Uncertainty-Aware Carbon Flux Estimation from Multispectral Landsat Imagery Using Mixture Density Networks

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Abstract

Accurately quantifying carbon fluxes across ecosystems is essential for monitoring and validating natural climate solutions (NCS) which promise to mitigate climate change. Measurement methods, such as eddy covariance towers, provide ground truth data at high temporal resolution but suffer from limited spatial coverage. Upscaling these measurements to ecosystem scales is performed with machine learning methods based on environmental drivers and satellite data. However, correctly quantifying uncertainty in these predictions remains a challenge, which limits its use in carbon markets. We propose an uncertainty-aware carbon flux estimation framework that integrates multispectral Landsat imagery, EC flux measurements, and ancillary environmental variables using Mixture Density Networks. Our framework provides estimates of both aleatoric and epistemic uncertainties that enhance the reliability and scalability of carbon monitoring efforts.

Introduction

- Natural Climate Solutions (NCS) like reforestation and conservation are vital for climate change mitigation, policy decisions, and integrity of carbon markets.
- Ground methods like eddy covariance towers offer precision but lack spatial coverage.
- Remote sensing + ML enable upscaling, but most traditional models provide point estimates with no uncertainty.
- Mixture Density Networks (MDNs) offer a solution: We explore MDNs for uncertainty-aware carbon flux estimation using Landsat imagery + environmental data.
- Accurate carbon-flux estimates with quantified uncertainty are critical: larger uncertainty leads to steeper discounts on the carbon credits projects can claim.

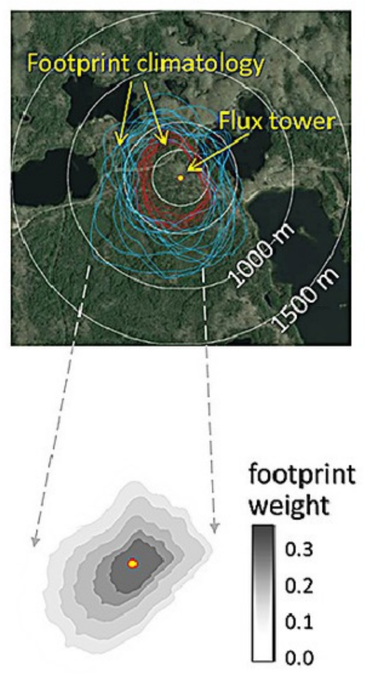


Figure: Flux tower footprint

Methodology

1. Data Collection & Preprocessing
   - EC Flux Towers: 209 Ameriflux sites
   - Landsat 8/9 imagery: 128*128, 30m resolution pixel
   - Removed sites lacking key variables (e.g., wind direction, tower height) and physically implausible values (e.g., negative solar radiation)
2. Model Architecture
   - Carbon Flux Estimator (MLP + MDN): Predicts parameters of mixture of Gaussians $\{\alpha_k, \mu_k, \sigma_k^2\}$ for every pixel.

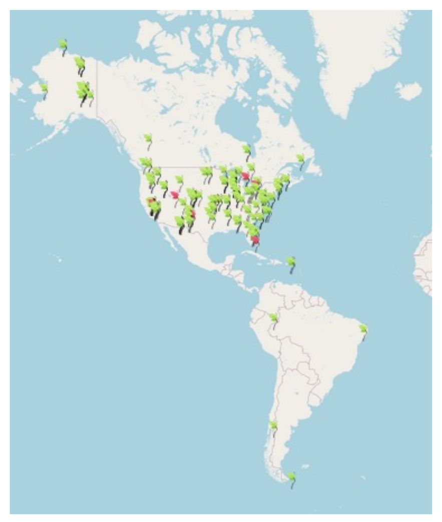


Figure: Tower locations included in our dataset

$$p(y \mid x) = \sum_{k=1}^{K} \alpha_k(x)\,\mathcal{N}\big(y \mid \mu_k(x), \sigma_k^2(x)\big).$$

   - Tower Footprint Attender: Learns to predict tower footprint based on tower information.
3. Training Objective
   - Negative Log-Likelihood of observed flux values. Encourages the MDN to learn multi-modal distributions and heteroscedastic noise for uncertainty-aware flux prediction.

