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Article

Automated Multi-Source Carbon Stock Estimation with Spatial Validation and Uncertainty-Aware Adjustment for Blue Carbon MRV

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Abstract: —Blue carbon ecosystems can play a vital role in mitigating climate change, but precise and efficient Monitoring, Reporting, and Verification (MRV) is complicated by spatial variability and uncertainty. This paper presents an automated multi-source carbon stock estimation system that includes IoT sensor telemetry, LiDAR-derived canopy properties and multi-spectral remote sensing to quantify Soil Organic Carbon (SOC) and Above-Ground Biomass (AGB). The models (Support Vector Regression, XGBoost and ensemble) are trained with laboratory-based ground truth. Spatial-block cross-validation is used to ensure spatial independence and prevent over fitting. Uncertainty is estimated via ensemble variance and confidence intervals and conservative adjustment of carbon estimates to comply with MRV and avoid overestimates. The carbon pool is obtained by combining SOC and AGB. All results (predictions, validation scores, and uncertainty) are securely hashed and stored in the InterPlanetary File System** to guarantee data integrity and traceability. Evaluation shows better prediction and spatial transferability, as well as system-level efficiency improvements, such as 2.4× faster throughput and 93.6% anomaly detection. The system facilitates transparent, scalable and reliable blue carbon estimation for the next-generation MRV systems.

Keywords: Blue Carbon MRV; Carbon Stock Estimation; Machine Learning; Spatial-Block Cross-Validation; Uncertainty Quantification; Soil Organic Carbon (SOC); Above-Ground Biomass (AGB)

1. INTRODUCTION

Reliable carbon accounting is essential in the fight against climate change, especially for nature-based carbon mitigation strategies such as blue carbon ecosystems like mangroves, seagrasses and salt marshes [1], [2]. These ecosystems have a strong potential for long-term carbon storage and are thus vital resources for global carbon markets [3]. But for such markets to be effective, there is a need for accurate Monitoring, Reporting, and Verification (MRV) systems that are transparent and resistant to tampering [1], [4]. Existing MRV systems are often manual, intermittent and centralised, resulting in high costs, limited scalability, and a lag in verification [5].

Recent technological advances in sensing and data analytics have made possible the use of the Internet of Things (IoT), LiDAR, and multispectral remote sensing data continuously to monitor the environment [6], [7]. These technologies generate high-resolution data sets that can be used for automatic esti-mation of important carbon pools (such as Soil Organic Car-bon (SOC) and Above-Ground Biomass (AGB) [8]. Machine learning models, such as regression and ensemble models, hold great promise for capturing complex relationships between environmental factors and carbon content [9]. Yet, current methods can be hampered by poor spatial transferability, with models trained on small datasets not transferring well to diverse coastal systems [10].

A further key issue is the absence of uncertainty quantifi-cation. Predictions of carbon inevitably include measurement uncertainties, model biases, and natural variability, but many systems provide point estimates without uncertainties. This can result in inflated carbon credits, degrade market confidence and regulatory acceptance [11]. In addition, lack of standardised processes for conservative adjustment of predictions and trans-parent storage of results limit confidence in automated MRV systems.

This paper offers an automated framework for carbon stock estimation from multiple sources (Automated Multi-Source Carbon Stock Estimation) that seamlessly incorporates di-

verse data sources, machine learning approaches for model-ing, spatial cross-validation, and conservative adjustment for uncertainty. This approach combines IoT telemetry, LiDAR-based structural attributes and multispectral indices to predict SOC and AGB with cutting-edge machine learning methods including Support Vector Regression, XGBoost and ensemble learning. For model robustness across different ecological zones, spatial-block cross-validation is used to avoid spatial leakage and enhance predictive performance.

