CarbonSense: A Multimodal Dataset and Baseline for Carbon Flux Modelling (Incomplete Manuscript)

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Abstract

Understanding terrestrial carbon fluxes is essential for gaining insights into the biosphere's response to climate change and the capacity of ecosystems to absorb anthropogenic CO2 emissions. However, directly measuring these fluxes requires long-term maintenance of field sensors, and the resulting data is typically formatted for ecological research, not for deep learning applications. To address these challenges we present CarbonSense, the first machine learning-ready dataset specifically designed for carbon flux modelling. Alongside this dataset, we present a baseline model which achieves state-of-the-art performance in this domain. By providing these resources, we aim to lower the barrier to entry for deep learning researchers and stimulate advancements in data-driven carbon flux modelling.

1 Introduction

The biosphere plays a critical role in regulating Earth's climate. Since the mid-20th century, terrestrial ecosystems have absorbed up to a third of anthropogenic carbon emissions [1]. However, climate change introduces uncertainty about the future resilience and capacity of these ecosystems. Understanding the carbon dynamics of our biosphere, and how those dynamics are changing in response to climate change, will give crucial insight into the health of our ecosystems and their ability to sequester carbon in the future.

Carbon fluxes describe the movement of carbon into and out of these ecosystems resulting from processes like photosynthesis and cellular respiration. They are often analogised as the "breathing of the biosphere" [2]. However, the large number of dependent processes makes these fluxes challenging to simulate with process-based models[1]. Normally, large scale observational data helps climate scientists to parameterize their models, but carbon fluxes can only be measured in small areas with long-term sensor deployment, creating a data bottleneck.

In recent years, machine learning techniques have been used to upscale carbon flux data using meteorological and geospatial variables. This is known as data-driven carbon flux modelling (DCFM), and it can be used to produce global carbon flux maps that are useful both as an end product for

[1]Process-based models simulate biological, chemical, and physical processes using parameterized equations based on scientific understanding. Historically, the term "climate model" has referred to a process-based model as opposed to a machine learning model.

Submitted to the 38th Conference on Neural Information Processing Systems (NeurIPS 2024) Track on Datasets and Benchmarks. Do not distribute.

studying ecosystem health, and as a benchmark for improving process-based models [3]. Most studies perform DCFM with random forests [4]–[6], XGBoost [7], or ensembles of similar methods [8], [9]. But these models cannot fully capitalize on the multimodality of the input data, often resorting to heavy compression techniques that compromise the quality of the end product.

Deep learning techniques could vastly improve our ability to model carbon fluxes. Multimodal models have been successfully applied to many niche domains [10] such as clinical diagnostics [11], land use cover classification [12], and wildfire surface fuel estimates [13]. Bridging the gap between the deep learning and carbon dynamics research communities will require a sustained effort, but the benefit to our understanding of the changing climate will be substantial.

Our work seeks to establish a foothold for deep learning research in DCFM and lower the barrier to entry for future researchers by providing the following:

- An overview of DCFM for deep learning researchers (Section 2)
- A multimodal ML-ready dataset for DCFM (Section 3)
- A baseline model which achieves state-of-the-art performance in DCFM (Section 4)

We will discuss our experiments in section 5 and provide guidelines for reporting results in this domain.

2 Data-Driven Carbon Flux Modelling

At its core, DCFM is a regression problem. The target (carbon flux) depends on many factors including ecosystem makeup, meteorological conditions, local topography and geology, and disturbances (fires, animal activity, etc). Meteorological data is easy to obtain, but the other predictors are challenging to measure and represent, especially at a global scale. Geospatial and semantic data are commonly employed as a proxy for the other predictors.

2.1 Measuring Fluxes

The most common technique for measuring fluxes is eddy covariance (EC) [14]. This is a micrometeorological technique where researchers erect a tower (typically above canopy height) and mount sensors which measure atmospheric gas fluxes across small turbulent vortices ("eddies"). A simplified EC station is depicted in Figure 1. CO2 and water vapour are the most widely measured, but some towers also measure methane (CH4) [4], [5] or nitrous oxide (N2O) [15]. Our work focuses on CO2 due to the prevalance of standardized data collections.

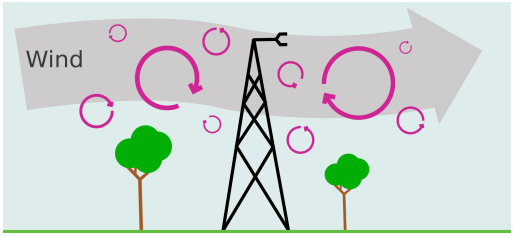

Figure 1: Simplified EC station. Sensors measure atmospheric CO2 gradients across small sensore

Carbon fluxes can be recorded and expressed in many ways, but most represent the movement of carbon in terms of mass / area / time (ex $g \cdot C \cdot m^{-2} \cdot hr$). Gross primary productivity (GPP) refers to the total carbon uptake by plants for photosynthesis. Ecosystem respiration (RECO) is the total carbon returned to the atmosphere through both plant and microbial respiration. Net ecosystem exchange (NEE) is the net carbon flux from GPP and RECO; a carbon sink will have a negative NEE as more carbon is being consumed through GPP than released through RECO. NEE is the flux that is directly measured by EC stations, and for that reason will be the main focus of our experiments, but we provide GPP and RECO data in our dataset.

