International Journal of Natural Resources and Environmental Studies

ISSN: 3006-2012 (Print), ISSN: 3006-0834 (Online) | Volume 8, Number 7, Year 2026
DOI: https://doi.org/10.62051/ijnres.v8n7.03
Journal homepage: https://wepub.org/index.php/IJNRES/index

Assessing Terrestrial Ecosystem Carbon Storage Under Land Use and Cover Change: Methods, Models, and Spatiotemporal Dynamics

Jiashuo Hou*

School of Surveying and Land Information Engineering, Henan Polytechnic University, Jiaozuo 454000, China

*Corresponding Author: Jiashuo Hou (hjs@home.hpu.edu.cn)

ABSTRACT

Quantifying terrestrial ecosystem carbon storage is critical for understanding the global carbon cycle, mitigating climate change, and achieving carbon neutrality targets. Land use and land cover change (LUCC) represents one of the most significant anthropogenic drivers of terrestrial carbon dynamics. Within the peer-reviewed English-language literature, the integration of remote sensing, geographic information systems (GIS), and spatially explicit models has become a prominent approach for carbon storage assessment. This review synthesizes a purposive sample of 23 peer-reviewed studies (2006–2025) across four analytical dimensions: (1) carbon storage estimation models, including the InVEST framework, Gaussian process regression (GPR), DNDC, and CBM-CFS3; (2) land use simulation models such as FLUS, PLUS, and CLUE-S; (3) multi-scenario prediction frameworks; and (4) driving factor analyses. A structured comparison of model architectures, validation approaches, and reported accuracies reveals systematic strengths and limitations within each model class as represented in this corpus. The synthesis identifies five cross-cutting concerns in the reviewed literature: (i) a pronounced geographic concentration on Chinese study sites (65% of the corpus), which limits the global generalizability of the synthesized findings; (ii) the near-absence of out-of-sample validation for coupled LUCC–carbon frameworks within the reviewed studies; (iii) potential confirmation bias toward positive model performance reporting; (iv) a conceptual gap between static carbon density look-up approaches and dynamic biogeochemical process representations; and (v) a temporal scale mismatch between land use simulation time steps and carbon flux timescales. Future research priorities identified from this corpus include independent multi-model validation against field measurements, formal uncertainty propagation through coupled model chains, and the operationalization of carbon storage modeling within the Sustainable Development Goal (SDG) monitoring framework—each contingent on geographic diversification beyond the currently dominant Chinese study sites.

KEYWORDS

Carbon Storage; Land Use/Cover Change; Invest Model; FLUS Model; Remote Sensing Estimation; Scenario Simulation; Uncertainty Quantification.

1. INTRODUCTION

Global climate change is among the most urgent environmental challenges of the twenty-first century. Terrestrial ecosystems function as a critical carbon sink, sequestering approximately 30% of anthropogenic CO2 emissions annually[17] and playing an irreplaceable role in regulating the global carbon cycle. Accurate assessment and prediction of ecosystem carbon storage dynamics address both a foundational scientific question in carbon cycle research and an urgent policy need for nations formulating carbon neutrality strategies[6] [15].

Land use and land cover change (LUCC) is widely recognized as the most significant anthropogenic factor influencing terrestrial carbon storage[28]. The conversion of forests, grasslands, and wetlands to cropland and impervious surfaces substantially alters aboveground biomass carbon pools, belowground biomass carbon pools, soil organic carbon (SOC) pools, and dead organic matter carbon pools. Consequently, elucidating the coupling relationship between LUCC and carbon storage, and projecting future carbon trajectories under alternative development pathways, has become a central research priority.

Advances in remote sensing technology, geographic information systems (GIS), and artificial intelligence have progressively transformed carbon storage assessment from field-based empirical estimation toward integrated frameworks that couple multi-source remote sensing data, spatially explicit land use simulation models, and ecosystem service valuation tools. This review draws on a curated corpus of 23 peer-reviewed studies, predominantly published between 2021 and 2024 (74%), with foundational work extending back to 2006, to address three guiding questions:

1. What are the comparative strengths and limitations of the major carbon storage estimation and land use simulation paradigms?
2. How consistent are multi-scenario carbon storage projections across different models, ecosystems, and geographic contexts?
3. What methodological gaps and biases currently constrain the policy applicability of coupled LUCC–carbon frameworks?

This review complements and extends several prior syntheses. Among reviews of ecosystem service modeling tools, the Comparative Ecosystem Service Assessment framework of Bagstad et al. Bagstad et al. [1] evaluated InVEST and other tools but did not focus on carbon storage specifically or address land use simulation coupling. Ouyang et al.[2] reviewed the application of InVEST across multiple ecosystem services globally, yet their carbon storage coverage was limited to descriptive summaries of model outputs rather than critical analysis of model architecture. More recently, Chen et al.[3] conducted a bibliometric analysis of LUCC–carbon storage research covering 2000–2022, identifying broad publication trends but without the structured model comparison and gap analysis that distinguish the present review. The contribution of this review is therefore threefold: (i) a structured, criterion-based comparison of carbon estimation paradigms (static bookkeeping, statistical/ML, process-based) as applied in coupled LUCC–carbon frameworks; (ii) an explicit analysis of how land use simulation model choices (CLUE-S, FLUS, PLUS) propagate to carbon storage estimates through their differing spatial representations; and (iii) a set of corpus-specific, actionable research priorities derived from systematic cross-study comparison rather than from general methodological commentary.

The review is organized as follows. Section 2 describes the literature selection approach and corpus characteristics. Section 3 examines carbon storage estimation models and their mechanistic differences. Section 4 analyzes coupled LUCC–carbon simulation frameworks and scenario applications. Section 5 synthesizes carbon dynamics across ecosystem types and their driving mechanisms. Section 6 evaluates methodological trends and identifies literature-specific research gaps. Section 7 charts future research directions, and Section 8 concludes.

2. LITERATURE SELECTION

This review draws on a purposive sample of 23 peer-reviewed studies published between 2006 and 2025, identified through a targeted search of Web of Science, Scopus, and Google Scholar for English-language articles coupling land use/cover change analysis with spatially explicit carbon storage estimation. The corpus is predominantly composed of studies applying the InVEST carbon module in conjunction with land use simulation models (FLUS, PLUS, and CLUE-S), supplemented by selected process-based (DNDC, CBM-CFS3) and remote sensing–driven (GPR, Sentinel-based) approaches to enable cross-paradigm comparison. Three scope limitations should be noted: (i) the search targeted named models and therefore underrepresents the broader process-based modeling literature (e.g., CENTURY, RothC, Biome-BGC, DGVMs); (ii) English-language restriction excludes relevant research published in Chinese-language journals, which is consequential given that 65% of the corpus is set in China (Section 6.2.1); and (iii) the 23-study corpus constitutes a purposive rather than exhaustive sample. The studies are distributed across four ecosystem types (forest, coastal wetland, cropland, and dryland/savannah) and span geographic contexts in China ($_{n=15}$), India, Sri Lanka, Sudan, Ecuador, Italy, and a global-scale analysis. A summary of study characteristics is provided in the Supplementary Materials.

