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aiLand v1: Physics-Based Land Surface Emulator with Observational Fine-Tuning

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Abstract. A stand-alone emulator of ECMWF's land surface scheme (ecLand) has been developed. This emulator, aiLand, uses a multi-layer perceptron architecture, chosen for its balance of accuracy and efficiency and for its differentiability, which is crucial for integration into data assimilation and parameter estimation systems. In this study, we introduce a two-stage learning framework that leverages both synthetic land surface model simulations and real-world observations. We first pretrain the surrogate on extensive ecLand outputs to capture the core dynamical behaviour of key land surface states, evaluating its accuracy, long-term stability, and transferability across variables, depths, and climates. We then fine-tune the pretrained model on in situ eddy-covariance flux observations for selected diagnostic variables, validating against independent flux-tower sites. The pretrained emulator reproduces ecLand's prognostic soil state with a 90-day RMSE of 1.19 K for surface soil temperature and $0.014\,\mathrm{m}^3\,\mathrm{m}^{-3}$ for surface soil moisture, and remains stable over continuous 4-year autoregressive integrations. A single globally trained model outperforms biome-specialist baselines in cross-biome transfer, with residual errors concentrating in snow-insulated cold biomes where an insulating snowpack decouples the soil from atmospheric forcing. Fine-tuning on FLUXNET observations reduces latent heat flux RMSE by 30% and sensible heat flux by 20% at validation sites, while preserving prognostic state integrity and improving the physical consistency of the surface energy budget: per-site Bowen ratio error drops by 42% and energy balance closure residuals fall from $13.4\,\mathrm{W\,m^2 m^{-2}}$ to $3\,\mathrm{W\,m^{-2}}$ and below. These results demonstrate that combining physics-based pretraining with observation-based fine-tuning provides a flexible pathway for building accurate, stable, and differentiable land surface emulators suitable for data assimilation and coupled modelling applications.

1 Introduction

Land surface models (LSMs) are essential components of Earth system and weather prediction frameworks. They represent exchanges of water, energy, and carbon between the land surface and the atmosphere, informing weather forecasts (e.g., Boussetta et al., 2021; Bush et al., 2025), climate projections (e.g., Lawrence et al., 2019; Cheruy et al., 2020), and hydrological assessments (e.g., Clark et al., 2015). However, despite decades of development, LSMs continue to exhibit systematic biases in key variables such as soil moisture, evapotranspiration, runoff, and surface heat fluxes. These biases reflect a combination of structural simplifications (Fisher and Koven, 2020; Blyth et al., 2021), uncertain parameter values (Raoult et al., 2025a; Pin-

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nington et al., 2021), unresolved spatial heterogeneity (Chaney et al., 2018), and a simple lack of local information on soil and vegetation properties (Verhoef et al., 2026). This complexity motivates the exploration of complementary machine-learning (ML) methods that can both emulate LSM behaviour and adjust for real-world biases.

Large model intercomparison efforts have highlighted the magnitude and persistence of these biases. In particular, the PLUMBER2 Model Intercomparison Project evaluated multiple LSMs against eddy-covariance flux measurements across hundreds of sites worldwide and revealed substantial systematic differences in latent heat, sensible heat, and carbon fluxes (Abramowitz et al., 2024). Subsequent analyses have further shown that LSM underperformance is particularly pronounced under rare or extreme meteorological conditions, whereas models generally perform better under typical conditions (Cranko Page et al., 2026). Notably, these studies also showed that relatively simple empirical and ML models trained on meteorological forcing data could outperform many complex mechanistic LSMs in out-of-sample predictions at site level (although LSMs serve a broader purpose, providing globally consistent, physically constrained representations of the land surface for coupling within Earth system models). These findings underscore both the limitations of current LSM parameterisations and the potential for data-driven approaches to improve predictive skill.

