root systems, improving soil stability and sand retention capacity. These improvements have led to notable increases in soil conservation, particularly within watersheds affected by reforestation and revegetation efforts (Wang et al., 2016). The spatial patterns of increased soil conservation are closely associated with the implementation areas of the GFPP and NFPP. Simultaneously, the observed reduction in desertified land and improvements in sandstorm prevention capacity correspond well with the effects of the TSFP and anti-desertification efforts (Li et al., 2023b). These spatial patterns indicate that this high-resolution dataset can serve as an effective tool for assessing the ecological outcomes of national policy initiatives. Nevertheless, the increased vegetation cover has also affected hydrological processes, particularly through increased evapotranspiration and reduced surface runoff, which may result in declining water yield in afforested regions (Zhao et al., 2021). This highlights the importance of considering potential trade-offs between restoration benefits and water resource availability, especially in arid and semi-arid regions.

Lu, F., Hu, H., Sun, W., Yu, G.: Effects of national ecological restoration projects on carbon sequestration in China from 2001 to 2010, *Proc. Natl Acad. Sci. USA.*, 115, 4039-4044, <https://doi.org/10.1073/pnas.1700294115>, 2018.

Li, H., Wu, Y., Liu, S., Xiao, J.: Regional contributions to interannual variability of net primary production and climatic attributions, *Agric. For. Meteorol.*, 303, 108384, <https://doi.org/10.1016/j.agrformet.2021.108384>, 2021.

Rao, W., Shen, Z., Duan, X.: Spatiotemporal patterns and drivers of soil erosion in Yunnan, Southwest China: RULSE assessments for recent 30 years and future predictions based on CMIP6, *Catena.*, 220, 106703, <https://doi.org/10.1016/j.catena.2022.106703>, 2023.

Piao, S., Wang, X., Park, T., Chen, C., Lian, X., He, Y., Bjerke, J., Chen, A., Ciais, P., Tømmervik, H., Nemani, R., Myneni, B.: Characteristics, drivers and feedbacks of global greening, *Nat. Rev. Earth Envir.*, 1, 14-27, <https://doi.org/10.1038/s43017-019-0001-x>, 2020.

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- Zhou, G., Wei, X., Chen, X., Zhou, P., Liu, X., Xiao, Y., Sun, G., Scott, D., Zhou, S., Han, L.,m Su, Y.: Global pattern for the effect of climate and land cover on water yield, *Nat Commun.*, 6, 5918, <https://doi.org/10.1038/ncomms6918>, 2015.
- Huang, S., Gan, Y., Chen, N., Wang, C., Zhang, X., Li, C., Horton, D.: Urbanization enhances channel and surface runoff: A quantitative analysis using both physical and empirical models over the Yangtze River basin, *J. Hydrol.*, 635, 131194, <https://doi.org/10.1016/j.jhydrol.2024.131194>, 2024.
- Cai, Y., Zhang, F., Duan, P.: Vegetation cover changes in China induced by ecological restoration-protection projects and land-use changes from 2000 to 2020, *Catena.*, 217, 106530, <https://doi.org/10.1016/j.catena.2022.106530>, 2022.
- Song, Z., Yang, H., Huang, X., Ma, M.: The spatiotemporal pattern and influencing factors of land surface temperature change in China from 2003 to 2019, *Int J Appl Earth Obs Geoinf.*, 104, 102537, <https://doi.org/10.1016/j.jag.2021.102537>, 2021.
- Wang, S., Fu, B., Piao, S., Lu, Y., Ciais., Feng, X., Wang, Y: Reduced sediment transport in the Yellow River due to anthropogenic changes, *Nat. Geosci.*, 9, 38-41, <https://doi.org/10.1038/ngeo2602>, 2016.
- Li, J., He, H., Zeng, Q., Chen, L., Sun, R.: A Chinese soil conservation dataset preventing soil water erosion from 1992 to 2019, *Sci Data.*, 10, 319, <https://doi.org/10.1038/s41597-023-02246-4>, 2023b.
- Zhao, M., Zhang, J., Velicogna, L., Liang, C., Li, Z.: Ecological restoration impact on total terrestrial water storage, *Nat Sustain.*, 4, 56-62, <https://doi.org/10.1038/s41893-020-00600-7>, 2021.

Comment 5: The Discussion section should be expanded to address limitations more thoroughly, including model simplifications (e.g., InVEST's omission of groundwater processes), data scarcity in remote regions, and remote sensing artifacts (e.g., NDVI distortions due to cloud cover). Additionally, suggestions for future improvements - such as annual dataset generation, inclusion of additional ES (e.g., biodiversity), or integration with socioeconomic data- -would help outline pathways for further development and application.