2.2 Flux Predictors

Meteorological Data DCFM meteorological data comes from EC stations. In addition to carbon fluxes, EC stations measure local atmospheric conditions such as wind velocity and direction,

precipitation, surface temperature, soil moisture, and others. The exact number and type of variables depends on the site, but regional networks maintain a minimum mandatory set for researchers wishing to submit their data [16]. For trained models looking to run global inference, meteorological variables can be obtained from publicly available reanalysis products such as ERA5 [17] which provides the variables on a 0.05 degree grid.

Geospatial Data Satellite imagery of the area surrounding an EC station can give useful information about the land cover and ecosystem makeup. The most common products for DCFM are based on Moderate Resolution Imaging Spectroradiometer (MODIS) data [18]. This satellite constellation produces new imagery for Earth's surface every 1-2 days and has 36 spectral bands with resolutions varying between 250m and 1km. The MCD43A4 derived product is particularly common - it fuses MODIS data in a 16-day sliding window to produce a single image each day. This not only helps to address cloud coverage, but produces nadir BRDF-adjusted reflectance (NBAR) images which remove angle effects from directional reflectance [19]. Each image therefore appears as it would from directly overhead at solar noon. MCD43A2 is also widely used, which contains categorical values for each pixel indicating snow and water cover [20]. The terms "geospatial data", "satellite data" and "remote sensing data" are often used interchangeably.

Semantic Data Some models ingest semantic data such as ecosystem classification ("Croplands", "Evergreen needleleaf forest", "Snow and ice", etc). These classifications follow standardized schemes such as the International Geosphere-Biosphere Programme (IGBP). Ecosystem classification is performed by domain experts, but some MODIS products coarsely approximate this information on a global grid [21], allowing this data to also be used for global inference.

3 The CarbonSense Dataset

We provide the first ML-ready dataset for DCFM, CarbonSense. CarbonSense consists of EC station data and corresponding MODIS geospatial data for 385 sites across the globe, totalling over 27 million hourly observations. This section covers our data sources, processing pipeline, and usage guidelines.

3.1 Data Collection

All meteorological data was aggregated from major EC data networks, including FLUXNET 2015 [16], the Integrated Carbon Observation System (ICOS) 2023 release [22], ICOS Warm Winter release [23], and Ameriflux 2023 release [24]. These source datasets were chosen due to their use of the ONEFlux processing pipeline [16], ensuring standardized coding and units. A map of EC sites and their source networks is shown in Figure 2. North America and Europe are over-represented in this site list due greater data accessibility, and we discuss the implications of this in section 3.3.

Geospatial data in CarbonSense are sourced from MODIS products. Specifically, we utilize the seven spectral bands from the MCD43A4 product [19], as well as the water and snow cover bands from MCD43A2 [20]. Following the guidelines from [18], we extract images in a 4km by 4km square centered on each EC station. Given a spatial resolution of 500m per pixel, this yields an 8x8 pixel image with 9 channels for every site-day.

3.2 Data Pipeline

The first stage in the pipeline is EC data fusion. Many sites had overlapping data from different source networks. For example, the site Degero in Sweden (SE-Deg) had data from 2001-2020 in the ICOS Warm Winter release, and data from 2019-2022 in the ICOS 2023 release. Data were fused with overlapping values taken from the more recent release as in previous DCFM work [7]. Any sites which report half-hourly data were downsampled to hourly at this stage, and daily and monthly recordings were discarded.

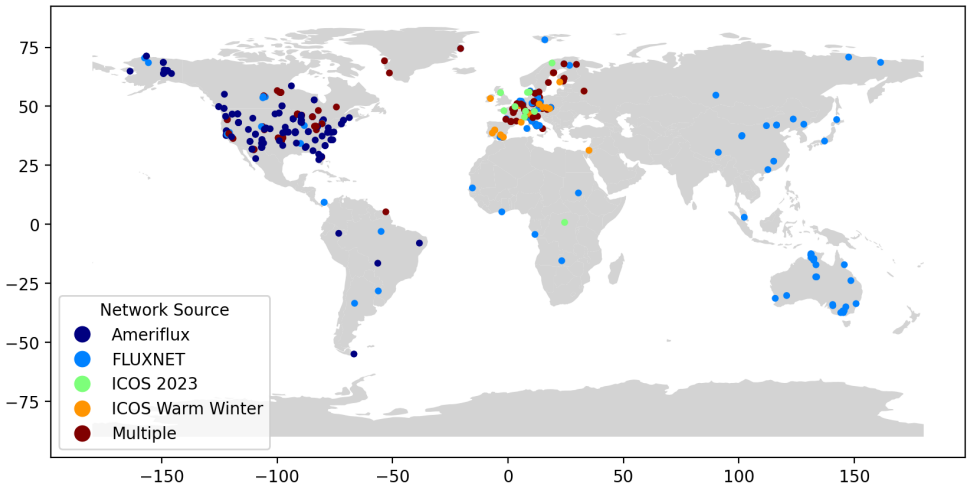

Figure 2: Global map of eddy covariance sites used in CarbonSense, with corresponding source networks. Some sites were present in multiple networks.

Once fused, we extracted the relevant time blocks for each EC station along with its geographic location. This metadata was used to obtain the appropriate MODIS data for each site. Data was pulled procedurally from Google Earth Engine [25].

Meteorological data was pruned to remove unwanted variables. Some, like soil moisture and temperature, were either unavailable for most sites or were heavily gap-filled. We removed these variables in order to reduce the risk of compounding errors on the underlying pipeline gapfilling techniques. A full list of variables at this stage is given in table 6.