Beyond flux evaluation, several studies have demonstrated how ML can inform land surface model development and correction. Neural regression models have been shown to learn mappings from meteorological inputs to satellite observations, improving the quality control of physiographic fields and guiding refinements in LSM representations (Kimpson et al., 2023). ML-based approaches have also been applied to parameter estimation and uncertainty reduction in LSMs (Fer et al., 2018; Dagon et al., 2020; Raoult et al., 2024), although sparse observations and high-dimensional parameter spaces remain important practical challenges (Raoult et al., 2025a). Recent studies have shown that ML can be used to infer spatially varying ecosystem parameters, revealing strong heterogeneity in carbon–water sensitivities that is obscured by conventional plant functional type parameterisations (Bao et al., 2023, 2025; Fang et al., 2024). Collectively, this body of work suggests that ML can play a role in enabling more effective use of information contained in forcing and observational datasets, both in situ and satellite-based, that are often underutilised by traditional LSMs.

One major research direction embeds ML components within physical models (also known as hybrid modelling). For instance, JAX-CanVeg implements differentiable neural network parameterisations within the CanVeg LSM, allowing end-to-end training against flux tower measurements while retaining most of the original physics (Jiang et al., 2025). Similarly, ElGhawi et al. (2025) added ML-based parameterisations to the JSBACH4 LSM in the ICON-ESM framework to improve land–atmosphere flux simulations. More generally, process-informed neural network frameworks illustrate how mechanistic constraints can be incorporated into ML-based ecosystem models, providing a flexible approach to hybrid modelling (Wesselkamp et al., 2024). While these hybrid approaches are promising, they share some limitations. The full LSM typically remains in the prediction loop, making the simulations computationally expensive and tightly coupled to the underlying model.

In parallel, purely observations-driven approaches bypass physical models by training ML systems directly on observational datasets to emulate land surface behaviour or predict individual fluxes and states. Empirical and neural network models trained on eddy-covariance measurements have been shown to reproduce surface energy and carbon fluxes with skill comparable to, or exceeding, that of many mechanistic LSMs at site scale (Tramontana et al., 2016; Jung et al., 2020). Similarly, ML

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applied to satellite and remote sensing data can estimate soil moisture at high resolution (Kolassa et al., 2018; O. and Orth, 2021), while deep learning with multi-sensor inputs captures surface soil moisture variability across regional scales (Singh and Gaurav, 2023). These studies illustrate the potential of observation-only learning to capture effective land–atmosphere responses without explicit process representation. However, the spatial sparsity, temporal discontinuity, and variable quality of observational datasets strongly limit the scalability and generalisation of purely observations-driven models. Earth observation also imposes a fundamental observability limit: satellites sense only the skin layer of the surface, with no direct visibility into sub-surface soil moisture, deep soil temperature, or canopy water storage—states that are central to mechanistic LSM dynamics, mediating land–atmosphere coupling on subseasonal timescales.

An alternative and complementary opportunity lies in the extensive synthetic data generated by LSM simulations themselves. Long simulation records provide dense, physically consistent training samples that capture multivariate temporal dynamics. ML surrogate models trained on these simulations can emulate LSM behaviour at a fraction of the computational cost, offering a pathway towards efficient surrogate LSMs for experimentation or operational use (Wesselkamp et al., 2025). At the same time, models trained exclusively on synthetic data risk inheriting the structural biases of the underlying LSM if not subsequently constrained by independent observations.

Reanalysis products such as ERA5 (the fifth generation of European ReAnalysis; Hersbach et al., 2020), which merge physical model outputs with assimilated observations, provide spatially and temporally complete datasets and underpin several recent data-driven forecasting systems, including ECMWF's Artificial Intelligence Forecasting System (AIFS; Lang et al., 2024; Moldovan et al., 2025). However, ERA5 land surface variables are generated within a land data assimilation framework in which the land surface model is continuously constrained by atmospheric observations. This introduces two key challenges: first, reanalysis land states are not fully independent observations but reflect a mixture of model dynamics and assimilation increments; second, atmospheric biases, abrupt adjustments, and discontinuities in reanalysis can propagate into land surface fields, producing potential unrealistic jumps or breaking the intrinsic land–atmosphere dynamics. As a result, while reanalysis products are valuable for large-scale evaluation and benchmarking, they are less suitable as a training or calibration target for ML-based land surface emulators intended to learn physically meaningful temporal dynamics.