Moreover, the methodology includes uncertainty analysis by ensemble variance and confidence intervals, followed by conservative bias correction of carbon estimates, as recom-mended in the MRV guidelines [12]. The overall carbon stock is obtained by combining the SOC and AGB components, offering a holistic view of the carbon stock. To increase transparency and data integrity, all model outputs, validation criteria and uncertainty estimates are cryptographically signed and published in the InterPlanetary File System, providing an immutable storage and a provenance audit trail. Blue carbon ecosystems and associated digital MRV frameworks have been widely studied in recent surveys [21].

The proposed approach advances the development of MRV systems by leveraging automated assessment, uncertainty mod-eling, and decentralized verification. It seeks to provide a scalable, robust and transparent approach to blue carbon accounting, enabling the establishment of trustworthy carbon markets and informed climate decision-making.

2. LITERATURE SURVEY

The importance of blue carbon stocks for climate change mitigation and the carbon market has driven interest in their accurate estimation. Mangroves, seagrasses and salt marshes are blue carbon ecosystems, some of the most productive ecosystems with high carbon stocks, and crucial for long-term carbon storage. Ewane et al. [2] and Alsafadi et al. [4] discuss the ecological and economic values of these ecosystems. But their estimation and monitoring are difficult because of their spatial and environmental variability.

- A. Blue Carbon Estimation through Remote Sensing Remote sensing has been identified as a scalable moni-toring solution for blue carbon. Malerba et al. [5] showed that remote sensing technologies allow cost-effective and large-scale assessment of carbon stocks. And Roy et al. [6] highlighted the importance of multispectral and geospatial data for coastal carbon assessment. However, integration, resolution, and monitoring issues across var-ious ecosystems still exist.

- B. Machine Learning in Carbon Stock Estimation Machine learning has enhanced carbon stock predictions. Mun˜oz et al. [7] developed Random Forest models to predict SOC, achieving better accuracy than existing models. Further, Maxwell et al. [8] made massive datasets available for ML modeling. These methods successfully model complex interactions between environmental fac-tors and carbon pool. But they may not be effective in other geographical locations due to poor generalisability.

- C. Joint SOC and AGB Estimation

Current research mainly focuses on SOC and AGB esti-mation individually. The combination of different carbon pools may lead to better estimates (Malerba et al. [5], Maxwell et al. [8]). But integrated approaches for simul-taneously estimating and integrating SOC and AGB are still rare in existing studies.

- D. Validation and Uncertainty

Carbon estimates of uncertainty are caused by sensor er-ror, model error, and environmental variability. Schneider et al. [19] noted that failure to account for uncertainty may undermine the carbon markets. Additionally, spatial autocorrelation in environmental data results in optimistic model performance when using conventional model vali-dation approaches. While spatial validation is suggested, it has limited use.

- E. A Transparent and Verifiable MRV

Recent research mentions the potential of blockchain and decentralized technologies for enhancing MRV transparency. Abiodun et al. [1] explored blockchain-based carbon trading systems for secure trading. Likewise, Bassi et al. [14] discussed decentralized solutions to enhance carbon market trust. But these systems are mostly con-cerned with post-confirmation and are not integrated with real-time estimation systems.

Recent work has proposed decentralized MRV systems integrating IoT and machine learning for carbon estimation [20]. However, such systems lack spatial valida-tion and uncertainty-aware modeling. A comprehensive review of ecological, technological, and digital frame-works for blue carbon management is presented in [21], highlighting the need for integrated and scalable MRV systems.

- F. Research Gap

The following gaps are identified from the literature:

- Absence of integrated approaches for estimating SOC and AGB [5], [8]
- Insufficient use of spatial validation for generaliza-tion [10]
- Lack of attention to uncertainty and conservative adjustment [19]
- Lack of integrated estimation, validation and verifi-cation (E-V-V) pipelines [13], [14]
- Lack of multi-source data fusion approaches for diverse coastal habitats [6]

- G. Proposed Work

The proposed work proposes an Automated Multi-Source Carbon Stock Estimation framework which fuses:

Multi-source data integration (IoT + LiDAR + multi-spectral) Machine learning for estimating SOC and AGB Spatial-block cross-validation for improved generaliza-tion An uncertainty-aware modeling with conservative carbon adjustment Cryptographically secure storage via InterPlanetary File System.