As a final stage in the pipeline, we apply a min-max normalization on predictor variables. We map cyclic variables (those with a cyclic range such as wind direction) to the range $[-1, 1)$ and acyclic variables to the range $[-0.5, 0.5)$. This normalization procedure is conducive to our Fourier encoding method discussed in section 4.1.

We offer CarbonSense both before ("raw") and after ("normalized") our normalization step. Our pipeline can be configured to have variable "leniency" for gap-filled values. Those who wish to use CarbonSense with strictly observed values may do so at the cost of a smaller number of samples. The full pipeline code is also available so that researchers can add more source networks with minimal modifications. A diagram of the entire pipeline is shown in Figure 3, and we provide a more detailed description of all these steps in the supplementary material.

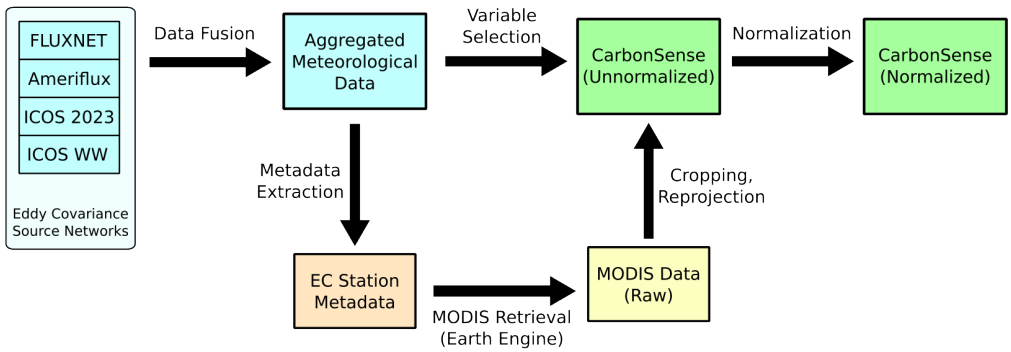

Figure 3: Data pipeline used to create CarbonSense from EC and MODIS data.

3.3 Using the Dataset

Site Sampling The geographic and ecological distribution of sites remains a challenge in statistical CFM, and CarbonSense is no different. Given the significant overrepresentation of certain regions (North America, Europe) and ecosystems (evergreen needleleaf forests, grasslands), we maintain a partitioned structure where each site has its own directory containing EC data, geospatial data, and metadata. Researchers may choose to select sites for training and validation which allow for fair out-of-distribution performance estimates, or to achieve a balanced sampling of ecosystems.

Dataloader We supply an example PyTorch dataloader for CarbonSense specifically tailored to our baseline model. Using the dataloader requires specifying which carbon flux to use as the target, which sites to include in each dataloader instance, and the context window length for multi-timestep training.

Licensing CarbonSense is available under the CC-BY-4.0 license, meaning it can be shared, transformed, and used for any purpose given proper attribution. This is an extension of the same license for all three source networks, and MODIS data is provided under public domain. We feel that permissive licensing is essential in order to foster greater scientific interest in CFM in the deep learning community.

4 The EcoPerceiver Architecture

In this section we present EcoPerceiver, a multimodal architecture for CFM. The state-of-the-art for CFM are simple tabular methods, and we felt it would be appropriate to include a baseline model which demonstrates how deep learning concepts can be leveraged for this unique problem domain.

EcoPerceiver is based on the Perceiver architceture [26], which cross attends a variable number of inputs onto a compact latent space, allowing for extreme input flexibility. Missing inputs are common in DCFM due to coverage gaps, outlier values, or failing sensors. Rather than rely on gapfilling techniques, we chose this architecture for its robustness to missing inputs.

We also wanted a model which could ingest data from a varying time window. All available DCFM models treat carbon dynamics as a Markovian process, predicting a flux value from immediate conditions. But biological processes are not Markovian; a plant's rate of photosynthesis may depend on conditions hours or days into the past (or further!). Our model achieves this through the use of windowed cross attention, detailezd below.

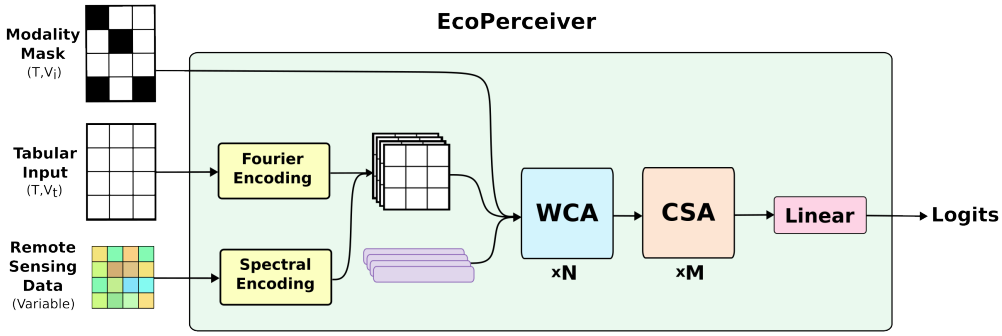

Figure 4: Overview of EcoPerceiver architecture.