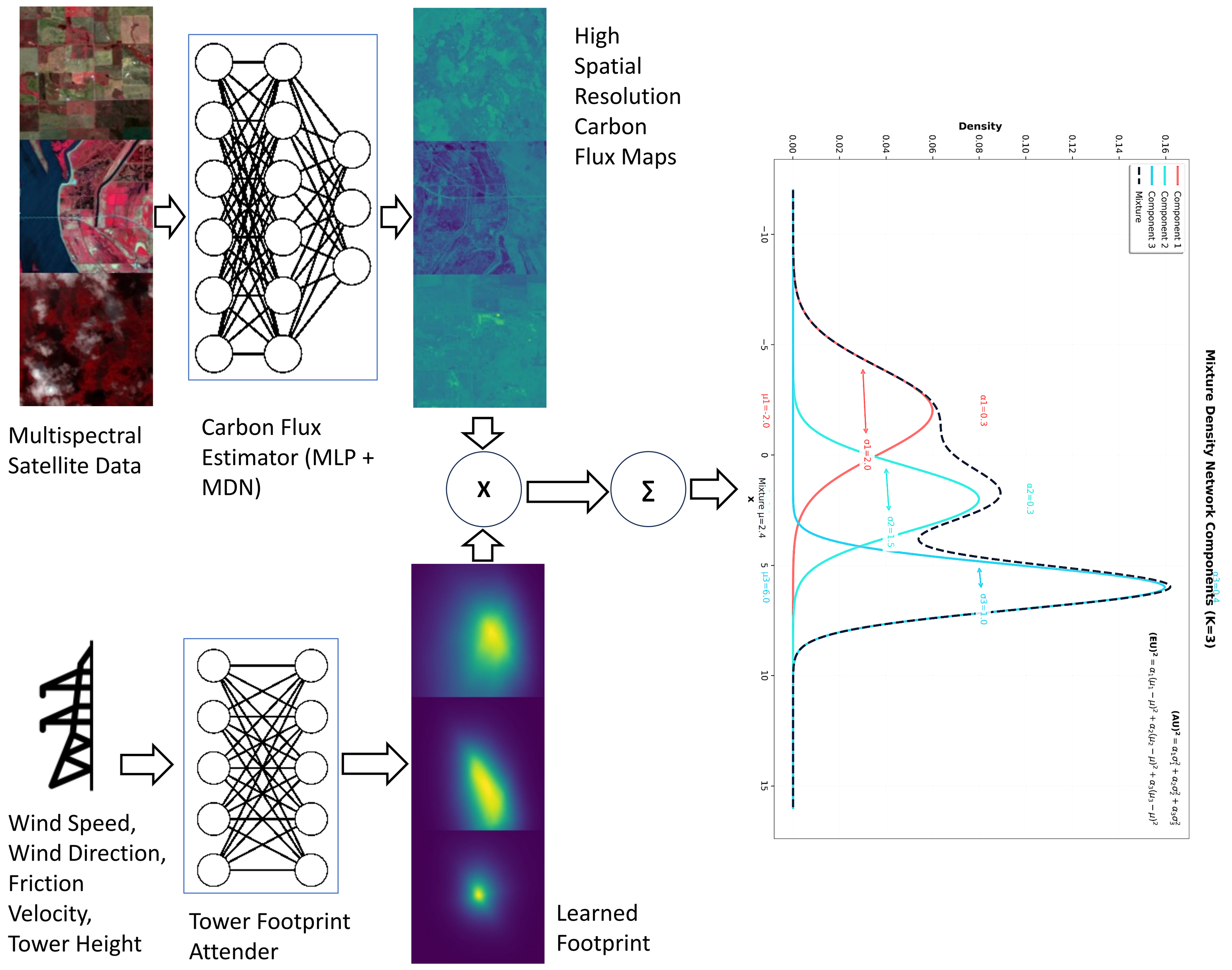


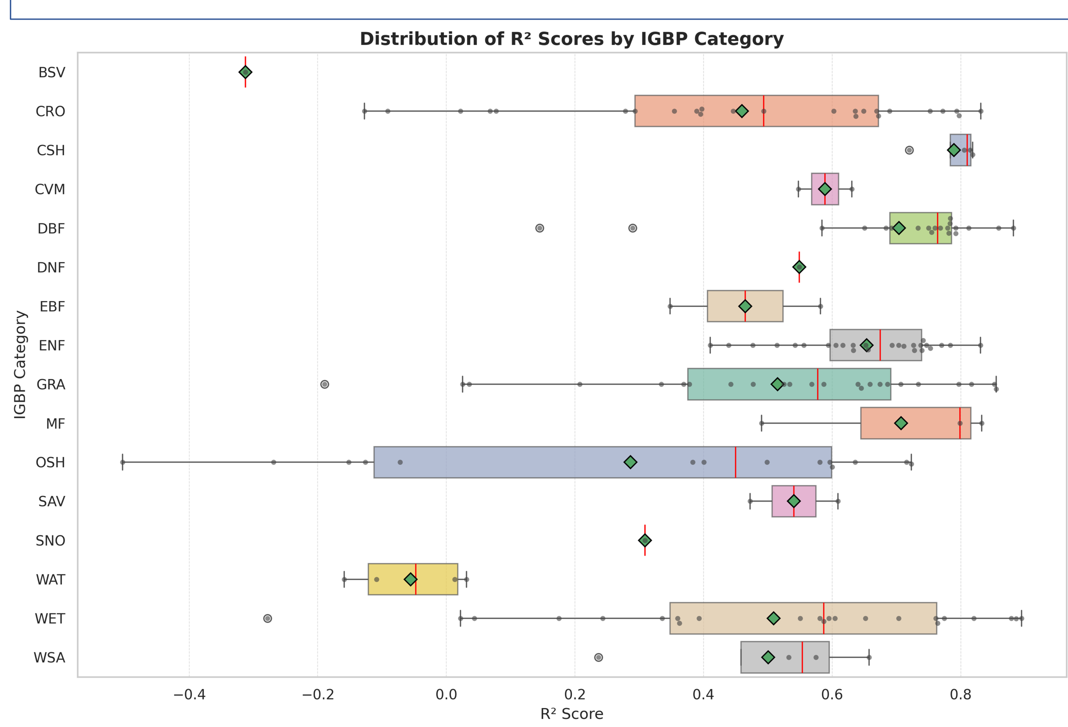
Figure: MDN-based architecture combining Landsat and meteorological inputs for carbon flux prediction and uncertainty estimation.

4. Uncertainty Quantification
   - Aleatoric Uncertainty: Noise inherent in the data (modeled via σ^2 within each Gaussian component).
   - Epistemic Uncertainty: Model uncertainty captured by dispersion among mixture components (μ_k).
   - Single Forward Pass approach (no expensive Monte Carlo sampling) to efficiently estimate both uncertainties:

$$\sigma^2_{\text{total}}(x) = \underbrace{\sum_{k=1}^{K} \alpha_k \sigma_k^2}_{\text{aleatoric}} + \underbrace{\sum_{k=1}^{K} \alpha_k \left(\mu_k - \sum_{j=1}^{K} \alpha_j \mu_j\right)^2}_{\text{epistemic}}$$

Results

The model achieves R^2 values of 0.7958, 0.7363, 0.7239, and 0.5829 on the training, validation, future test(withheld data from the last year of each training site), and site test set(withheld sites), respectively.