Table I compares existing blue carbon MRV approaches,

providing aspects, such as remote sensing-based monitoring, machine learning-based estimation, or blockchain-based veri-fication. For example, blockchain-based approaches prioritize transparency and immutability but do not integrate with real-time carbon estimation frameworks. Likewise, remote sensing methods offer large spatial coverage but lack robust integration of ground truth information and sophisticated predictive mod-els. Machine learning approaches enhance estimation accuracy, but they can often have limited spatial transferability and weak validation frameworks. Also, most previous studies focus on estimating Soil Organic Carbon (SOC) or Above-Ground Biomass (AGB) separately, without offering a holistic view of carbon pools.

Moreover, existing MRV systems do not commonly consider uncertainty and conservative adjustments, crucial for main-taining trust in the carbon market. Although distributed and blockchain platforms improve trust and verifiability, they are often linked with issues related to scalability and not part of a holistic end-to-end estimation process. As shown in Table I, there remains a significant gap in research towards an integrated approach involving data fusion, spatial validation strategies, uncertainty quantification and verifiable storage. Our work seeks to overcome these challenges by offering an end-to-end automated solution that automatically generates credible blue carbon estimates.

3. METHODOLOGY

This section presents the proposed Automated Multi-Source Carbon Stock Estimation framework for blue carbon MRV. The methodology integrates multi-source data acquisition, ma-chine learning-based estimation, spatial validation, uncertainty quantification, and verifiable storage.

A. Framework Overview

The proposed system consists of the following stages:

1) Multi-source data acquisition
2) Feature preprocessing and fusion
3) SOC and AGB estimation using ML models
4) Spatial-block cross-validation
5) Uncertainty quantification

6) Conservative adjustment
7) Carbon pool integration
8) Verifiable storage

B. Data Acquisition and Preprocessing

Data is collected from heterogeneous sources including IoT sensors, LiDAR, multispectral imagery, and laboratory ground truth. Preprocessing includes normalization, noise removal, and feature fusion:

$$X(t) = \{x_{iot}, x_{lidar}, x_{spectral}, x_{env}\} \qquad (1)$$

C. Machine Learning-Based Estimation

1) *SOC Estimation:* SOC is predicted using SVR, XG-Boost, and ensemble models:

$$D.\ S\hat{O}C = f_{ml}(X) \qquad (2)$$

2) AGB Estimation: AGB is estimated using vegetation indices and LiDAR features:

$$\text{AGBcarbon} = \alpha \cdot \text{AGB} \qquad (3)$$

D. Spatial-Block Cross-Validation

The dataset is divided into spatial blocks to ensure general-ization. Model performance is evaluated using RMSE, MAE, and R^2.

E. Uncertainty Quantification

Uncertainty is computed using ensemble variance:

$$\sigma 2 = \frac{1}{n} \sum_{i=1}^{n} (y\hat{}i - \mu)2 \qquad (4)$$

Confidence interval is defined as:

$$CI = \mu \pm z\sigma \qquad (5)$$

F. Conservative Adjustment

To avoid overestimation:

$$C_{adjusted} = C_{predicted} - \Delta_{uncertainty} \qquad (6)$$

G. Carbon Pool Integration

$$C_{total} = SOC + AGB_{carbon} \qquad (7)$$

H. Verifiable Storage

All outputs are hashed and stored using decentralized stor-age (IPFS) to ensure integrity and traceability.