3. CARBON STORAGE ESTIMATION MODELS

3.1. The InVEST Carbon Module

The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model, developed by the Natural Capital Project, is the most widely applied tool for spatially explicit carbon storage assessment **within the coupled LUCC–carbon literature captured by this review's search** (15 of the 23 reviewed studies employ InVEST as their primary carbon estimation module). Its carbon storage module estimates regional carbon stocks based on land use/cover maps and carbon density values assigned to four pools: aboveground biomass carbon, belowground biomass carbon, soil organic carbon, and dead organic matter carbon. Crucially—and as the model's own documentation makes clear[27]—InVEST operates as a **static bookkeeping model:** it multiplies land use area by assigned carbon density coefficients and does not simulate biogeochemical processes dynamically. This design choice makes InVEST computationally efficient and easy to parameterize but also means that its results are entirely determined by the accuracy and spatial representativeness of the input carbon density values.

Babbar et al. (2021) combined a Markov chain model with InVEST to assess and predict carbon sequestration in the Sariska Tiger Reserve, India, from 1990 to 2020. Their results demonstrated that the conversion of forest to other land cover types was the primary driver of carbon storage decline, with the Markov chain providing a probabilistic basis for projecting future land cover transitions. He et al. (2023) extended this framework in Guilin, China, by integrating four future scenarios aligned with the Sustainable Development Goals (SDGs)[18]. Under the ecological priority scenario, total carbon storage in 2035 reached $874.76{\times}10^6$ t, substantially exceeding the other three scenarios. However, it is important to recognize that this result is **model-inherent rather than empirically discovered**: InVEST calculates carbon storage as the area-weighted sum of land use $\times$ carbon density, and ecological protection scenarios allocate more area to forest and wetland—land cover classes with the highest assigned carbon densities. The finding that "ecological protection yields higher carbon storage" is thus a direct algebraic consequence of the model architecture, not an independent empirical validation of conservation effectiveness. This observation applies with equal force to all reviewed InVEST-based scenario studies.

Piyathilake et al. (2022) validated the applicability of the InVEST model in the tropical context of Uva Province, Sri Lanka[25]. Their findings revealed that agricultural expansion exerted the most pronounced negative impact on carbon storage, and that forest conservation constituted the most cost-effective strategy for preserving regional carbon balance. Together, these three studies illustrate the cross-continental applicability of the InVEST carbon module. However, **no study in this corpus independently validated InVEST-derived carbon storage estimates against field-measured carbon stocks for the same spatial extent**—a significant evidence gap that is revisited in Section 6.2.

3.2. Land Use Simulation Models: FLUS, PLUS, and CLUE-S

Accurate simulation of future land use patterns is a prerequisite for predicting carbon storage trajectories. Three models have gained prominence, and their differences in spatial representation and transition modeling carry direct implications for downstream carbon estimates.

Table 1 Comparison of Land Use Simulation Model Architectures

Feature	CLUE-S	FLUS	PLUS
Core mechanism	Logistic regression + CA	ANN + CA with adaptive inertia	Land expansion analysis + CA with multi-type random seeds
Spatial grain	–1000 m	–100 m	–100 m
Transition rule learning	Statistical (logit)	Machine learning (ANN)	Machine learning (random forest + ANN)
Patch generation	Coarse—grid-based	Moderate—neighborhood effects	Fine—patch-level seed expansion
Handling of multiple land types	Constrained by regression df	ANN handles co-evolution well	Explicit patch-level competition
Key limitation	Over-smoothing in heterogeneous landscapes	ANN black box interpretability	Computationally more expensive
Carbon-relevant application in corpus	[20]	[18]; [28]; [9]	[33]

The **FLUS (Future Land Use Simulation) model** integrates an artificial neural network (ANN) with a cellular automaton (CA) mechanism, enabling it to simulate the co-evolution of multiple land use types. In the Guilin study, He et al. (2023) identified forestland as the most important conversion type across all scenarios[18]. Shao et al. (2023) applied FLUS-InVEST to the Chengdu–Chongqing urban agglomeration and documented a total carbon storage loss of 29.45×10^6 Mg from 2010 to 2020 (approximately 3.7 Mg/ha when normalized by study area extent) [28]. Cao et al. (2022) enhanced the framework by introducing a quantitative carbon value loss assessment in the Qiantang River source region, finding that the food security scenario incurred the smallest economic carbon loss (approximately US$1.39 $\times$ 109) [9].

The **PLUS (Patch-generating Land Use Simulation) model** improves upon FLUS through an enhanced land expansion analysis strategy that better captures patch-level dynamics. In a coastal application in Dalian, PLUS-InVEST identified fine-scale urban expansion effects on carbon storage that would have been smoothed over by coarser models, projecting 8–12% mitigation of carbon losses under ecologically constrained development[33].

The **CLUE-S model** was the earliest of the three to be coupled with InVEST. Its application to urban carbon storage produced early evidence that compact urban development patterns preserve the largest carbon stocks—a finding that underpins the land-sparing hypothesis in urban carbon management[20].

A **critical methodological observation** is that none of the reviewed studies formally quantified the uncertainty propagated from the land use simulation step to the carbon estimation step. FLUS/PLUS land use projections are treated as deterministic inputs to InVEST, yet land use simulation accuracy typically ranges from 75–90% (as measured by kappa coefficients). The resulting carbon storage estimates thus carry unquantified compound uncertainty—a concern elaborated in Section 6.2.

3.3. Remote Sensing–Driven Carbon Estimation

Satellite remote sensing bypasses the intermediate step of land use classification by directly establishing quantitative relationships between spectral variables and carbon stock parameters. This approach offers the advantage of **continuous spatial coverage and repeatable temporal observations**, but its accuracy depends on the quality of ground-truth training data and the representativeness of the spectral signal for subsurface carbon.

Ayala Izurieta et al. (2022) combined Sentinel-2 multispectral imagery with Gaussian process regression (GPR) to predict SOC in the páramo ecosystem of Ecuador. Their models achieved an R^2 of 0.85 (SOC%) for the 0–30 cm profile and R^2=0.86 for the 30–60 cm profile—notably the **only study in the corpus to assess deep(er) soil carbon (>30 cm)**. Canopy water content (CWC) emerged as the single most relevant predictor, improving estimation accuracy by 3–21% over models relying solely on GIS predictors (elevation, slope, precipitation). Reyes-Muñoz et al. (2024) scaled the GPR approach globally using Sentinel-3 and Sentinel-5P observations, demonstrating that hybrid physical–machine learning frameworks can constrain continental-scale carbon flux estimates[26].

Deng et al. (2011) provided an early GIS-based quantitative framework for mapping forest carbon sink values, establishing the spatial analysis workflow that underpins contemporary approaches[16]. Table 2 summarizes the performance characteristics of the three main estimation paradigms.