To address these challenges, this study proposes a two-stage learning strategy that leverages the strengths of both synthetic simulation data and real observations. We first pretrain a multilayer perceptron (MLP) surrogate on extensive LSM outputs to capture the core dynamical behaviour of key land surface states, evaluating its accuracy, long-term stability, and transferability across variables, depths, and climates. We then fine-tune this surrogate using observational data for selected diagnostic variables, assessing improvements over the pretrained model, and validating against flux tower sites. This approach provides a flexible pathway for integrating physical knowledge and observations in ML-based land surface emulators.

Beyond simply accelerating ecLand integrations, the resulting emulator opens applications that the physical model alone cannot easily support. By combining ecLand's physical consistency with observational constraints incorporated through fine-tuning, aiLand can correct systematic biases that ecLand inherits from structural simplifications and parameter uncertainty—something the closed physical model cannot do directly without extensive offline calibration. The emulator's differentiability further enables gradient-based parameter sensitivity analysis and observation-constrained parameter estimation, while its com-

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putational efficiency supports rapid generation of high-resolution multi-decadal land reanalyses. Looking forward, the same architecture supports coupling with ML-based atmospheric models such as the AIFS within a fully data-driven Earth system framework, and provides a diagnostic for identifying where ecLand's parameterisations are hardest to learn.

2 Methods and Data

2.1 Data sources

The aiLand machine-learning model is first pretrained using simulations from ecLand (ECMWF's land surface model) to create aiLand-base. Prognostic land surface states, meteorological forcing, and static surface physiographic fields are used as inputs to predict subsequent land states, consistent with the time-stepping of the physical model. Observations are then incorporated during fine-tuning to constrain selected diagnostic variables, producing the aiLand-S1 to aiLand-S5 variants. Table 1 summarises the forcings and state variables used for training and their respective data sources.

2.1.1 ecLand

The ecLand model is the land surface component of the ECMWF Integrated Forecasting System (IFS) (Boussetta et al., 2021), building on the Carbon–Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land (CHTESSEL; van den Hurk et al., 2000; Balsamo et al., 2009; Boussetta et al., 2013). It simulates the exchange of energy, water, and carbon between the land surface and the atmosphere, including associated subsurface processes. The model can be run either fully coupled within the IFS or in offline (uncoupled) mode forced by prescribed atmospheric fields.

Each grid box at the land–atmosphere interface is subdivided into surface tiles, with seven distinct classifications used over land: high and low vegetation, bare ground, shaded and exposed snow, intercepted water, lake, and urban. Each tile has its own physical parameters, allowing separate computation of water, heat, and momentum fluxes, and solution of an energy balance equation for tile skin temperature. Grid-box mean fluxes are obtained by area-weighted aggregation of tile-level fluxes and are passed to the atmospheric model.

For the ML emulator, we consider a subset of ecLand variables. In aiLand, soil water content and soil temperature in three layers (0-7 cm, 7-28 cm, and 28-100 cm) are treated as prognostic states, as in ecLand. Snow cover fraction is also treated as prognostic in aiLand, although in ecLand it is a diagnostic variable derived from the underlying prognostic snow water equivalent and snow density. Latent and sensible heat fluxes, 2 m air temperature, 2 m dew point temperature, and skin temperature are predicted as diagnostic outputs. In this study, ecLand CY49R2 (https://github.com/ecmwf-ifs/ecland, last accessed May 2026) is run in offline mode, forced by ERA5 meteorological reanalysis (Hersbach et al., 2020). A global simulation covering 1998–2024 was performed at hourly temporal resolution on the native ERA5 Tco399 reduced Gaussian grid (~31 km). Outputs were aggregated to 6-hourly time steps for training, to be consistent with that used in the AIFS.