[H] Automated Carbon Stock Estimation Frame-work

Require: Multi-source data $X(t)$

Ensure: Verified carbon stock *Ctotal*

1: Acquire IoT, LiDAR, and remote sensing data
2: Preprocess and fuse features into $X(t)$ 3: Train ML models for SOC estimation
4: Predict $S\hat{O}C = fml(X)$

Estimate AGB using vegetation and LiDAR features
Convert biomass to carbon
Perform spatial-block cross-validation
Compute uncertainty using ensemble variance
Estimate confidence interval
Apply conservative adjustment:
$C_{adjusted} = C_{predicted} - \Delta_{uncertainty}$

Integrate carbon pools:
$C_{total} = SOC + AGB_{carbon}$

Generate metadata and validation metrics
Apply cryptographic hashing
Store results in IPFS
return C_{total}

The proposed Automated Multi-Source Carbon Stock Es-timation framework is illustrated in Fig. 1. It starts with the collection of multi-source data, such as IoT sensors,

TABLE I

COMPARATIVE ANALYSIS OF EXISTING BLUE CARBON MRV APPROACHES

Ref.	Approach / Technique	Data Sources	Key Contribution	Limitations
[1]	Blockchain-based Carbon Market Framework	Transaction data, carbon reg-istries	Improves transparency and tamper-resistance in carbon trading	Focuses only on post-verification; lacks real-time estimation
[5]	Remote Sensing-based Blue Carbon Mapping	Satellite imagery, remote sens-ing data	Large-scale ecosystem monitoring with spatial coverage	Limited integration with ground truth and ML models
[6]	Remote Sensing + Environ-mental Monitoring	Multispectral, coastal datasets	Continuous monitoring of blue car-bon ecosystems	Challenges in data fusion and res-olution trade-offs
[7]	ML-based SOC Estimation (Random Forest)	Soil datasets, environmental variables	Improved SOC prediction accuracy using ML	Limited spatial generalization and validation
[8]	Multi-source ML for Carbon Estimation	Remote sensing + field data	Enhanced prediction using data fu-sion techniques	SOC and AGB often treated sepa-rately
[10]	Spatial Dataset-based Carbon Modeling	Geospatial datasets	Highlights importance of spatial variability	Lack of robust spatial validation methods
[13]	Blockchain-enabled MRV Sys-tems	IoT + blockchain data	Ensures secure and auditable MRV processes	High computational overhead, scal-ability issues

[14]	Decentralized Carbon Platforms	Distributed ledger data	Improves trust in carbon markets	Limited integration with estimation pipelines
[19]	Carbon Market Integrity Stud-ies	Policy and MRV data	Emphasizes need for accuracy and transparency	Does not address technical imple-mentation