4.1 Data Ingestion

Small fluctuations in meteorological variables have the potential to influence ecological processes. For this reason, it is important that the model is sensitive to small changes in input values. We take

inspiration from NeRF's Fourier encoding [27] which maps continuous values to higher dimensional space with high frequency sinusoids. As discussed previously, cyclic variables in CarbonSense are mapped to $[-0.5, 0.5)$ and acyclic variables are mapped to $[-1.0, 1.0)$. We start by taking each variable x, and applying it to a series of sinusoids to produce an encoded vector with:

$$f(x) = \left[\left[\dots, \sin(2^k \pi x), \cos(2^k \pi x), \dots \right] \,\middle|\, k \in [0, K) \right] \tag{1}$$

where K is a hyperparameter indicating the maximum sampling frequency. Higher values of K allow the model to better discern between small differences in input. With our normalization scheme, cyclic variables at values of -1 and 1 will produce identical vectors under this transform as intended.

Each input is given a learned embedding specific to the underlying variable. This is then concatenated with the Fourier encoding to produce a final input vector of length $H_i = 2K + l_{emb}$ for each input. It should be noted that EcoPerceiver requires a list of all possible observation types at creation time so that these embeddings can be created.

Geospatial data is similarly processed, except that each spectral band is flattened into a vector of length $2K$ via linear transformation instead of Fourier encoding. Each band is then given an embedding to produce a vector of length H_i.

The tabular and geospatial data are then stacked to create a matrix of shape (V_t, H_i) where V_t is the sum of the number of meteorological variables and spectral bands at timestep t. Since EcoPerceiver conditions on observations in a fixed context window of length T, the final data cube used for input to the attention layers is of shape (T, V_t, H_i). Figure 5 gives a visualization of the encoding procedure.

Not every timestep has a value for every variable, and this is certainly true of geospatial data which is typically provided once per 24 hours. To account for this, EcoPerceiver takes a modality mask indicating which values to ignore in the cross attentive layers.

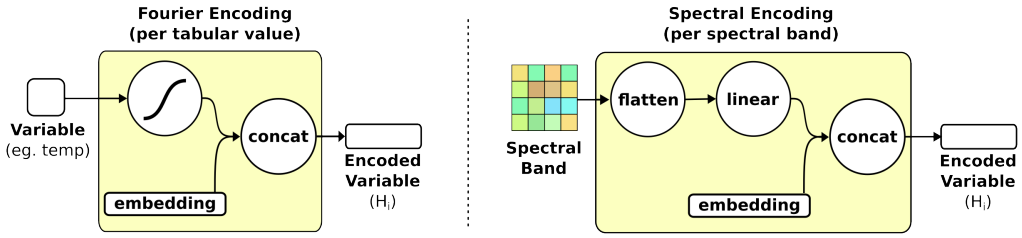

Figure 5: Input encoding for EcoPerceiver. Left: Tabular values are fed into the Fourier encoding function (1) and concatenated with an embedding. Right: Spectral bands are similarly processed except with linear projection instead of Fourier encoding.

4.2 Windowed Cross Attention

We build on Perceiver's core concept of cross-attending data onto a compact latent space for processing. EcoPerceiver uses a latent space of size (T, H_l) where T is the context window length and H_l is the hidden token length (hyperparameter). Each token extracts input data via cross-attention from its respective timestep's observations. In this way each token can be thought of as representing the ecosystem's "state" in time, as it pertains to the carbon cycle.

This operation would be very inefficient with vanilla cross attention, as each token would use at most $\frac{1}{T}$ observations with an attention mask removing the rest. We take inspiration from SWin Transformer [28] and instead push the context window dimension (T) into the batch dimension for both input and latent space. The resulting Windowed Cross Attention (WCA) has a runtime of $O(T \cdot V_t \cdot H_a)$ where H_a is the projection dimension.

In keeping with Perceiver, each WCA operation is followed by a self-attention operation in the latent space. We pass a causal mask to the self attention so each timestep is conditioned only on past and

present observations. We refer to this as Causal Self Attention (CSA). This constitutes a full WCA block as shown in Figure 6.

WCA blocks are repeated N times, repeatedly cross attending inputs onto the latent space with self attention in between. We then apply a series of M CSA operations and use the final timestep's token as input to a linear layer. The output of this is the estimate of the desired carbon flux.

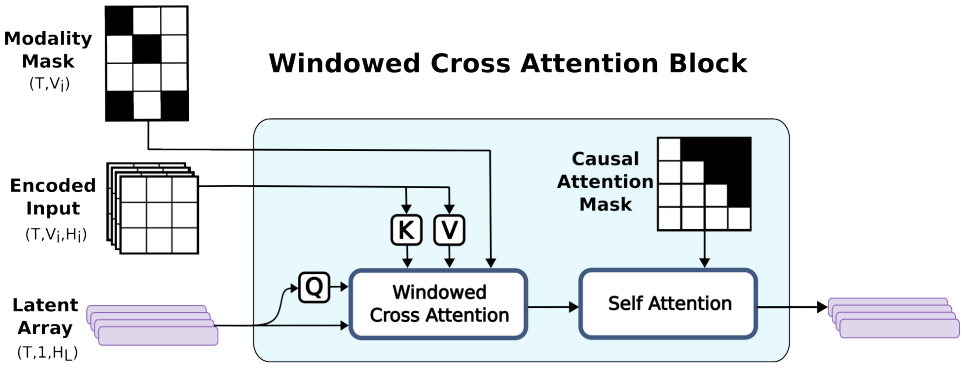

Figure 6: Windowed Cross Attention (WCA) block. Encoded inputs are cross-attended onto the latent space with a modality mask to indicate missing values. The time dimension is pushed into the batch dimension, so this operation is performed $B \cdot T$ times per batch. Causal self attention proceeds as normal.