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Table 1. Overview of forcings and state variables used to train aiLand and their respective data sources. All units are provided in parentheses and symbols used to refer to the state variables in the text shown in bold. Note that surface heat fluxes (LE, H) are represented internally as 6-hourly accumulated energy fluxes (J m^{-2}), reflecting the model's 6-hourly timestep; for reporting, these are converted to equivalent time-averaged power fluxes in W m^{-2} to align with standard flux-tower evaluation conventions.

Forcings	**State Variables**
*Dynamic Forcing (ERA5, * from surface physiographic fields)*	*Prognostic State (ecLand simulation; ‡ diagnostic in ecLand)*
Air temperature (K)	Soil temperature, layers 1–3, **stl1-3** (K)
Downward radiation, longwave and shortwave (W m^{-2})	Soil water content, layers 1-3, **swvl1-3** (m^3 m^{-3})
Total precipitation (m)	Snow cover fraction‡, **snowc** (–)
Snowfall (m)	
Specific humidity (kg kg^{-1})	
Wind speed (u, v) (m s^{-1})	
Seasonal leaf area index* (high/low vegetation) (–)	
Dynamic Forcing (temporal/astronomical)	
Time of day (–)	
Day of year (–)	
Top-of-atmosphere insolation (W m^{-2})	
Static Forcing (surface physiographic fields)	*Diagnostic State (ecLand simulation; † fine-tuned on Fluxnet)*
Lake cover (–)	2 m air temperature, **2t** (K)
Lake depth (m)	2 m dew point temperature, **2d** (K)
Photosynthetic pathway type (–)	Skin temperature, **skt** (K)
Land–sea mask (–)	Latent heat flux†, **LE** (W m^{-2})
Urban cover (–)	Sensible heat flux†, **H** (W m^{-2})
Vegetation cover, low/high (–)	
Vegetation type, low/high (–)	
Minimum stomatal resistance, low/high (s m^{-1})	
Roughness length, low/high (m)	
Permanent wilting point (m^3 m^{-3})	
Field capacity (m^3 m^{-3})	
Geopotential (m^2 s^{-2})	
Sub-gridscale orography (standard deviation) (m)	

2.1.2 Surface physiographic fields

Surface physiographic fields are assumed to be static and describe land surface characteristics such as orography, vegetation, soil type, land–sea mask, and surface albedo, capturing spatial heterogeneity relevant for land surface parameterisations. These fields determine the tile properties in ecLand and influence the computation of turbulent fluxes and tile skin temperatures.

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The fields are prescribed independently of model initial conditions. Leaf area index is provided using monthly climatologies to represent seasonal variability. All datasets are remapped to the model grid before use. In this study, physiographic fields derived from ERA5 (Hersbach et al., 2020) and their updated versions (Boussetta et al., 2021; Choulga et al., 2019; Muñoz-Sabater et al., 2021) are used, as described in (Kimpson et al., 2023).

2.1.3 ERA5 reanalysis data

ERA5 is the fifth-generation atmospheric reanalysis produced by ECMWF (Hersbach et al., 2020). It is generated using IFS cycle 41R2 with 4D-Var data assimilation for the atmosphere, a land data assimilation system (de Rosnay et al., 2022), and a coupled land-atmosphere modelling approach using ecLand (Boussetta et al., 2021). ERA5 provides hourly atmospheric and surface fields at approximately 31 km horizontal resolution with 137 vertical levels extending to 80 km height. Uncertainty estimates are available at ~63 km resolution from a 10-member ensemble. In this study, hourly ERA5 surface fields at ~31 km resolution on the cubic octahedral reduced Gaussian grid (Tco399; N320) are used as dynamic forcing inputs.