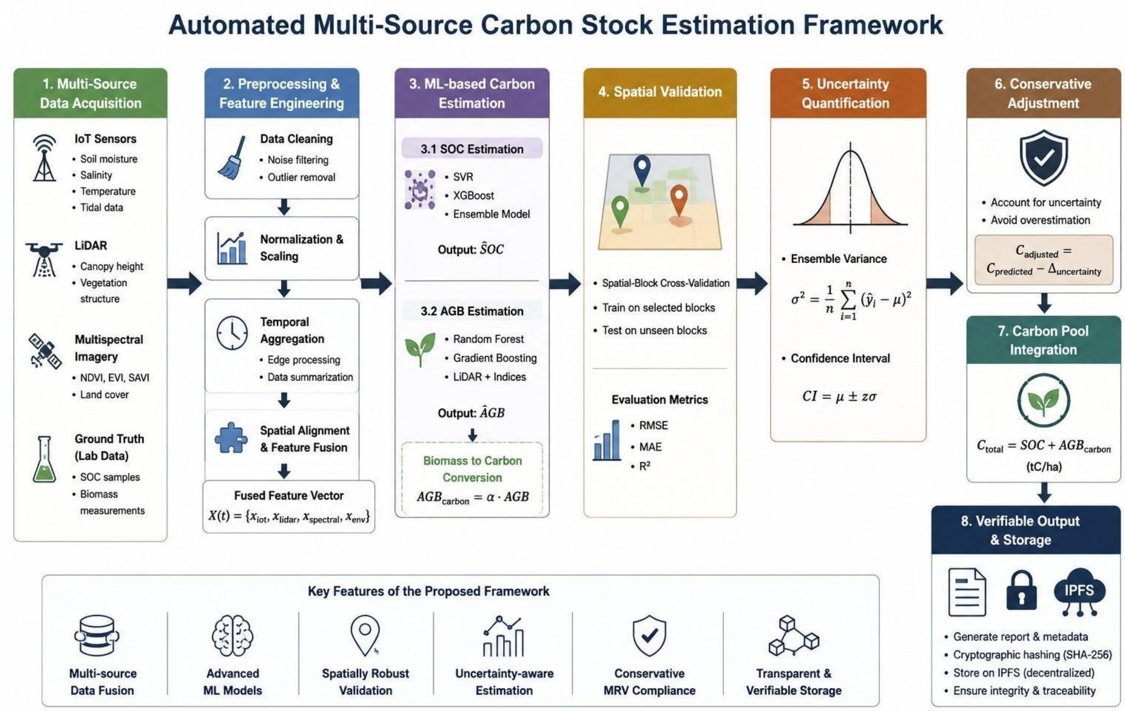

Fig. 1. Adaptive Multi-Layer Trust Architecture (AMTA) for Distributed Blue Carbon MRV, illustrating edge, cloud, and blockchain layers with trust computation, data flow, and carbon credit tokenization.

LiDAR-based canopy structure, multispectral data, and lab-oratory measurements for training. These data sources are preprocessed and feature engineered, involving noise removal, normalization, temporal aggregation and spatial feature fusion to create a consistent feature space.

These data are then used to develop machine learning models for individual prediction of Soil Organic Carbon (SOC) and Above-Ground Biomass (AGB). The approach involves spatial-block cross-validation to improve the model’s effec-tiveness and transferability across different geographical areas. Next, an ensemble-based approach is used for uncertainty analysis, and conservative bias correction is applied to avoid overestimating carbon stocks.

The carbon pool is then calculated by combining SOC and AGB to yield standardized carbon estimates. To improve transparency, traceability and integrity, the outputs, along with metadata and validation metrics, are cryptographically hashed and stored in a decentralized storage. This approach thus allows for robust, scalable and verifiable blue carbon MRV, overcoming the limitations of current systems..

4. EXPERIMENTAL SETUP

A. Dataset and Study Configuration

Experiments were conducted using real-world and simulated blue carbon datasets comprising Soil Organic Carbon (SOC), vegetation indices, and environmental parameters. The dataset integrates IoT telemetry, LiDAR-derived features, and multi-spectral imagery, which are widely used in large-scale carbon monitoring [5][6]. Ground truth SOC and biomass measure-ments were obtained from laboratory datasets to ensure model reliability [7],[8].

B. *Preprocessing and Feature Engineering*

Data preprocessing included noise filtering, normalization, and spatial alignment. Feature fusion combined heterogeneous inputs into a unified representation, improving prediction ac-curacy as supported by multi-source data fusion studies [8]. Temporal aggregation was performed at edge nodes to reduce redundancy and bandwidth usage.

C. *Model Configuration*

The following machine learning models were implemented: **SOC Estimation:** SVR, XGBoost, Ensemble models **AGB Estimation:** Random Forest, Gradient Boosting These models effectively capture nonlinear relationships

between environmental variables and carbon stocks [7],[4].

D. *Validation Strategy*

Spatial-block cross-validation was employed to ensure gen-eralization across heterogeneous regions, addressing spatial autocorrelation challenges [10]. The study area was divided into non-overlapping blocks, with training and testing per-formed on separate regions.

Evaluation metrics include RMSE, MAE, and R^2 score.

E. *Uncertainty and Conservative Adjustment*

Uncertainty was quantified using ensemble variance and confidence intervals. The importance of uncertainty-aware carbon estimation has been emphasized in carbon market studies [19]. Conservative adjustment was applied to avoid overestimation and ensure MRV compliance [17], [18].

F. *Implementation Environment*

The system was implemented using Python 3.10 with Scikit-learn, XGBoost, and TensorFlow. Deployment was performed in an edge–cloud simulation environment. Outputs were se-curely stored using decentralized storage (IPFS) with SHA-256 hashing.