4.3 Observational Dropout

Overconditioning on a small subset of variables could reduce EcoPerceiver's ability to generalize. Since our architecture is robust to missing observations, we implemented an observational dropout scheme to combat this. Given a hyperparameter $(0 < \epsilon < 1)$, we use the modality mask to randomly remove a portion of observations during training equal to ϵ (in addition to any missing observations). We find that this improves validation performance as seen in the ablation studies in Appendix B.

5 Experiments

In this section, we present a series of experiments using CarbonSense. Our analysis includes two models: an EcoPerceiver model as introduced in 4, and an XGBoost model implemented to mimic current state-of-the-art approaches in DCFM. We aim to demonstrate the power of tailored deep architectures for DCFM and establish a robust baseline that will support and inspire future research efforts. We also present guidelines for running similar experiments and presenting results.

5.1 Data Splitting

EC stations were randomly divided into train, validation, and test sets based on their IGBP classification. We wanted to keep at least 5 of each ecosystem type held out for testing, but several types did not have enough data to accommodate this. In particular, snow and ice (SNO), water bodies (WAT), cropland/vegetation mosaics (CVM) and deciduous needleleaf forests (DNF) only had 1 or 2 sites each, so we use them to measure the zero- and one-shot performance of our model.

The main focus of this research is on models trained *across* different ecosystem types, as opposed to other research studying CFM *within a single* type (ex: [4] [8] [9]). However, the partitioned nature of CarbonSenseaffords any researcher the ability to develop, for example, a model meant for grassland flux modelling. We give an example of this, along with other experimental results, in Appendix B.

5.2 Model Configurations

All experiments were performed on the Compute Canada cluster. To ensure accurate confidence intervals, we ran 10 experiments per model once optimal hyperparameters were found (as suggested by [29]).

EcoPerceiver experiments were each run on 4 A100 GPUs using dataset parallelization. We used the AdamW optimizer [30] with a learning rate of 8e-5 and a batch size of 4096. A single warm-up epoch was performed followed by a cosine annealing learning rate schedule over 20 epochs. Most experiments converged between 4 and 10 epochs. Hyperparameters were initially selected by hand and then refined by experimental perturbation; methods such as random search were infeasible due to the large hyperparameter space, compute constraints, and lack of similar experiments to draw inspiration from.

XGBoost experiments were run on CPU nodes. Hyperparameters were found by random search over 50 iterations. Since XGBoost is a tabular algorithm, we prepared geospatial data in a similar fashion to XBASE [7]; each spectral band represents a single input value to the model. The value is obtained by taking a weighted average of pixels based on Euclidean distance from the center of the image. The code for this processing, as well as the final list of hyperparameters, is provided in the supplementary material.

Table 1: Number of EC sites in train / validation / test splits, by IGBP ecosystem type

IGBP	Train	Valid	Test
WET	34	8	5
DNF	0	0	1
WSA	7	1	2
EBF	8	1	4
ENF	64	15	6
DBF	34	8	5
CRO	36	8	5
MF	7	1	5
GRA	48	11	5
OSH	20	5	5
CVM	1	0	1
CSH	4	1	2
SAV	8	2	4
SNO	0	0	1
WAT	1	0	1

5.3 Reproducibility and Reliability

Both EcoPerceiver and XGBoost were trained with reproducibility in mind. Once optimal hyperparameters were found, we performed 10 experiments with each model in order to obtain a reliable measure of performance (inspired by [29]). Set seeds were provided to all frameworks utilizing RNG, and distributed dataloader workers were also seed-controlled to ensure full reproducibility of our results.

5.4 Metrics

The most commonly used performance metric in DCFM (and any form of hydrologic modelling) is the Nash-Sutcliffe Modelling Efficiency (NSE) [31], described with the following equation:

$$\text{NSE}(x) = 1 - \frac{\sum_i (y_i - x_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{2}$$

where a value of 1 represents perfect correlation between x and y. A value of 0 represents the same performance as guessing the mean of y, and negative values indicate that the mean of y is a better predictor than x. NSE is more challenging to use directly as a loss function since it would require the dataloader to also provide the mean of the data for a given site or ecosystem type. We therefore use mean squared error (MSE) as a loss function and report its root (RMSE) as well as NSE in our results, and encourage future researchers to do the same.

Data balance in results reporting is also a concern. At first glance, the data appears very imbalanced with respect to ecosystem prevalence. CarbonSense contains 62 grassland sites, but only 1 deciduous needleleaf forest site. While this is an extreme gap, ecosystems are more diverse than IGBP taxonomies can capture; grasslands in central North America will differ significantly from those in

Europe or Asia. Still, it is prudent to separate results by ecosystem type to give a better picture of model performance.

5.5 Results

EcoPerceiver consistently outperformed the XGBoost baseline across most ecosystem types as shown in Table 2. In the low-shot regime, EcoPerceiver performed better in CVM and SNO ecosystems, but worse in DNF and WAT. In sites with greater train set prevalence EcoPerceiver scored better in all except permanent wetlands (WET)[2].