Table 2 Comparison of Carbon Storage Estimation Paradigms

Paradigm	Models	Process Representation	Key Inputs	Typ. R^2	Main Limitation
Static bookkeeping	InVEST	None—look-up table multiplication	Land use map + C density coefficients	N/A[a]	Accuracy entirely dependent on C density parameter quality
Statistical/ML	GPR, Sentinel-based	None—empirical correlation	Satellite bands + GIS predictors + training data	0.79–0.86	May not generalize across climatic/edaphic zones
Process-based	DNDC, CBM-CFS3	Full—simulates biogeochemistry	Climate data, soil properties, management, inventory	RMSE 15–30%[b]	High data requirements; computationally intensive

[a]No independent field validation available in the reviewed corpus.
[b]Modeled vs. inventory RMSE; not directly comparable to R^2 from statistical models.

3.4. Process-Based Models and Statistical Approaches

Process-based biogeochemical models represent a fundamentally different paradigm from InVEST and GPR: they **simulate the mechanisms** governing carbon fluxes rather than empirically mapping or statistically correlating carbon stocks.

The **DNDC (DeNitrification-DeComposition) model** simulates carbon and nitrogen biogeochemistry in agroecosystems through a series of interacting sub-models representing soil climate, crop growth, decomposition, nitrification, denitrification, and fermentation. Unlike InVEST, which treats SOC as a static parameter, DNDC dynamically simulates SOC changes in response to management practices (tillage, fertilization, irrigation) and climate variability. Tang et al. (2006) applied DNDC to estimate SOC storage across Chinese croplands, providing one of the earliest spatially explicit national-scale SOC assessments[30]. The model's process richness, however, comes at the cost of high input data requirements (daily climate data, soil texture profiles, crop management calendars) that limit its applicability in data-sparse regions.

The **CBM-CFS3 (Carbon Budget Model of the Canadian Forest Sector)** simulates forest carbon dynamics through a system of empirically derived yield curves, decomposition parameters, and disturbance matrices. Pilli et al. (2013) adapted CBM-CFS3 to estimate Italy's national forest carbon budget for 1995–2020, integrating national forest inventory data with modeled carbon transfers among biomass, dead organic matter, and soil pools[24]. This framework has directly informed Italy's national greenhouse gas reporting under the UNFCCC, establishing it as **an operationally validated Tier 3 methodology** under the IPCC Guidelines.

A critical model-selection consideration emerges: for researchers whose primary objective is spatial carbon storage mapping at regional scales, InVEST's simplicity and ease of parameterization make it the pragmatic choice. For those requiring mechanistic understanding of carbon dynamics under environmental change, process-based models are indispensable. The GPR approach occupies an intermediate niche, providing high accuracy where dense ground-truth data exist but offering limited insight into process mechanisms. **No study in the corpus simultaneously applied and compared estimates from two or more of these paradigms for the same study area**—a comparison that would provide valuable evidence for model selection guidance.

An important caveat on model evaluation: the three paradigms serve fundamentally different purposes, and evaluating them all against a single standard of mechanistic completeness would be inappropriate. InVEST was designed as a rapid ecosystem service assessment tool for data-sparse contexts; criticizing it for lacking biogeochemical process representation is akin to criticizing a bicycle for lacking an engine—the tool was optimized for accessibility and ease of use, not mechanistic depth[27]. Process-based models (DNDC, CBM-CFS3, and the broader families of CENTURY/RothC SOC models and dynamic global vegetation models such as LPJ-GUESS and ORCHIDEE not captured by this review's search strategy) were designed for mechanistic simulation and require substantially greater data infrastructure. GPR was designed for empirical prediction accuracy where training data permit. The appropriate evaluation question is therefore not "which paradigm is best?" but "which paradigm is fit for which purpose?"—and the answer depends on the decision context. A national carbon inventory compiler requiring Tier 3 IPCC compliance needs process-based transparency; a regional land use planner conducting rapid scenario screening may be adequately served by InVEST's order-of-magnitude estimates, provided the uncertainty is transparently communicated. The review's critiques should be understood as identifying limitations given the model's intended use—an InVEST limitation that matters for carbon accounting (no process representation of SOC stabilization) is different from a limitation that matters for land use screening (the tautology described in Section 3.1). This review does not establish that any specific model limitation has caused a documented policy error; rather, it identifies gaps whose practical consequences remain to be empirically demonstrated[19].

In the statistical domain, Wu et al. (2018) applied spatiotemporal statistical analysis to evaluate the effectiveness of China's Natural Forest Protection Program (NFPP), identifying forest age structure and species composition as the key determinants of carbon accumulation rates[34].

4. MULTI-SCENARIO SIMULATION AND PREDICTIVE ASSESSMENT

A defining feature of contemporary carbon storage research is the incorporation of multi-scenario simulations. Studies in this corpus typically define three to four contrasting pathways, which can be conceptually organized along two orthogonal axes: development intensity (ecological protection ↔ economic growth) and policy intervention (planned ↔ laissez-faire).

1) Natural development (business-as-usual) scenario.

Land use evolves according to historical trends. The largest carbon losses consistently emerge under this trajectory—in the Qiantang River source region, continued forest conversion at historical rates would produce the most severe carbon depletion among all scenarios tested[9].

2) Economic development priority scenario.

Urban expansion is prioritized. Under this scenario in Wuhan, built-up land expanded by 751.24 km2 ($>$ 10% increase), producing the most pronounced carbon storage decline among all tested pathways[32]. The finding is replicated across the corpus—the economic priority scenario is consistently associated with the lowest carbon storage outcomes[28] [33].

3) Ecological protection priority scenario.

High-carbon-density land covers (forests, wetlands, grasslands) are protected. He et al. (2023) and Wu et al. (2024) found this scenario yielded the highest total carbon storage[18], [33]. However, as noted in Section 3.1, this outcome is tautologically embedded in the InVEST model architecture: protecting high-carbon-density land covers mathematically guarantees higher modeled carbon storage. The genuinely informative question—whether ecological protection policies produce carbon storage outcomes that exceed model predictions—cannot be answered within the current modeling paradigm without independent field validation.

4) Sustainable development scenario.

A middle path balancing economic growth with ecological protection. Chuai et al. (2013) provided an early optimization framework introducing the concept of low-carbon-emission, high-carbon-storage land allocation .

4.1. Cross-study comparison.

Despite the consistency in scenario typology, the quantitative outcomes vary substantially across studies. Normalized carbon storage change under the ecological protection scenario ranges from a slight decline (Cao et al., 2022, in the Qiantang River region) to a clear increase (He et al., 2023, in Guilin) [9], [18]. This variability likely reflects differences in baseline land use patterns, carbon density parameterization, and the stringency of ecological constraints—factors that are not standardized across studies and limit inter-study comparability.

Zhang et al. (2023) expanded the analytical lens beyond carbon storage alone, linking wetland carbon dynamics in coastal urban agglomerations to SDG target 15.1 (conservation of terrestrial and freshwater ecosystems) [36]. This study stands out as the only one in the corpus to **operationalize carbon storage as an SDG indicator**, a direction developed further in Section 7.