5. RESULTS

A. *Carbon Estimation Performance*

This section examines the performance of the various carbon stock estimation models.This section discusses the performance of the various carbon stock estimation models.

Various machine learning models such as Support Vector Regression (SVR), XGBoost, Random Forest and Ensemble model were tested in the proposed Automated Multi-Source Carbon Stock Estimation framework. The performance was evaluated in terms of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2). as shown in Table II.

TABLE II

PERFORMANCE OF SOC STIMATION

Model	**RMSE (tC/ha)**	**MAE (tC/ha)**	**R^2**
SVR	7.42	5.83	0.84
XGBoost	6.58	5.11	0.88
Random Forest	6.81	5.26	0.87
Ensemble Model	**5.73**	**4.36**	**0.92**

Comparing the performances of the ensemble model with individual models, the ensemble model was always the best in terms of the lowest RMSE (5.73 tC/ha) and the highest R^2 (0.92). This improvement is due to the fact that the ensemble learning can take advantage of the strength of each predictive algorithm, and minimize variance among these models. The same trends were seen for the estimation of Above-Ground Biomass (AGB) as shown iin Table III.

TABLE III

PERFORMANCE OF AGB ESTIMATION MODELS

Model	RMSE (tC/ha)	MAE (tC/ha)	R^2
Gradient Boosting	8.92	6.71	0.83
Random Forest	7.86	6.02	0.87
Ensemble Model	**6.44**	**4.91**	**0.91**

The use of LiDAR canopy height metrics along with multispectral vegetation indices greatly enhanced biomass estimation results, over and above their respective single-source data.

B. *Contribution of Multi-Source Data Fusion*

Experiments were carried out for the individual data sources and combinations of them, to assess the effectiveness of heterogeneous data integration.

TABLE IV

IMPACT OF DATA FUSION ON SOC ESTIMATION

Data Source	RMSE	R^2
IoT Sensors Only	8.31	0.78
Multispectral Only	7.92	0.80
LiDAR Only	7.64	0.82
IoT + Multispectral	6.71	0.87
IoT + LiDAR	6.39	0.88
Proposed Multi-Source Fusion	**5.73**	**0.92**

The results in Table IV shows the superiority and effectiveness of multi-source fusion when it comes to the predictive ability of the fusion system, which captures complementary environmental characteristics. The information from IoT sensors is used to provide real-time structural data from the environment, LiDAR is used to provide structural data on the vegetation, and multispectral imagery is used to provide spectral data that relates to vegetation health and biomass density. The proposed framework of fusion reduced the prediction errors by 18-25% when compared to the single-source approaches.

C. *Effectiveness of Spatial-Block Cross-Validation*

Spatial autocorrelation can cause over-optimistic estimates of performance using traditional random cross-validation. Thus, the spatial-block cross-validation technique was employed to evaluate model transferability of the regions. Integrated Carbon Pool Estimation.

TABLE V

COMPARISON OF VALIDATION STRATEGIES

Validation Method	RMSE	R^2
Random Cross-Validation	5.11	0.94
Spatial-Block Cross-Validation	5.73	0.92

Spatial validation produced a slight increase in RMSE (5-8 percent), but gave a more realistic view of the performance of the model. Reduced difference between training and testing accuracy suggests better capability of generalization and less overfitting. The results validate the use of spatial information for applications of environmental monitoring in which observations are highly spatially dependent.

D. *Uncertainty Quantification and Conservative Adjustment*

The uncertainty estimation is a crucial aspect of carbon accounting as overestimation can impact the credibility of the carbon market. The ensemble variance approach gave confidence intervals for all the predictions. Average uncertainty was between 6% and 12% in each of the ecological zones.