IGBP	R^2	AU	EU
BSV	-0.3122	6.8947	1.6044
CRO	0.6698	1.5946	0.7543
CSH	0.7899	1.6778	0.6059
CVM	0.5904	0.9245	0.4504
DBF	0.7716	0.9600	0.2654
DNF	0.5491	1.4683	0.5509
EBF	0.4108	0.6323	0.3058
ENF	0.7061	1.2395	0.3810
GRA	0.6560	1.2268	0.4899
MF	0.8421	0.8286	0.1853
OSH	0.5161	2.0621	0.6658
SAV	0.5270	1.8952	0.5542
SNO	0.3090	2.0744	0.5727
WAT	0.0236	9.8240	2.0399
WET	0.7850	1.1754	0.3749
WSA	0.6248	1.5159	0.4556

Figure: Distribution of R2 scores by site (left) and scaled aleatoric (AU) and epistemic uncertainty (EU) summary (right) across IGBP categories for the future test set. AU and EU are scaled by the predicted mean to allow comparison across categories.

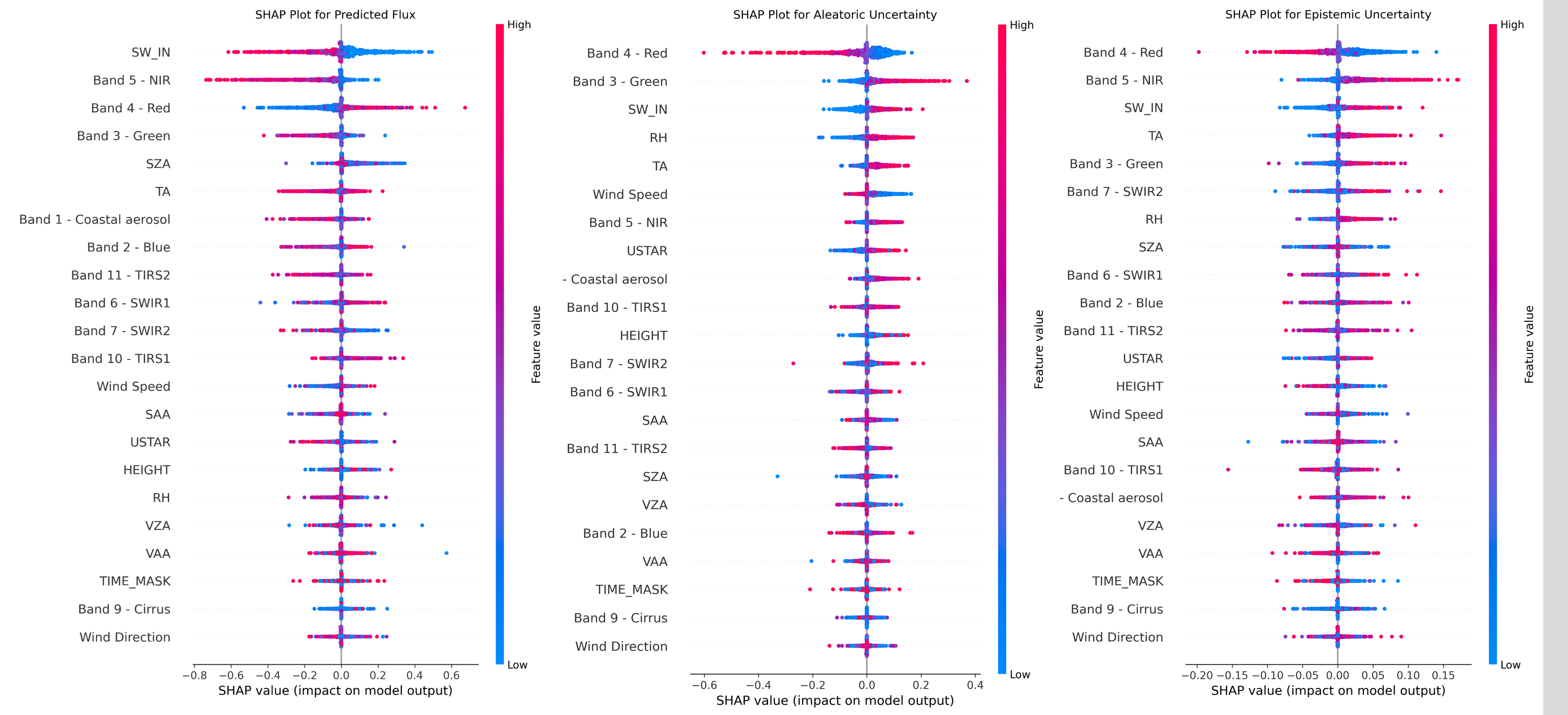


Figure: SHAP plots for predicted flux (left), aleatoric uncertainty (middle) and epistemic uncertainty (right)

Discussion

- Performance: R² 0.74 (val) → 0.72 (temporal test) shows strong time-generalization; drop to 0.58 on unseen sites pinpoints the spatial gap.
- Key insights: Water & Barren land exhibit the largest uncertainties; solar radiation, air temperature and Landsat Bands 3, 4 & 5 dominate both flux and uncertainty (SHAP).

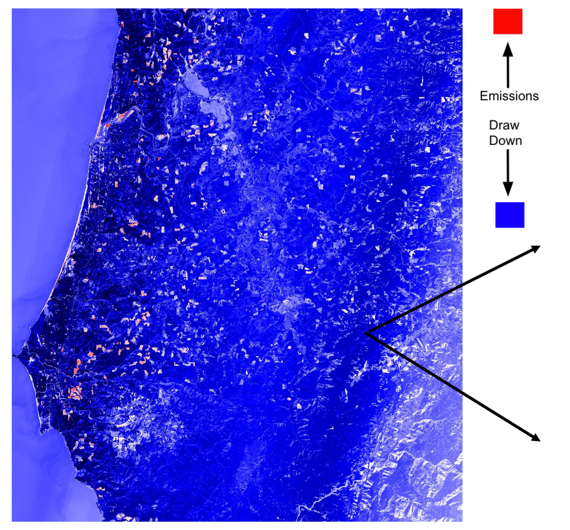


Figure: 1-day integral of carbon flux

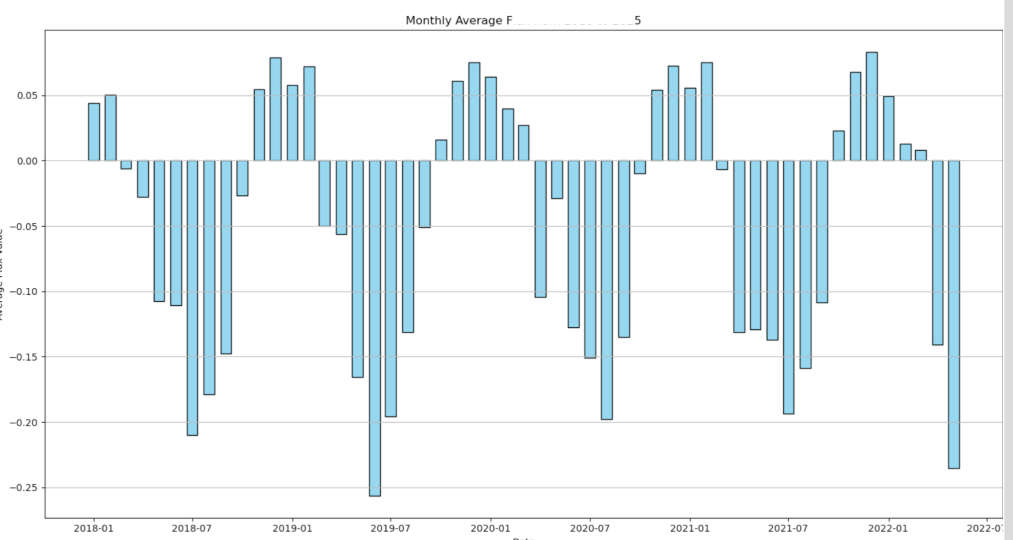


Figure: Average carbon flux emission per month. Net emission is positive during few months in winter.