5. CARBON STORAGE ACROSS ECOSYSTEM TYPES AND THEIR DRIVERS

A note on synthesis approach. Section 3.1 established that InVEST-based carbon storage estimates are model-inherent—the model's scenario rankings are algebraically determined by land use allocation rather than empirically discovered. This critique raises a legitimate question: if InVEST outputs are tautologically conditioned on land use inputs, what value do they add to an ecosystem-level synthesis? The answer is that InVEST studies contribute two types of information that remain useful despite the tautology: (i) they provide **spatially explicit carbon storage baselines** derived from land use maps and carbon density parameters, which—while not independently validated—represent the best available spatially continuous estimates for many regions; and (ii) they enable **cross-ecosystem comparison of carbon density parameterization**, which reveals how different studies assign carbon values to the same land cover classes. The synthesis below draws on InVEST-based studies for these purposes while noting where findings are conditioned on model architecture. Process-based and field-survey studies in the corpus provide independent lines of evidence against which InVEST-based patterns can be qualitatively compared.

5.1. Forest Ecosystems

Forests constitute the largest terrestrial carbon reservoir, and five studies in the corpus focus specifically on forest carbon dynamics. Xiang et al. (2022) reported a synergistic effect of rotation age extension in Chinese fir plantations—simultaneously increasing ecosystem carbon storage and timber production—a notable "win-win" outcome[35]. Chu et al. (2019) quantified carbon sequestration across the Three-North Shelterbelt Program (TNSP) region, confirming the positive contribution of this large-scale afforestation initiative while noting constraints from climatic factors and species selection[12]. Wu et al. (2018) found that forest age structure and species composition—rather than total forest area alone—were the primary determinants of carbon accumulation rates under the NFPP[34]. Pilli et al. (2013) and Alam et al. (2013) extended the forest carbon evidence base to Italian national forests and Sudanese woodland savannah, respectively, demonstrating that process-based and field-survey approaches converge on the primacy of forest management intensity for carbon outcomes[4] [24].

Driving mechanisms. The dominant drivers of forest carbon storage change across the corpus are: (a) afforestation/deforestation dynamics (policy-driven in China; land-use-competition-driven elsewhere), (b) forest age structure (younger forests sequester carbon faster; older forests store more total carbon), and (c) species composition (broadleaf vs. conifer; native vs. plantation). Climate change exerts an indirect influence through drought stress and disturbance regime intensification, yet **no reviewed forest study incorporated climate feedback into its scenario projections**.

5.2. Coastal Wetlands and Saltmarshes

Coastal wetlands and saltmarshes—"blue carbon" ecosystems—are characterized by carbon densities an order of magnitude higher than most terrestrial ecosystems, owing to anaerobic soil conditions that suppress decomposition. Four studies in the corpus address blue carbon systems. Li et al. (2022) conducted a 33-year (1987–2020) monitoring of saltmarsh carbon storage along China's eastern coast, documenting a net decline of 10.44 Tg, with reclamation as the dominant driver[22]. Paradoxically, Spartina alterniflora invasion increased carbon storage in Shanghai and Jiangsu—a finding that raises an important **carbon-biodiversity trade-off**: the invasive species enhances one ecosystem service (carbon sequestration) while undermining another (native biodiversity).

Zhu et al. (2022) modeled the 1980–2050 trajectory of coastal carbon storage, finding that the combined effects of sea-level rise, reclamation, and land use change produce regionally heterogeneous outcomes[37]. Zhang et al. (2023) connected wetland carbon dynamics to SDG 15.1[36]. Chen et al. (2025) enriched the blue carbon methodological toolkit by quantifying coastal zone carbon dynamics from a remote sensing perspective[10].

Driving mechanisms. Reclamation is the dominant driver of blue carbon loss[22] [37]. Biological invasion exerts a bidirectional effect (carbon gain vs. biodiversity loss). Sea-level rise and hurricane disturbances interact with anthropogenic pressures to produce non-linear carbon responses that are poorly captured by the static carbon density approach used in InVEST-based coastal assessments.

5.3. Cropland and Grassland Ecosystems

Cropland SOC dynamics are governed by a fundamentally different set of processes than forest or wetland carbon. **Soil organic carbon stabilization**—the conversion of plant inputs into mineral-protected, long-residence-time carbon—depends on three interacting mechanisms: (i) **mineral association** (sorption of organic matter onto clay and silt particles, forming mineral-associated organic matter, MAOM), (ii) **aggregate occlusion** (physical protection of particulate organic matter, POM, within soil aggregates), and (iii) **microbial carbon use efficiency** (the proportion of decomposed carbon incorporated into microbial biomass rather than respired as CO2). These mechanisms have been synthesized into the **MAOM/POM conceptual framework**, which distinguishes two functionally distinct SOC pools with different formation pathways, residence times, and responses to land use change[13] [14] [21]. POM consists primarily of partially decomposed plant litter and is stabilized through aggregate occlusion; it is fast-cycling (residence time: years to decades) and highly responsive to management changes such as tillage regime and residue retention.

MAOM consists of low-molecular-weight compounds sorbed to mineral surfaces; it is slow-cycling (residence time: decades to centuries) and has a finite formation capacity determined by soil texture and mineralogy—the **soil carbon saturation** concept[7] [29]. When a soil approaches its MAOM saturation limit, additional carbon inputs are partitioned toward POM or lost as CO2, producing a nonlinear relationship between carbon input rate and SOC storage.

None of these mechanisms is represented in the InVEST carbon module, which treats SOC as a static parameter. This is consequential for land use change assessments: InVEST applies a single SOC density coefficient per land cover class, which means it cannot distinguish between (a) a sandy cropland with low MAOM capacity that is near saturation and would show negligible SOC gain upon afforestation, and (b) a clay-rich cropland far from saturation that would show substantial SOC accumulation. The model thus systematically misestimates SOC responses to land use change in soil-type-dependent ways that are non-random with respect to the carbon density classification. DNDC partially captures decomposition dynamics but does not resolve mineral-organic interactions explicitly. This mechanistic gap is significant because land use changes that alter soil pH, aggregate stability, or microbial community composition can shift SOC stocks through pathways that static look-up tables cannot capture—and the direction and magnitude of the resulting errors depend on soil properties not represented in the model architecture.

Tang et al. (2006) established the methodological foundation for national-scale cropland SOC estimation in China using DNDC[30]. The model's dynamic representation of tillage effects, residue management, and fertilization on SOC provides process-level insight that InVEST-based cropland assessments lack, although the data requirements (daily climate, soil profile characteristics, crop calendars) constrain its spatial coverage. In arid regions, Alam et al. (2013) assessed tree biomass and SOC density across the Sudanese woodland savannah, providing rare dryland baseline data that reveal substantially lower carbon densities ($\sim$10–30 Mg C/ha) than those reported for temperate and tropical forests in the China-focused studies (typically 50–150 Mg C/ha) [4].

Driving mechanisms. Agricultural management intensity (tillage regime, residue retention, fertilization), soil texture (clay content drives MAOM formation capacity), and climate (temperature controls decomposition rates; precipitation controls net primary productivity) interact to determine cropland and grassland carbon trajectories. Wang, Chen, et al. (2022) demonstrated on the Loess Plateau that the Grain for Green Program produced spatially heterogeneous carbon recovery, with the magnitude of SOC increase varying by a factor of $\sim$3 depending on topographic position and restoration age[31].

5.4. Cross-Ecosystem Synthesis

Table 3 synthesizes the carbon storage dynamics and dominant drivers across the four ecosystem types.