Our results also underline the importance of using NSE as the main metric for evaluation. Consider the models' performance on open shrublands (OSH). XGBoost had an RMSE of 2.2995 versus EcoPerceiver's 1.6860. The magnitude of difference is small, and both values are significantly lower than the RMSE of many other ecosystem types. But XGBoost has an NSE of -0.0945 indicating it is worse than simply guessing the mean, as opposed to EcoPerceiver achieving 0.4117. Ecosystems may have wildly different variances in their carbon fluxes, and NSE accounts for this by dividing the performance by the variance of the target.

Table 2: NSE and RMSE for each model, by IGBP ecosystem type

	XGBoost		EcoPerceiver	
IGBP	NSE	RMSE	NSE	RMSE
CRO	0.5685	4.4995	**0.7009**	**3.7461**
CSH	0.5671	2.3625	**0.6253**	**2.1980**
CVM	0.5397	2.9535	**0.7029**	**2.3728**
DBF	0.7084	3.9390	**0.7820**	**3.4056**
DNF	**0.3158**	**3.7062**	0.1745	4.0710
EBF	0.6319	5.1209	**0.6451**	**5.0286**
ENF	0.7078	3.0073	**0.7156**	**2.9667**
GRA	0.6610	2.8464	**0.7229**	**2.5731**
MF	0.6931	4.5301	**0.7237**	**4.2984**
OSH	-0.0945	2.2995	**0.4117**	**1.6860**
SAV	0.7305	2.1478	**0.7909**	**1.8916**
SNO	-1.4167	1.8208	**-0.1228**	**1.2411**
WAT	**-23.7044**	**3.6076**	-46.1290	4.9829
WET	**0.5540**	**1.7064**	0.3356	2.0828
WSA	0.4175	2.7485	**0.4448**	**2.6832**

6 Conclusion

Our work establishes a foothold for deep learning in the field of DCFM. We provide an open source ML-ready dataset, CarbonSense, using EC station data and geospatial data from a variety of ecosystems. DCFM is an inherently a time-dependent and multimodal task, and our baseline model EcoPerceiver demonstrates that recent advances in deep learning can unlock substantial performance gains in this domain. We implore more deep learning researchers to help develop this field further, because the potential of artificial intelligence to improve our world can only be realized if we actively apply it to solve pressing social and environmental issues.

Limitations Data diversity remains the biggest challenge in this domain. CarbonSense has a data imbalance in not only ecosystem types, but geographic location. Africa, Central Asia, and South America are all underrepresented. While these areas contain many EC stations, most do not have readily available data in ONEFlux format, presenting a barrier to their inclusion. Researchers should be aware of the consequences of developing models with imbalanced data, including poor performance in underrepresented areas.

[2]Many wetlands in CarbonSense are in the arctic-boreal reagion and are notoriously challenging to model due to their complex processes [6]. Inclusion of more data could potentially tip the scales.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See 6
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] Our limitations cover this
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? **[TODO]**Still need to properly document all code
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments (e.g. for benchmarks)...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? **[TODO]**
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? **[TODO]**Briefly discussed in section 5, but need to finish details in appendices / supplementary
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No] The error bars with different seeds were very small and were not visible in our figures
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See section 5
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] See section 3.1 for data attributions. Appendix contains full EC site list.
   (b) Did you mention the license of the assets? [Yes] Section 3.3 has info on licensing of EC data and MODIS data
   (c) Did you include any new assets either in the supplemental material or as a URL? **[TODO]**
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A] Covered under licensing
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A] Our dataset contains no PII.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

Appendices

A Eddy Covariance Site Details

Here we provide an exhaustive list of EC sites used in CarbonSense along with their most recent publication. As per Ameriflux's data policy, each site has an individual citation with DOI; other networks simply required citation of the unified release. It would be impractical to have each site's full description in these tables, but the first two letters of each code represent the country where the site is located (ex. "DE" for Germany).

We also enumerate all meteorological predictors and targets in table 6.

Table 3: EC Sites

Croplands (CRO)

BE-Lon [22]	CA-ER1 [32]	CA-MA1 [33]	CA-MA2 [34]	CH-Oe2 [23]	CZ-KrP [23]
DE-Geb [22]	DE-Kli [22]	DE-RuS [22]	DE-Seh [16]	DK-Fou [16]	DK-Vng [22]
FI-Jok [16]	FI-Qvd [23]	FR-Aur [22]	FR-EM2 [22]	FR-Gri [22]	FR-Lam [22]
IT-BCi [23]	IT-CA2 [16]	US-A74 [35]	US-ARM [36]	US-Bi1 [37]	US-Bi2 [38]
US-CF1 [39]	US-CF2 [40]	US-CF3 [41]	US-CF4 [42]	US-CRT [43]	US-CS1 [44]
US-CS3 [45]	US-CS4 [46]	US-DFC [47]	US-DS3 [48]	US-Lin [49]	US-Mo1 [50]
US-Mo3 [51]	US-Ne1 [52]	US-RGA [53]	US-RGB [54]	US-RGo [55]	US-Ro1 [56]
US-Ro2 [57]	US-Ro5 [58]	US-Ro6 [59]	US-Tw2 [60]	US-Tw3 [61]	US-Twt [16]
US-xSL [62]					

Closed Shrublands (CSH)

BE-Maa [22]	IT-Noe [16]	US-KS2 [63]	US-Rls [64]	US-Rms [65]	US-Rwe [66]
US-Rwf [67]					

Cropland/Natural Vegetation Mosaics (CVM)

US-HWB [68]	US-xDS [69]