2.1.4 Fluxnet observations

Flux-tower measurements from the FLUXNET network (Baldocchi et al., 2001; Pastorello et al., 2020) provide in situ observations of land–atmosphere exchanges of energy, water, and carbon based on the eddy covariance technique. These observations include turbulent fluxes such as latent heat (LE) and sensible heat (H), together with meteorological drivers (e.g., radiation, air temperature, and precipitation) typically measured at half-hourly resolution.

In this study, we use the harmonised flux tower dataset provided by FluxDataKit (Hufkens and Stocker, 2025), which compiles and standardises observations from several openly available flux data products including PLUMBER-2 (Abramowitz et al., 2024), AmeriFlux (Novick et al., 2018), and ICOS releases (e.g., Warm Winter, 2022). The dataset provides quality-controlled and gap-filled fluxes and meteorological variables with consistent formatting across sites, as well as site metadata and continuous multi-year records suitable for model calibration and benchmarking. We use FluxDataKit's energy-balance-closed variant of the turbulent fluxes, in which raw H and LE are scaled proportionally to satisfy H+LE=Rn-G at each timestep (where R_n is net radiation and G is ground (soil) heat flux). This follows standard FLUXNET2015 conventions and removes the well-documented systematic underestimation of turbulent fluxes by raw eddy-covariance measurements (Wilson et al., 2002; Stoy et al., 2013) and preserves the observed Bowen ratio at each site.

The observational dataset is split into training and validation subsets (see Appendix A), ensuring spatial separation between training and evaluation periods. For the fine-tuning part of this study, we train the model over the years 2000-2019 for 199 calibration sites, retaining 42 validation sites to also be evaluated over this period. For the main evaluation, the validation period of 2020–2023 was used, at the 84 training and 17 validation sites with valid post-2020 FLUXNET data. All metrics are computed on daily means, only where both prediction and observation are non-missing.

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2.1.5 Data preprocessing

All datasets are prepared using the `anemoi-datasets` framework (https://anemoi.ecmwf.int/) and stored in Zarr format, chunked in time to optimise input/output (I/O) performance. Dataset generation is controlled via YAML-based recipe files to ensure reproducibility. Feature-wise statistics (mean and standard deviation) are computed over the ecLand training period as part of the dataset creation pipeline and stored for subsequent use during model training.

The final dataset used for model pretraining comprises global ecLand simulations and ERA5 reanalysis time series for 1998–2024 at 6-hourly temporal resolution, together with static surface physiographic fields, defined on the model grid (N320, 171039 land points). Two separate observational datasets are created for training and validation for the fine-tuning step, covering 199 and 42 sites respectively, reducing the spatial dimension compared to the full model grid. FLUXNET observations (or missing values) replace model-derived surface fluxes, while other prognostic and diagnostic variables are retained from the simulations.

2.2 Machine learning model

In preliminary experiments (Wesselkamp et al., 2025), several ML models were tested to emulate ecLand, including LSTM (Long-Short Term Memory, Hochreiter and Schmidhuber, 1997), XGB (eXtreme-Gradient Boosting, Chen et al., 2015), and MLP (Multi-Layered Preceptor, as described in Goodfellow, 2016). While the LSTM excelled in long-range forecasts of soil temperature and snow cover, and XGB was robust for soil moisture, the MLP offered a favourable balance between accuracy and computational efficiency. For this study, we have expanded the scope of the MLP, including refined hyperparameters, longer rollouts, an extended input space (adding temporal and astronomical forcings shown to improve soil temperature predictions), and a set diagnostic outputs, building substantially on the prototype introduced in Wesselkamp et al. (2025).

2.2.1 Model architecture

The MLP emulator is a feed-forward neural network approximating ecLand's mapping from static, dynamic, and prognostic inputs to land surface states and fluxes:

$$f : \mathcal{X} \to \mathcal{Y}. \tag{1}$$

Here, the input vector $\mathbf{x} \in \mathcal{X}$ consists of static, dynamic, and prognostic state variables, while the output vector $\mathbf{y} \in \mathcal{Y}$ contains prognostic state variable increments and diagnostic variables at the next timestep. The true mapping f is approximated by a learned function $f^*(\mathbf{x})$ via stochastic gradient-based optimisation.