Table 3 Carbon Storage Dynamics and Dominant Drivers by Ecosystem Type

Ecosystem	C Density (typical)	Primary C Pool	Dominant Driver of Change	Key Model Limitation	Representative Studies
Forest	50–150 Mg C/ha	Aboveground biomass	Policy-driven afforestation/ deforestation	Climate feedbacks not incorporated	[12] 24] [34] [35]
Coastal wetland / saltmarsh	150–300 Mg C/ha	Soil organic carbon	Reclamation; sea-level rise	Static C density ignores anaerobic C dynamics	[22] [36] [37]
Cropland	30–80 Mg C/ha	Soil organic carbon	Management intensity (tillage, residue)	MAOM/POM dynamics not represented in InVEST	[30] [31]
Dryland/savannah	10–50 Mg C/ha	SOC + scattered woody biomass	Climate variability; grazing pressure	Severely under-studied; only 1 study in corpus	[4]

Note: Carbon density ranges reflect the predominantly temperate and subtropical Asian ecosystems represented in this corpus (65% of studies set in China). Tropical forests on highly weathered soils may have aboveground biomass carbon exceeding 200 Mg C/ha; boreal forests on Histosols may have SOC exceeding 500 Mg C/ha but lower biomass carbon. Ranges should be interpreted as corpus-representative rather than globally comprehensive.

6. METHODOLOGICAL TRENDS AND RESEARCH GAPS

6.1. Methodological Evolution

A chronological analysis of the corpus reveals four clear trajectories:

- **From statistical models to machine learning.** The progression from geostatistical interpolation [16] [30] to Gaussian process regression[5] to hybrid physical–ML approaches[26] tracks the broader shift in environmental modeling toward data-driven methods. However, the interpretability trade-off is real: GPR models provide accurate predictions but offer no mechanistic insight into why particular spectral bands predict SOC.
- **From single-model to coupled frameworks.** The CLUE-S → FLUS → PLUS progression [18] [20] [33] reflects continuous improvement in spatial simulation fidelity. However, the coupling is currently unidirectional and deterministic—land use model outputs feed into carbon models without feedback or uncertainty propagation.
- **From historical assessment to multi-scenario prediction.** The scope of analysis has expanded from documenting past changes[4] to projecting alternative futures[6] [9]. This expansion is policy-relevant but also introduces new uncertainties associated with scenario assumptions.
- **From local to regional scales.** Most studies remain focused on specific regions. Reyes-Muñoz et al. (2024) is the only study operating at a true global scale, and it addresses carbon fluxes rather than stocks[26].

6.2. Research Gaps

The following gaps are identified through **cross-study analysis of this specific corpus**—they represent limitations observed in the reviewed literature, not generic modeling critiques.

6.2.1. Geographic Concentration

Fifteen of the 23 reviewed studies (65%) are set in China, with the remaining studies distributed across India ($n=1$), Sri Lanka ($n=1$), Sudan ($n=1$), Ecuador ($n=1$), Italy ($n=1$), and global-scale ($n=1$), plus two studies without specific geographic constraints. This concentration has three implications for the review's conclusions. First, the carbon density parameters used in InVEST-based Chinese studies may not transfer to tropical, boreal, or arid ecosystems with fundamentally different carbon density profiles. Second, China's unique policy context—characterized by strong state-led ecological programs (TNSP, NFPP, Grain for Green)—may not generalize to regions with different governance structures. Third, the predominance of temperate and subtropical Asian ecosystems means that boreal, tropical rainforest, and dryland carbon dynamics are underrepresented in the synthesized findings. Future reviews should deliberately seek out studies from Africa, South America, and Southeast Asia to balance geographic coverage. **Counterfactual significance:** If this gap were closed through deliberate investment in carbon storage modeling studies across underrepresented biomes, the global evidence base would support (a) region-specific carbon density coefficients that reflect the substantially different carbon density profiles of tropical forests (high biomass, variable SOC), drylands (low but extensive SOC), and boreal systems (peat-rich SOC), (b) model selection guidance that accounts for the different data infrastructures and policy contexts of developing-country settings, and (c) an assessment of whether the InVEST tautology identified in this review (Section 3.1) is specific to China's policy context or generalizes across governance regimes.

6.2.2. Absence of Independent Validation

A striking finding of this review is that **no study in the corpus independently validated InVEST-derived carbon storage estimates against coincident field measurements**. The InVEST carbon module produces spatially explicit carbon storage maps, but the accuracy of these maps is inherited entirely from the carbon density look-up table—typically derived from literature values, national inventory data, or measurements from ecologically similar (but not identical) sites. This creates a **validation gap**: the model's output accuracy is assumed rather than demonstrated. Studies using GPR [5] and DNDC[30] do report validation statistics, but these are internal to the model training/evaluation process rather than independent comparisons with an external measurement dataset. A high-priority methodological need is a multi-site study that compares InVEST-derived, GPR-derived, and field-measured carbon storage for the same spatial domains. **Counterfactual significance**: Closing this gap would provide the first systematic evidence on whether InVEST's simplicity trades off accuracy, and by how much—enabling practitioners to make evidence-based model selection decisions. If InVEST-derived estimates were shown to deviate from field measurements by, for example, $\pm$30–50%, policy documents citing InVEST projections as precise figures (e.g., "$1{,}844.68 \times 10^6$ Mg") would need to be reinterpreted as order-of-magnitude indicators. Conversely, if InVEST performed within $\pm$10–15% of field measurements, the criticism of its static architecture would be primarily conceptual rather than practically consequential.

6.2.3. Potential Publication Bias

Every study in the corpus reports favorable model performance: R^2 values range from 0.79 to 0.86 for GPR-based studies, and all InVEST-based scenario studies report internally consistent, policy-relevant findings. **The complete absence of null results, model failures, or negative validation outcomes** is statistically improbable for a literature of this size and raises the possibility of publication bias—studies finding poor model performance may go unpublished, or authors may selectively report only their best-performing model configurations. The review cannot determine whether this reflects genuine uniformly high model performance or a reporting bias, but the pattern warrants explicit acknowledgment. Future primary research should pre-register model validation protocols and report both successful and unsuccessful model configurations. **Counterfactual significance:** If publication bias were eliminated through pre-registration and registered reports, the literature would reveal the true distribution of model performance—including failure cases that are currently invisible. This would allow practitioners to estimate the probability that a given model configuration will perform adequately in a new study area, rather than relying on a literature that may represent only the right tail of the performance distribution. For carbon accounting and policy applications, knowing when and where models fail is as important as knowing when they succeed.

6.2.4. Unquantified Uncertainty Propagation

In coupled FLUS/PLUS-InVEST frameworks, the land use simulation output serves as the direct input to the carbon storage module, but the uncertainty inherent in the land use projection (kappa coefficients typically 0.75–0.90) is not propagated to the carbon storage estimate. This means that reported carbon storage projections (e.g., "1,844.68 × 106 Mg under the ecological protection scenario") are presented as point estimates without confidence intervals—a practice that overstates precision and complicates scenario comparison. A Monte Carlo uncertainty propagation framework, sampling from the land use simulation's error distribution and re-calculating carbon storage for each realization, would address this gap. **Counterfactual significance:** If uncertainty were formally propagated, scenario comparisons—which currently report deterministic differences (e.g., "Scenario A stores X Mg more than Scenario B")—would instead report overlapping or non-overlapping probability distributions. This would transform policy interpretation: a scenario difference that is statistically indistinguishable from zero (overlapping 95% CIs) would not support policy preference for one scenario over another, regardless of the point estimate difference. Conversely, a scenario difference that survives uncertainty propagation would constitute substantially stronger evidence for policy action.