Deciduous Broadleaf Forests (DBF)

AU-Lox [16]	BE-Lcr [22]	CA-Cbo [70]	CA-Oas [16]	CA-TPD [71]	CZ-Lnz [22]
CZ-Stn [23]	DE-Hai [22]	DE-Hzd [23]	DE-Lnf [16]	DK-Sor [22]	FR-Fon [22]
FR-Hes [22]	IT-BFt [22]	IT-CA1 [16]	IT-CA3 [16]	IT-Col [16]	IT-Isp [16]
IT-PT1 [16]	IT-Ro1 [16]	IT-Ro2 [16]	JP-MBF [16]	MX-Tes [72]	PA-SPn [16]
US-Bar [73]	US-Ha1 [74]	US-MMS [75]	US-MOz [76]	US-Oho [77]	US-Rpf [78]
US-UMB [79]	US-UMd [80]	US-WCr [16]	US-Wi1 [81]	US-Wi3 [82]	US-Wi8 [83]
US-xBL [84]	US-xBR [85]	US-xGR [86]	US-xHA [87]	US-xML [88]	US-xSC [89]
US-xSE [90]	US-xST [91]	US-xTR [92]	US-xUK [93]	ZM-Mon [16]	

Deciduous Needleleaf Forests (DNF)

BR-CST [94]

Evergreen Broadleaf Forests (EBF)

AU-Cum [16]	AU-Rob [16]	AU-Wac [16]	AU-Whr [16]	AU-Wom [16]	BR-Sa3 [16]
CN-Din [16]	FR-Pue [22]	GF-Guy [22]	GH-Ank [16]	IT-Cp2 [22]	IT-Cpz [16]
MY-PSO [16]					

Table 4: EC Sites (cont'd)

Evergreen Needleleaf Forests (ENF)

AR-Vir [16]	CA-Ca1 [95]	CA-Ca2 [96]	CA-LP1 [97]	CA-Man [16]	CA-NS1 [98]
CA-NS2 [99]	CA-NS3 [100]	CA-NS4 [101]	CA-NS5 [102]	CA-Obs [16]	CA-Qfo [103]
CA-SF1 [104]	CA-SF2 [105]	CA-TP1 [106]	CA-TP2 [16]	CA-TP3 [107]	CA-TP4 [16]
CH-Dav [22]	CN-Qia [16]	CZ-BK1 [22]	CZ-RAJ [23]	DE-Lkb [16]	DE-Msr [22]
DE-Obe [23]	DE-RuW [22]	DE-Tha [22]	DK-Gds [22]	FI-Hyy [22]	FI-Ken [22]
FI-Let [22]	FI-Sod [16]	FI-Var [22]	FR-Bil [22]	FR-FBn [23]	FR-LBr [16]
IL-Yat [23]	IT-La2 [16]	IT-Lav [23]	IT-Ren [22]	IT-SR2 [22]	IT-SRo [16]
NL-Loo [16]	RU-Fy2 [23]	RU-Fyo [23]	SE-Htm [22]	SE-Nor [22]	SE-Ros [23]
SE-Svb [22]	US-BZS [108]	US-Blo [16]	US-CS2 [109]	US-Fmf [110]	US-Fuf [111]
US-GBT [16]	US-GLE [112]	US-HB2 [113]	US-HB3 [114]	US-Ho2 [115]	US-KS1 [116]
US-Me1 [117]	US-Me2 [118]	US-Me3 [119]	US-Me4 [16]	US-Me5 [16]	US-Me6 [120]
US-NC1 [121]	US-NC3 [122]	US-NR1 [123]	US-Prr [16]	US-Vcm [124]	US-Vcp [125]
US-Wi0 [126]	US-Wi2 [16]	US-Wi4 [127]	US-Wi5 [128]	US-Wi9 [129]	US-xAB [130]
US-xBN [131]	US-xDJ [132]	US-xJE [133]	US-xRM [134]	US-xSB [135]	US-xTA [136]
US-xYE [137]					

Grasslands (GRA)

AT-Neu [16]	AU-DaP [16]	AU-Emr [16]	AU-Rig [16]	AU-Stp [16]	AU-TTE [16]
AU-Ync [16]	BE-Dor [23]	CA-MA3 [138]	CH-Aws [23]	CH-Cha [23]	CH-Fru [23]
CH-Oe1 [16]	CN-Cng [16]	CN-Dan [16]	CN-Du2 [16]	CN-Du3 [16]	CN-HaM [16]
CN-Sw2 [16]	CZ-BK2 [16]	DE-Gri [22]	DE-RuR [22]	DK-Eng [16]	FR-Mej [22]
FR-Tou [22]	GL-ZaH [22]	IT-MBo [23]	IT-Niv [22]	IT-Tor [22]	NL-Hor [16]
PA-SPs [16]	RU-Ha1 [16]	SE-Deg [22]	US-A32 [139]	US-AR1 [140]	US-AR2 [141]
US-ARb [142]	US-ARc [143]	US-BRG [144]	US-Cop [145]	US-Goo [16]	US-Hn2 [146]
US-IB2 [16]	US-KFS [147]	US-KLS [148]	US-Kon [149]	US-Mo2 [150]	US-NGC [151]
US-ONA [152]	US-Ro4 [153]	US-SRG [154]	US-Seg [155]	US-Sne [156]	US-Snf [157]
US-Var [158]	US-Wkg [159]	US-xAE [160]	US-xCL [161]	US-xCP [162]	US-xDC [163]
US-xKA [164]	US-xKZ [165]	US-xNG [166]	US-xWD [167]		