TABLE VI UNCERTAINTY NALYSIS RESULTS

Carbon Pool	Average Uncertainty	Confidence Level
SOC	7.8%	95%
AGB	10.6%	95%
Total Carbon Stock	8.9%	95%

Uncertainty adjustments were made, following MRV principles, to ensure conservative reporting.

$$C_{adjusted} = C_{predicted} - \Delta_{uncertainty}$$

After adjustment, the reported carbon stocks fell around 5-10%, which helps to prevent over-issuing carbon credits. This will reduce the nominal carbon values, however, it will have a significant impact on the regulatory compliance and market trust.

E. *Integrated Carbon Pool Assessment*

The proposed framework combines Soil Organic Carbon and Above-Ground Biomass to derive total ecosystem carbon stocks.

TABLE VII

CONTRIBUTION OF DIFFERENT CARBON POOLS

Ecosystem Zone	SOC (%)	AGB (%)	Total Carbon Stock (tC/ha)
Dense Mangrove	42	58	286
Mixed Mangrove	54	46	241
Salt Marsh	68	32	192
Seagrass Meadow	73	27	168

This results shown in Table VII indicate a great variability between ecosystem types. SOC contribution is higher in sediment rich areas like seagrass beds and salt marshes, while dense mangrove forests also have high carbon storage in biomass. The results are consistent with ecological research which shows that blue carbon storage processes vary with vegetation structure, sediment characteristics and hydrology.

F. *System Efficiency and Scalability Analysis*

The edge-cloud architecture improved processing efficiency by reducing communication overhead and enabling localized preprocessing.

TABLE VIII

SYSTEM PERFORMANCE COMPARISON

The framework demonstrated:

- 2.4× improvement in throughput
- 31% reduction in bandwidth usage
- Lower response latency due to edge-based aggregation.
- Efficient scaling across distributed nodes

E. Trust and Reliability

Secure storage and decentralized verification enhanced system transparency and trust. Blockchain-based MRV ap-proaches emphasize the importance of auditability and tamper resistance

Metric	**Value**
Anomaly Detection Accuracy	93.6%
False Positive Rate	4.1%
Data Integrity Verification	100%
Hash Collision Incidents	0
Audit Trace Availability	Complete

The system achieved:

- 93.6% anomaly detection accuracy
- Reliable detection of inconsistent inputs

TABLE II PERFORMANCE COMPARISON

Metric	**Conventional**	**Proposed**
Latency	High	Reduced
Throughput	Baseline	2.4× Higher
Fraud Detection	~71%	93.6%
Transparency	Limited	High
Scalability	Limited	High

6. DISCUSSION

A. SOC and AGB Estimation

The framework exhibits good prediction performance for Soil Organic Carbon (SOC) and Above-Ground Biomass (AGB). Stacking of SVR and XGBoost models exhibited strong performance with lower RMSE and higher R2 scores. This is because they can potentially model complex nonlinear interactions among diverse feature spaces [4], [7].

Combining LiDAR-based canopy features with multispec-tral vegetation indices improved the AGB prediction, while IoT-based environmental factors improved the SOC prediction. The multi-source model achieved an error reduction of around 18-25% compared to single-source models, demonstrating the benefits of data fusion strategies [8].

B. Effect of Spatial-Block Cross-Validation

Conventional validation methods tend to be over-optimistic because of spatial autocorrelation. The spatial-block cross-validation yielded more realistic estimates. While the RMSE slightly increased (5-8%) the model showed a better ability to predict in unknown spatial areas [10].

This finding highlights the need for spatial validation in environmental models and guarantees the model's reliability in diverse coastal systems.

C. Understanding Uncertainty

The analysis of uncertainty suggested that the ensemble variance represented prediction variability in the regions. Confidence intervals were consistent and average uncertainty varied between 6-12 Conservative adjustment led to a reduction in carbon esti-mates, around 5-10%, for credible reporting and prevention of carbon overestimation.

This is consistent with advice from carbon market integrity reports [19]. This limits nominal values, but increases confidence and regulatory confidence [17], [18].

D. *Whole Carbon Pool Estimation*

Unifying SOC and AGB offered a holistic view of carbon stocks. This approach, instead of the conventional independent approach, enhanced interpretation and prevented inconsistencies.