Response: Thanks for your comment. In the Limitation and Uncertainties section, we have now added discussions on model simplification, uncertainties caused by data loss, and suggestions for future improvements. The detailed content is as follows (**Lines 697-754**):

This study utilized remote sensing datasets and meteorological station data to compile long-term datasets of NDVI, vegetation coverage, evapotranspiration, potential evapotranspiration, and snow cover in China. These datasets effectively removed the missing or low-quality pixels in the original images, overcame the challenge of reconstructing data under cloud cover with limited information, and improved the precision of the monthly data. Although we used high-precision data to assess ecosystem services, there are several uncertainties and limitations. For example, we

calibrated the Landsat 5 and 8 spectral response data and calculated monthly and quarterly NDVI. However, there remains the possibility that sensor-related bias has not been fully eliminated (Anderson et al., 2020). Residual remote-sensing artifacts may remain after preprocessing, including undetected clouds/cloud-shadows and topographic illumination effects, mixed-pixel issues in ecotones, and NDVI saturation over dense-canopy regions (Lin et al., 2021). These factors may bias both spatial contrasts and temporal trends despite our cross-sensor harmonization. Although this study extensively utilizes site data to maximize available information and enhance spatial and temporal continuity, the ground observation data still face representativeness issues, and accuracy requires improvement in certain areas. Validating remote sensing products with site observation data is also subject to representativeness challenges, and uncertainties still exist in the accuracy verification process (Zhao et al., 2020).

The four ecosystem services were assessed using different satellite sources of data, while the ecosystem service maps are presented at 30m resolution - driven by the highest-resolution data (Landsat NDVI, GlobeLand30, and DEM) - other essential input data (e.g., climate and soil properties) were originally at coarser resolutions. Although these data were resampled to 30m resolution, this process inevitably introduces uncertainty (Yan et al., 2025). The fine-resolution output effectively captures spatial patterns defined by the land cover and NDVI. Still, the precision of absolute values in highly heterogeneous areas may be constrained by the inherent information content of the original coarser datasets (Liu et al., 2023).

Model-related structural limitations should also be acknowledged. Some of the ecosystem service modules (e.g., InVEST water yield) simplify hydrological and geomorphic processes and typically do not explicitly simulate groundwater recharge, surface – groundwater interactions, or threshold/nonlinear responses during extreme events (Redhead et al., 2016). Such simplifications can reduce accuracy in arid basins, karst areas, or groundwater-dependent systems. Data scarcity further increases uncertainty in remote regions. In high-elevation and desert areas (e.g., the Tibetan Plateau and arid Northwest), meteorological and hydrological stations are sparse, quality-controlled long time series are limited, and cloud/ice/snow contamination of optical imagery is more frequent (Walther et al., 2025).

Model-based assessments of ecosystem services inevitably involve multiple sources of uncertainty. These uncertainties primarily arise from errors in input data (such as climate variables, land cover types, and soil parameters, etc.), which propagate through the modeling process and have a cumulative effect on the results (Walther et al., 2025). Although cross-validation with existing products and ground-based observations demonstrates the overall robustness of the dataset, this study did not conduct a systematic approach to quantifying uncertainty. Future studies should incorporate quantitative uncertainty analysis, such as sensitivity analysis and error propagation analysis, to provide confidence intervals for key ecosystem service estimates. These potential uncertainties should be carefully considered when applying this dataset to fine-scale ecological planning, ecosystem restoration decision-making, and the design of payment for ecosystem services (PES) schemes.

In stable climatic conditions, many ecosystem services exhibit slow inter-annual variation. Thus, for numerous policy and management applications - such as evaluating long-term ecological restoration programs - a decadal assessment is often sufficient (Ouyang et al., 2016). However, we also note that with the increasing frequency of extreme climate events, which can significantly alter ecosystem services dynamics year-to-year, there is a growing scientific need for annual assessments (Dee et al., 2025). Moreover, improving data availability, particularly the emergence of more detailed annual land cover products, along with advancements in downscaling techniques, will further support the generation of annual ecosystem service datasets (Yang et al., 2021). We also provide suggestions for users who may wish to interpolate or model annual data, such as using our decadal data as benchmarks and integrating it with annually available coarser-resolution remote sensing indices (e.g., MODIS NDVI) for trend analysis and interpolation. Future research can also focus on other ecosystem services, including biodiversity and habitat quality, pollination, flood regulation, and water quality purification, thereby supporting a more comprehensive assessment. In addition, the biophysical layer can be combined with socio-economic data (such as population density, accessibility and infrastructure, water intake, economic activities and PES programs) to achieve scenario analysis, trade-off assessment and fair-oriented decision-making.

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