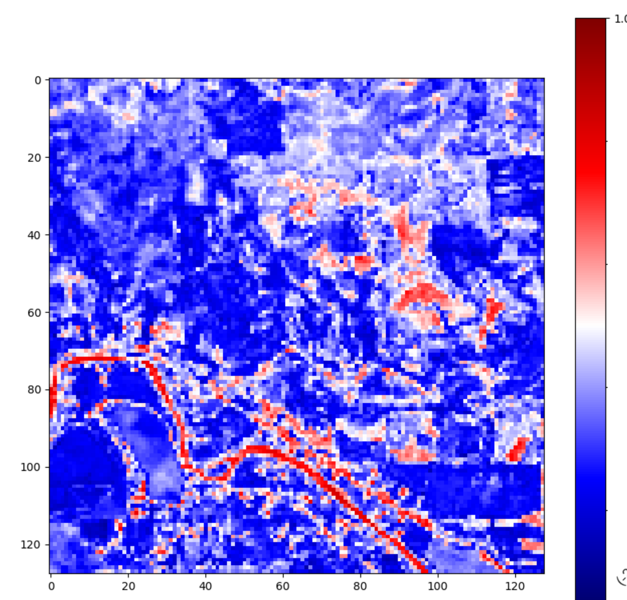


Figure: Spatial distribution of uncertainty in carbon flux predictions, with higher uncertainty observed in water bodies.

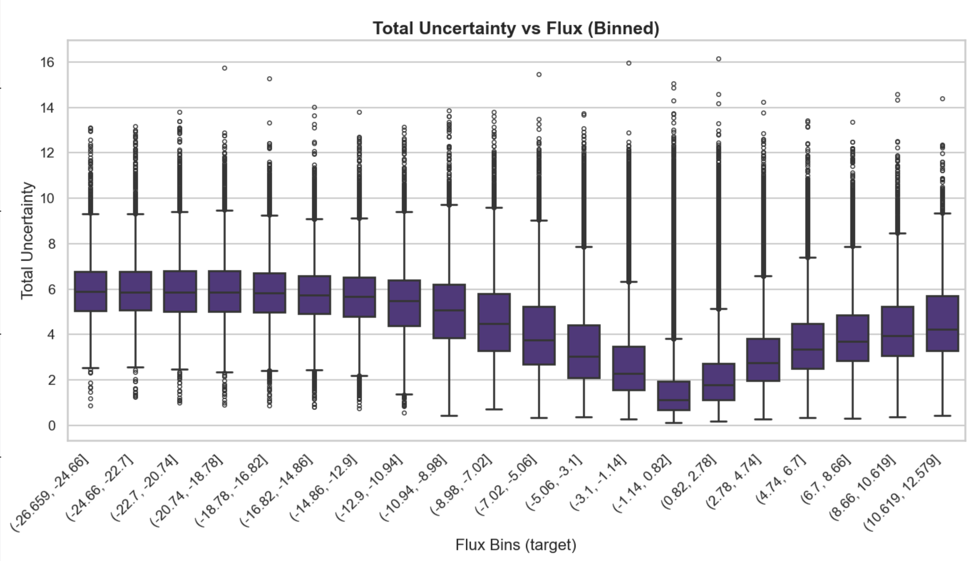


Figure: Relationship between uncertainty and flux values. Uncertainty increases with flux and plateaus beyond a certain value.

Conclusions

- Uncertainty-aware MDN: Combines Landsat imagery, eddy-covariance fluxes, and meteorological drivers, outputting carbon-flux predictions with separate aleatoric + epistemic uncertainty.
- Uncertainty quantification improves prediction reliability, directly informs data acquisition priorities, strengthens Natural Climate Solutions validation, and supports robust climate policy and carbon market integrity.

Full Paper

Acknowledgement

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