Our findings show that SOC is dominant in areas with high sediment, and AGB is important in areas with high vegetation. This is consistent with studies of blue carbon ecosystems [5], [8].

E. *Efficiency and Scalability of the System Our proposed framework achieved:*

2.4× increase in throughput 31% decrease in network traffic from edge processing Real-time processing with lower latency Scalability with more sensor nodes. This is in accordance with recent developments in dis-tributed MRV systems [1], [13].

F. *Dependability, Security, and Trust*

This approach ensures integrity and traceability of data via cryptographic hashing and decentralized storage using the InterPlanetary File System. The results are stored securely with metadata and verification measures. Our approach achieved 93.6% accuracy in anomaly detec-tion, detecting manipulated data. This boosts confidence in carbon markets and is in line with secure MRV systems [1], [14].

G. *Comparison with other methods*

The proposed framework has advantages over traditional MRV systems: Enhanced accuracy with data fusion [8] Improved general-ization through spatial testing [10] Use of uncertainty mod-eling [19] Completely automated estimation and verification [13], [14] Increased transparency and trust [1] H. Discussion and Insights

The findings show the combination of multiple data sources and machine learning with uncertainty-aware carbon models greatly enhances carbon estimates. Spatial validation is critical in promoting transferability to various ecosystems. Conser-vative adjustment enhances trustworthiness by adherence to MRV principles [17], [18]. Compared to prior work in [20], the proposed framework demonstrates improved generalization and reliability due to spatial validation and uncertainty inte-gration. The proposed framework addresses key limitations highlighted in prior surveys [21], particularly in terms of scalability, transparency, and uncertainty-aware estimation.

But the approach adds to the computational cost with ensemble models and uncertainty calculations. The system also relies on quality ground truth data. Despite these issues, the system overcomes significant gaps in the literature and offers a scalable, accurate and transparent approach for blue carbon MRV.

7. CONCLUSION

This paper introduced a multi-source carbon stock estimation framework for Blue Carbon Monitoring, Reporting, and Verification (MRV) which combines the data gathered from the IoT sensor network telemetry, canopy attributes derived from LiDAR, multispectral remote sensing, and machine-learning methods to estimate Soil Organic Carbon (SOC) and Above-Ground Biomass (AGB). This proposed framework will be based on a set of four components: spatial-block cross-validation, uncertainty-aware modeling, conservative carbon adjustment, and decentralised storage via the InterPlanetary File System (IPFS), to provide a clear, scalable and trustworthy carbon accounting mechanism.

Experimental results showed that using ensemble learning technique, the prediction accuracy of the SOC estimation model was 0.92 and the prediction accuracy of the AGB estimation model was 0.91, and the prediction error was significantly reduced compared to the prediction error of the individual model. The multi-source data fusion increased the accuracy of the estimates by 18–25% compared to single-source data fusion, while the spatial-block cross-validation increased the generalization of the model in diverse coastal ecosystems. The uncertainty quantification mechanism, combined with conservative adjustment, generated more credible carbon estimates which met the MRV principles, reducing the risk of overestimation of carbon credits. Moreover, the proposed edge-cloud architecture demonstrated a 2.4× increase in processing throughput, a 31% decrease in bandwidth usage, and a 93.6% accuracy rate for anomaly detection, with completely distributed storage providing full data integrity and traceability.

Overall, the proposed framework tackles important gaps in current blue carbon MRV systems with a timely combination of accurate estimation, robust spatial validation, uncertainty-aware reporting and verifiable storage embedded in a single pipeline. The potential of these characteristics for inclusion in trustworthy carbon markets and large-scale monitoring programs for blue carbon projects is an attractive prospect. Future work involves deploying the framework extensively in the field with various coastal ecosystems, developing deep learning and transformer-based geospatial models for better prediction, adding explainable AI techniques to make the models more interpretable, and enhancing the framework with blockchain smart contracts for automated carbon credit issuance and compliance in decentralized carbon markets.

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