The network comprises a shared prognostic backbone that produces a latent representation, which is projected to prognostic targets, and a diagnostic branch that combines climatological, meteorological, and prognostic information to predict diagnostic variables. Prognostic outputs are applied in a residual formulation, where predicted increments are added to the previous state, enabling stable autoregressive rollouts. Post-processing enforces variable-specific physical bounds. Physical consistency is

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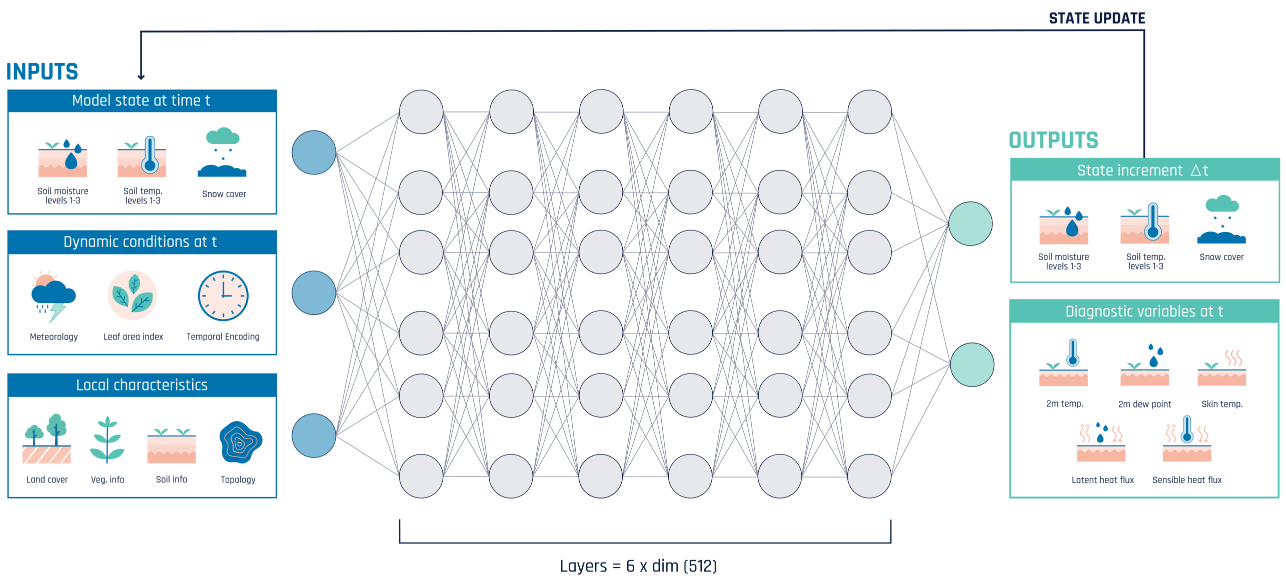

Figure 1. Schematic of the MLP emulator architecture, showing the shared prognostic backbone and diagnostic branch.

therefore inherited from the ecLand training target and reinforced by the residual formulation and output bounds, rather than imposed through conservation laws or physical penalties within the network.

Each hidden layer applies a fully connected (linear) transformation, followed by layer normalisation (Ba et al., 2016), followed by a rectified linear unit (ReLU) activation. Layer normalisation standardises each sample's activations across the feature dimension, stabilising training and reducing sensitivity to the differing scales of the input variables; ReLU introduces the non-linearity needed to capture ecLand's non-linear input–state mapping. The base model uses six hidden layers of width 512, with approximately 1.3M trainable parameters, and a single-block diagnostic head. Figure 1 illustrates the architecture. Note that this model is wider and deeper than the version presented in Wesselkamp et al. (2025) to account for the additional variables.