6.2.5. Temporal Scale Mismatch

Land use simulation models typically operate at 5–10 year time steps, while carbon flux processes (photosynthesis, respiration, decomposition) operate at daily to seasonal timescales. The static carbon density approach used in InVEST assumes instantaneous equilibrium between land use change and carbon stock adjustment, which is biologically unrealistic—soil carbon, in particular, requires decades to centuries to reach a new equilibrium following land use conversion. This temporal mismatch means that short-to-medium-term scenario projections (e.g., 2030, 2035) may systematically overestimate carbon stock changes, as the modeled equilibrium has not been reached in reality. Counterfactual significance: Closing this gap—through transient carbon response functions or dynamic carbon density coefficients that relax toward equilibrium values over biome-specific timescales—would produce more realistic near-term projections. For policy timelines targeting 2030 or 2035 (e.g., nationally determined contributions under the Paris Agreement), equilibrium-assuming models may overstate achievable carbon gains from land use interventions, creating an expectations gap between modeled potential and biophysical reality. Quantifying the magnitude of this overestimation would allow policy targets to be calibrated to the carbon accumulation rates that are actually achievable within policy-relevant time horizons.

7. FUTURE RESEARCH DIRECTIONS

Based on the gaps identified above, five research priorities are proposed:

1. **Independent multi-model validation.** A high-priority study design would apply InVEST, GPR, and at least one process-based model (e.g., DNDC or CBM-CFS3) to the same study area, with coincident field measurements serving as an independent validation dataset. This would provide the first systematic evidence on the relative accuracy of the three modeling paradigms and guide model selection for practitioners. The absence of such a comparison in the current corpus is the single most actionable gap identified by this review.
2. **Formal uncertainty quantification in coupled frameworks.** Monte Carlo or Bayesian approaches to propagating uncertainty from land use simulation outputs through carbon

estimation modules would transform the current practice of reporting deterministic point estimates into the more scientifically defensible practice of reporting probability distributions.

3. **Geographic diversification of study sites.** The 65% China concentration constrains global generalizability. Deliberate investment in carbon storage modeling studies in currently underrepresented regions—Sub-Saharan Africa, South America, Southeast Asia, and boreal zones—is essential for a globally representative evidence base.
4. **Operationalizing carbon storage as an SDG indicator.** Zhang et al. (2023) provided a proof-of-concept for linking carbon storage modeling to SDG 15.1[36]. However, operationalizing this linkage requires navigating the institutional architecture of the SDG indicator framework. Carbon storage is not currently a standalone SDG indicator; integration would most feasibly occur through SDG indicator 15.3.1 (proportion of land that is degraded over total land area), for which the UNCCD is the custodian agency, or through a sub-indicator of SDG 15.1.1 (forest area as a proportion of total land area, custodian: FAO). Both pathways require engagement with the IAEG-SDG methodological review process and would benefit from alignment with the IPCC Guidelines for national GHG inventories, which already provide a Tier-based framework for carbon stock reporting. Key technical requirements include: (a) defining standardized baseline periods and reporting intervals, (b) establishing uncertainty thresholds for indicator classification (e.g., "carbon storage significantly increasing/decreasing/stable"), and (c) ensuring interoperability between model-derived carbon storage estimates and the national statistics that feed into the SDG Global Database[8]. Without this institutional grounding, carbon storage modeling will remain a parallel academic exercise rather than an input to SDG monitoring.
5. **Integration of ecosystem service trade-offs and social equity.** Carbon storage maximization is not an unqualified good. As the Spartina alterniflora case[22] illustrates, carbon gains can come at the expense of biodiversity. Similarly, afforestation in water-limited regions can reduce streamflow, and intensive plantation forestry can degrade soil health. Future scenario studies should move beyond carbon-only optimization toward multi-objective frameworks that simultaneously assess carbon, biodiversity, water yield, and food security outcomes.

Beyond biophysical trade-offs, the **social equity dimensions** of carbon-focused land use policies warrant systematic attention. Carbon sequestration programs—from China's Grain for Green to international REDD+ initiatives—have documented distributional consequences: land tenure insecurity when forests acquire carbon value, displacement of traditional livelihoods from conservation set-asides, and unequal benefit-sharing when carbon revenues accrue to actors with formal land titles while excluding customary land users[11] [23]. Future coupled LUCC–carbon studies should, at minimum, overlay carbon storage projections with spatial data on land tenure, indigenous territories, and poverty incidence to identify potential equity hotspots. Multi-objective frameworks that include social indicators alongside biophysical carbon and biodiversity metrics would enable identification of land use pathways that are simultaneously high-carbon, biodiverse, and equitable—rather than optimizing one dimension at the expense of the others.

A note on the science-policy interface. The future directions above rest on an implicit premise—that more accurate and comprehensive carbon storage models will lead to better land use decisions. This "information deficit model" of science-policy interaction has been critiqued in environmental governance scholarship: decision-makers may selectively use, ignore, or strategically deploy scientific information for reasons unrelated to its accuracy, including political incentives, institutional path dependency, and stakeholder pressure[8]. Closing the research gaps identified in this review is necessary but may not be sufficient for policy impact. The parallel challenge—one this review can identify but not resolve—is understanding the institutional and political conditions under which improved carbon storage information actually influences land use governance.

8. CONCLUSION

This review synthesized a purposive sample of 23 peer-reviewed studies (2006–2025) on terrestrial ecosystem carbon storage assessment under land use and cover change, guided by three questions. The corpus is predominantly composed of InVEST-FLUS-PLUS-coupled studies (74% published 2021–2024) with a geographic concentration on Chinese study sites (65%), and the conclusions below are scoped to this literature rather than to the field as a whole.

With respect to **comparative model strengths** (Question 1), the analysis reveals that—within this corpus—InVEST's static bookkeeping approach offers computational simplicity at the cost of mechanistic depth, particularly for soil organic carbon where the MAOM/POM framework[13] [21] and soil carbon saturation concept[29] identify non-linear responses that static density coefficients cannot represent. GPR-based methods provide high accuracy ($R^2=0.79$–0.86) contingent on training data quality, and process-based models (DNDC, CBM-CFS3) capture biogeochemical dynamics but impose heavy data requirements. The sensitivity analysis reported in Section 2.3 confirms that the named-model search strategy excluded a broader process-based modeling literature (CENTURY, RothC, Biome-BGC, DGVMs) whose inclusion would enrich the process-based paradigm representation. No single paradigm is universally superior; model selection should be governed by the intended use—rapid regional screening (InVEST), empirical prediction where training data exist (GPR), or mechanistic understanding of environmental change responses (process-based models)—and by the decision context's tolerance for unvalidated estimates.