Mixed Forests (MF)

AR-SLu [16]	BE-Bra [22]	BE-Vie [22]	CA-Gro [168]	CD-Ygb [22]	CH-Lae [23]
CN-Cha [16]	DE-Har [22]	DE-HoH [22]	JP-SMF [16]	US-Syv [169]	US-xDL [170]
US-xUN [171]					

Open Shrublands (OSH)

CA-NS6 [172]	CA-NS7 [173]	CA-SF3 [16]	ES-Agu [23]	ES-Amo [16]	ES-LJu [23]
ES-LgS [16]	ES-Ln2 [16]	GL-Dsk [22]	IT-Lsn [22]	RU-Cok [16]	US-EML [174]
US-Fcr [175]	US-Hn3 [176]	US-ICh [177]	US-ICt [178]	US-Jo1 [179]	US-Jo2 [180]
US-Rws [181]	US-SRC [182]	US-Ses [183]	US-Sta [16]	US-Whs [184]	US-Wi6 [185]
US-Wi7 [186]	US-xHE [187]	US-xJR [188]	US-xMB [189]	US-xNQ [190]	US-xSR [191]

Savannas (SAV)

AU-ASM [16]	AU-Cpr [16]	AU-DaS [16]	AU-Dry [16]	AU-GWW [16]	CG-Tch [16]
ES-Abr [23]	ES-LM1 [23]	ES-LM2 [23]	SD-Dem [16]	SN-Dhr [16]	US-LS2 [192]
US-Wjs [193]	US-xSJ [194]				

Snow and Ice (SNO)

US-NGB [195]

Table 5: EC Sites (cont'd)

Water Bodies (WAT)					
US-Pnp [196]	US-UM3 [197]				
Permanent Wetlands (WET)					
AR-TF1 [198]	AU-Fog [16]	CA-ARB [199]	CA-ARF [200]	CA-CF1 [201]	CA-DB2 [202]
CA-DBB [203]	CN-Ha2 [16]	CZ-wet [22]	DE-Akm [23]	DE-SfN [16]	DE-Spw [16]
DE-Zrk [16]	DK-Skj [22]	FI-Lom [16]	FI-Sii [22]	FR-LGt [22]	GL-NuF [22]
GL-ZaF [16]	IE-Cra [23]	PE-QFR [204]	RU-Che [16]	SE-Sto [22]	SJ-Adv [16]
UK-AMo [22]	US-ALQ [205]	US-Atq [16]	US-BZB [206]	US-BZF [207]	US-BZo [208]
US-EDN [209]	US-HB1 [210]	US-ICs [211]	US-Ivo [16]	US-KS3 [212]	US-Los [16]
US-Myb [213]	US-NC4 [214]	US-ORv [215]	US-OWC [216]	US-Srr [217]	US-StJ [218]
US-Tw1 [219]	US-Tw4 [220]	US-Tw5 [221]	US-WPT [222]	US-xBA [223]	
Woody Savannas (WSA)					
AU-Ade [16]	AU-Gin [16]	AU-How [16]	AU-RDF [16]	BR-Npw [224]	ES-Cnd [23]

Table 6: Meteorological Variables in CarbonSense

Code	Description	Units
Predictors		
TA_F	Air temperature	deg C
PA_F	Atmospheric pressure	kPa
P_F	Precipitation	mm
RH	Relative humidity	%
VPD_F	Vapor pressure deficit	hPa
WS_F	Wind speed	m s-1
WD	Wind direction	decimal degrees
USTAR	Frictional wind velocity	m s^{-1}
NETRAD	Net radiation	W m^{-2}
SW_IN_F	Incoming shortwave radiation	W m^{-2}
SW_OUT	Outgoing shortwave radiation	W m^{-2}
SW_DIF	Incoming diffuse shortwave radiation	W m^{-2}
LW_IN_F	Incoming longwave radiation	W m^{-2}
LW_OUT	Outgoing longwave radiation	W m^{-2}
PPFD_IN	Incoming photosynthetic photon flux density	µmol Photon m^{-2} s^{-1}
PPFD_OUT	Outgoing photosynthetic photon flux density	µmol Photon m^{-2} s^{-1}
PPFD_DIF	Incoming diffuse photosynthetic photon flux density	µmol Photon m^{-2} s^{-1}
CO2_F_MDS	CO2 atmospheric concentration	µmol CO_2 mol^{-1}
G_F_MDS	Soil heat flux	W m^{-2}
LE_F_MDS	Latent heat flux	W m^{-2}
H_F_MDS	Sensible heat flux	W m^{-2}
Targets		
NEE_VUT_REF	Net Ecosystem Exchange (variable USTAR)	µmol CO_2 m^{-2} s^{-1}
GPP_DT_VUT_REF	Gross Primary Production (daytime partitioning)	µmol CO_2 m^{-2} s^{-1}
GPP_NT_VUT_REF	Gross Primary Production (nighttime partitioning)	µmol CO_2 m^{-2} s^{-1}
RECO_DT_VUT_REF	Ecosystem Respiration (daytime partitioning)	µmol CO_2 m^{-2} s^{-1}
RECO_NT_VUT_REF	Ecosystem Respiration (nighttime partitioning)	µmol CO_2 m^{-2} s^{-1}

B Experiment Details