Regarding **scenario consistency** (Question 2), multi-scenario projections within this corpus converge on higher carbon storage under ecological protection than under economic development pathways, but this result is partly an architectural artifact of the InVEST carbon module (Section 3.1) rather than an independent empirical finding. Cross-study quantitative comparisons are hindered by unstandardized carbon density parameterization and unquantified uncertainty propagation, and the counterfactual significance analysis (Section 6.2) demonstrates that closing the uncertainty quantification gap would transform scenario comparison from deterministic point-estimate ranking to probabilistic assessment of whether scenario differences survive uncertainty.

Concerning **methodological gaps** (Question 3), the review identifies five corpus-specific concerns, each with a distinct counterfactual significance: (i) pronounced geographic concentration on China (65% of studies), which limits the transferability of carbon density parameters and model selection guidance to underrepresented biomes; (ii) absence of independent field validation for InVEST-based estimates, whose resolution would provide the first evidence on whether InVEST's architectural simplicity produces practically consequential accuracy trade-offs; (iii) potential publication bias toward positive model performance, whose elimination through pre-registration would reveal the true performance distribution including currently invisible failure cases; (iv) unquantified uncertainty propagation through coupled model chains, whose resolution would distinguish statistically meaningful scenario differences from noise; and (v) a temporal scale mismatch between land use simulation time steps and carbon flux timescales, whose resolution would prevent systematic overestimation of near-term (2030–2035) carbon storage gains in policy-relevant projections.

The field—as represented by this corpus—would benefit most immediately from a multi-model, multi-site validation study that independently compares InVEST, GPR, and process-based carbon estimates against coincident field measurements across contrasting soil types and ecosystem contexts. This would address the validation gap (ii) while simultaneously informing the uncertainty quantification and model selection gaps. Beyond this, the integration of carbon storage modeling into the SDG indicator framework (specifically SDG 15.3.1, custodian: UNCCD) and the adoption of multi-objective optimization that simultaneously assesses carbon, biodiversity, water, food security, and social equity outcomes—rather than carbon-only maximization—represent the most consequential directions for translating modeling advances into policy impact. However, closing the science-policy gap requires not only improved model accuracy but also institutional conditions under which modeled information influences land use governance[8].

REFERENCES

[1] Bagstad, K. J., Semmens, D. J., Waage, S., & Winthrop, R. (2013). A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosystem Services, 5, 27–39. https://doi.org/10.1016/j.ecoser.2013.07.004

[2] Chen, Y., Li, X., Liu, X., & Zhang, Y. (2023). Research progress and trends in land use/cover change and terrestrial ecosystem carbon storage: A bibliometric analysis (2000–2022). Frontiers in Environmental Science, 11, 1156789. https://doi.org/10.3389/fenvs.2023.1156789

[3] Ouyang, Z., Zheng, H., Xiao, Y., Polasky, S., Liu, J., Xu, W., Wang, Q., Zhang, L., Xiao, Y., Rao, E., Jiang, L., Lu, F., Wang, X., Yang, G., Gong, S., Wu, B., Zeng, Y., Yang, W., & Daily, G. C. (2016). Improvements in ecosystem services from investments in natural capital. Science, 352(6292), 1455–1459. https://doi.org/10.1126/science.aaf2295

[4] Alam, S. A., Starr, M., & Clark, B. J. F. (2013). Tree biomass and soil organic carbon densities across the Sudanese woodland savannah: A regional carbon sequestration study. Journal of Arid Environments, 89, 67–76. https://doi.org/10.1016/j.jaridenv.2012.10.002

[5] Ayala Izurieta, J. E., Jara Santillán, C. A., Márquez, C. O., García, V. J., Rivera-Caicedo, J. P., Van Wittenberghe, S., Delegido, J., & Verrelst, J. (2022). Improving the remote estimation of soil organic carbon in complex ecosystems with Sentinel-2 and GIS using Gaussian processes regression. Plant and Soil, 479(1–2), 159–183. https://doi.org/10.1007/s11104-022-05506-1

[6] Babbar, D., Areendran, G., Sahana, M., Sarma, K., Raj, K., & Sivadas, A. (2021). Assessment and prediction of carbon sequestration using Markov chain and InVEST model in Sariska Tiger Reserve, India. Journal of Cleaner Production, 278, 123333. https://doi.org/10.1016/j.jclepro.2020.123333

[7] Castellano, M. J., Mueller, K. E., Olk, D. C., Sawyer, J. E., & Six, J. (2015). Integrating plant litter quality, soil organic matter stabilization, and the carbon saturation concept. Global Change Biology, 21(9), 3200–3209. https://doi.org/10.1111/gcb.12982

[8] Cash, D. W., Clark, W. C., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., Jäger, J., & Mitchell, R. B. (2003). Knowledge systems for sustainable development. Proceedings of the National Academy of Sciences, 100(14), 8086–8091. https://doi.org/10.1073/pnas.1231332100

[9] Cao, L., Kong, F., & Xu, C. (2022). Exploring ecosystem carbon storage change and scenario simulation in the Qiantang River source region of China. Science Progress, 105(3), 00368504221113186. https://doi.org/10.1177/00368504221113186

[10] Chen, C., Liang, J., & Zhang, W. (2025). Quantifying dynamics of ecosystem carbon storage under influence of land use and land cover change in coastal zone from remote sensing perspective. Sustainable Horizons, 14, 100146. https://doi.org/10.1016/j.horiz.2025.100146

[11] Chhatre, A., & Agrawal, A. (2009). Trade-offs and synergies between carbon storage and livelihood benefits from forest commons. Proceedings of the National Academy of Sciences, 106(42), 17667–17670. https://doi.org/10.1073/pnas.0905308106

[12] Chu, X., Zhan, J., Li, Z., Zhang, F., & Qi, W. (2019). Assessment on forest carbon sequestration in the Three-North Shelterbelt Program region, China. Journal of Cleaner Production, 215, 382–389. https://doi.org/10.1016/j.jclepro.2018.12.296

[13] Cotrufo, M. F., Wallenstein, M. D., Boot, C. M., Denef, K., & Paul, E. (2013). The Microbial Efficiency-Matrix Stabilization (MEMS) framework integrates plant litter decomposition with soil organic matter stabilization: Do labile plant inputs form stable soil organic matter? Global Change Biology, 19(4), 988–995. https://doi.org/10.1111/gcb.12113

[14] Cotrufo, M. F., Soong, J. L., Horton, A. J., Campbell, E. E., Haddix, M. L., Wall, D. H., & Parton, W. J. (2015). Formation of soil organic matter via biochemical and physical pathways of litter mass loss. Nature Geoscience, 8(10), 776–779. https://doi.org/10.1038/ngeo2520

[15] Chuai, X., Huang, X., Lai, L., Wang, W., Peng, J., & Zhao, R. (2013). Land use structure optimization based on carbon storage in several regional terrestrial ecosystems across China. Environmental Science & Policy, 25, 50–61. https://doi.org/10.1016/j.envsci.2012.05.005

[16] Deng, S., Shi, Y., Jin, Y., & Wang, L. (2011). A GIS-based approach for quantifying and mapping carbon sink and stock values of forest ecosystem: A case study. Energy Procedia, 5, 1535–1545. https://doi.org/10.1016/j.egypro.2011.03.263

[17] Friedlingstein, P., O'Sullivan, M., Jones, M. W., Andrew, R. M., Bakker, D. C. E., Hauck, J., Landschützer, P., Le Quéré, C., Luijkx, I. T., Peters, G. P., Peters, W., Pongratz, J., Schwingshackl, C., Sitch, S., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S. R., Anthoni, P., & Zheng, B. (2023). Global carbon budget 2023. Earth System Science Data, 15(12), 5301–5369. https://doi.org/10.5194/essd-15-5301-2023

[18] He, Y., Ma, J., Zhang, C., & Yang, H. (2023). Spatio-temporal evolution and prediction of carbon storage in Guilin based on FLUS and InVEST models. Remote Sensing, 15(5), 1445. https://doi.org/10.3390/rs15051445

[19] Jakeman, A. J., Letcher, R. A., & Norton, J. P. (2006). Ten iterative steps in development and evaluation of environmental models. Environmental Modelling & Software, 21(5), 602–614. https://doi.org/10.1016/j.envsoft.2006.01.004

[20] Jiang, W., Deng, Y., Tang, Z., Lei, X., & Chen, Z. (2017). Modelling the potential impacts of urban ecosystem changes on carbon storage under different scenarios by linking the CLUE-S and the InVEST models. Ecological Modelling, 345, 30–40. https://doi.org/10.1016/j.ecolmodel.2016.12.002

[21] Lavallee, J. M., Soong, J. L., & Cotrufo, M. F. (2020). Conceptualizing soil organic matter into particulate and mineral-associated forms to address global change in the 21st century. Global Change Biology, 26(1), 261–273. https://doi.org/10.1111/gcb.14859

[22] Li, J., Yan, D., Yao, X., Liu, Y., Xie, S., Sheng, Y., & Luan, Z. (2022). Dynamics of carbon storage in saltmarshes across China's eastern coastal wetlands from 1987 to 2020. Frontiers in Marine Science, 9, 915727. https://doi.org/10.3389/fmars.2022.915727

[23] Phelps, J., Webb, E. L., & Agrawal, A. (2010). Does REDD+ threaten to recentralize forest governance? Science, 328(5976), 312–313. https://doi.org/10.1126/science.1187774

[24] Pilli, R., Grassi, G., Kurz, W. A., Smyth, C. E., & Blujdea, V. (2013). Application of the CBM-CFS3 model to estimate Italy's forest carbon budget, 1995–2020. Ecological Modelling, 266, 144–171. https://doi.org/10.1016/j.ecolmodel.2013.07.007

[25] Piyathilake, I. D. U. H., Udayakumara, E. P. N., Ranaweera, L. V., & Gunatilake, S. K. (2022). Modeling predictive assessment of carbon storage using InVEST model in Uva province, Sri Lanka. Modeling Earth Systems and Environment, 8(2), 2213–2223. https://doi.org/10.1007/s40808-021-01207-3

[26] Reyes-Muñoz, P., Kovács, D. D., Berger, K., Pipia, L., Belda, S., Rivera-Caicedo, J. P., & Verrelst, J. (2024). Inferring global terrestrial carbon fluxes from the synergy of Sentinel 3 & 5P with Gaussian process hybrid models. Remote Sensing of Environment, 305, 114072. https://doi.org/10.1016/j.rse.2024.114072

[27] Sharp, R., Tallis, H. T., Ricketts, T., Guerry, A. D., Wood, S. A., Chaplin-Kramer, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Vigerstol, K., Pennington, D., Mendoza, G., Aukema, J., Foster, J., Forrest, J., Cameron, D., Arkema, K., Lonsdorf, E., & Douglass, J. (2020). InVEST 3.9.0 User's Guide. The Natural Capital Project, Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund. https://storage.googleapis.com/releases.naturalcapitalproject.org/invest-userguide/latest/index.html

[28] Shao, Z., Chen, C., Liu, Y., Cao, J., Liao, G., & Lin, Z. (2023). Impact of land use change on carbon storage based on FLUS-InVEST model: A case study of Chengdu–Chongqing urban agglomeration, China. Land, 12(8), 1531. https://doi.org/10.3390/land12081531

[29] Stewart, C. E., Paustian, K., Conant, R. T., Plante, A. F., & Six, J. (2007). Soil carbon saturation: Concept, evidence and evaluation. Biogeochemistry, 86(1), 19–31. https://doi.org/10.1007/s10533-007-9140-0

[30] Tang, H., Qiu, J., Van Ranst, E., & Li, C. (2006). Estimations of soil organic carbon storage in cropland of China based on DNDC model. Geoderma, 134(1–2), 200–206. https://doi.org/10.1016/j.geoderma.2005.10.005

[31] Wang, N., Chen, X., Zhang, Z., & Pang, J. (2022). Spatiotemporal dynamics and driving factors of county-level carbon storage in the Loess Plateau: A case study in Qingcheng County, China. Ecological Indicators, 144, 109460. https://doi.org/10.1016/j.ecolind.2022.109460

[32] Wang, Z., Zeng, J., & Chen, W. (2022). Impact of urban expansion on carbon storage under multi-scenario simulations in Wuhan, China. Environmental Science and Pollution Research, 29(30), 45507–45526. https://doi.org/10.1007/s11356-022-19146-6

[33] Wu, Q., Wang, L., Wang, T., Ruan, Z., & Du, P. (2024). Spatial–temporal evolution analysis of multi-scenario land use and carbon storage based on PLUS-InVEST model: A case study in Dalian, China. Ecological Indicators, 166, 112448. https://doi.org/10.1016/j.ecolind.2024.112448

[34] Wu, S., Li, J., Zhou, W., Lewis, B. J., Yu, D., Zhou, L., Jiang, L., & Dai, L. (2018). A statistical analysis of spatiotemporal variations and determinant factors of forest carbon storage under China's Natural Forest Protection Program. Journal of Forestry Research, 29(2), 415–424. https://doi.org/10.1007/s11676-017-0462-z

[35] Xiang, W., Xu, L., Lei, P., Ouyang, S., Deng, X., Chen, L., Zeng, Y., Hu, Y., Zhao, Z., Wu, H., Zeng, L., & Xiao, W. (2022). Rotation age extension synergistically increases ecosystem carbon storage and timber production of Chinese fir plantations in southern China. Journal of Environmental Management, 317, 115426. https://doi.org/10.1016/j.jenvman.2022.115426

[36] Zhang, Z., Jiang, W., Peng, K., Wu, Z., Ling, Z., & Li, Z. (2023). Assessment of the impact of wetland changes on carbon storage in coastal urban agglomerations from 1990 to 2035 in support of SDG15.1. Science of The Total Environment, 877, 162824. https://doi.org/10.1016/j.scitotenv.2023.162824

[37] Zhu, L., Song, R., Sun, S., Li, Y., & Hu, K. (2022). Land use/land cover change and its impact on ecosystem carbon storage in coastal areas of China from 1980 to 2050. Ecological Indicators, 142, 109178. https://doi.org/10.1016/j.ecolind.2022.109178