2.2.2 Loss function

The model is trained using a smooth L1 loss (Huber loss with β=1). Loss is accumulated across the autoregressive rollout: errors at each forecast step are summed and then scaled by the inverse rollout length. Global weights balance prognostic and diagnostic contributions, with optional per-variable weighting for individual targets (here all set to 1); when per-variable weights are used, the weighted losses are averaged over the number of variables. Prognostic increments are normalised before the loss by dividing by tendency scalers—the standard deviation of 6-hourly increments over the training set—ensuring balanced contributions across variables with different characteristic evolution rates. Diagnostic variables are not normalised before loss computation. During fine-tuning to observations, the loss is computed only over valid (non-NaN) target elements, allowing the model to

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learn from sparse observational datasets where only a subset of variables or grid points carry valid values at any given time. Input features (meteorological forcing, prognostic states, and static physiographic fields) are sourced from the complete ERA5 reanalysis and ecLand simulations, which do not contain missing values at valid land grid points; a residual safety guard replaces any unexpected NaN in inputs with zero in normalised space.

2.2.3 Training stategy

Pretraining uses global ecLand simulations at N320 resolution from 1998–2019 (approximately 32,000 six-hourly timesteps over 171,039 land points), with 2022 reserved for validation. Input features are normalised using feature-wise statistics computed over the full dataset, with variable-specific schemes (e.g., standardisation, max-scaling, or identity for categorical inputs). Missing values are masked during loss computation and set to zero in inputs.

Training proceeds in two phases with increasing rollout horizon. In Phase 1, the model is trained for 80 epochs (160,000 steps) with rollout length R=4 (24 h). The Adam optimiser is used with a peak learning rate of 5×10^{-4}, decayed to 3×10^{-7} using a cosine schedule with 1,000-step linear warmup. In Phase 2, the best checkpoint is fine-tuned with rollout R=8 (48 h) for 8 epochs (16,000 steps) at a reduced learning rate of 3×10^{-5}. Gradient clipping (global norm 5.0) is applied throughout, and gradient checkpointing is enabled for longer rollouts to manage memory.

Each training step processes one sample, defined as a rollout window of R consecutive 6-hourly timesteps spanning all valid land grid points (171,039 for global pretraining; 199 for FLUXNET fine-tuning). Training is performed on 4 GPUs using distributed data parallelism with mixed precision, giving an effective batch of 4 rollout windows per gradient update. The smaller effective batch during fine-tuning (constrained by FLUXNET data volume) interacts with the choice of low fine-tuning learning rates: the very low rates used (10^{-5} to 10^{-7}, Table 2) help mitigate noise from small batches, but rigorous separation of batch-size effects from data-distribution effects on fine-tuning quality would require a dedicated ablation study, which we defer to future work. The best checkpoint is selected based on validation loss.

2.2.4 Fine-tuning on observations

For the second part of this study, we fine-tune the aiLand-base emulator using in situ flux data. The observational data are normalised using the same statistics as during pretraining for consistency. We investigate five fine-tuning strategies (Table 2) spanning a methodological spectrum from minimum-intervention to full-model adaptation, designed to test how aggressively the pretrained backbone should be modified during fine-tuning. Higher backbone learning rates risk catastrophic forgetting of the pretrained dynamics, while overly low rates limit fine-tuning's ability to correct inherited LSM biases; the five strategies span this trade-off. Diagnostic-only strategies (S1, S2) freeze the prognostic backbone entirely and update only the diagnostic head, ensuring that the state dynamics learned from ecLand pretraining are preserved exactly. S2 tests whether additional learning capacity in the diagnostic head improves flux predictions, by extending it to 3 blocks (two randomly initialised) before fine-tuning. Backbone-adaptive strategies (S3, S4, S5) update the prognostic backbone at a substantially lower learning rate than the diagnostic head, allowing gradual adaptation while protecting the pretrained dynamics. S3 uses a single training phase with explicit differential learning rates (backbone 10^{-7}, diagnostic 10^{-4}). S4 adopts a two-phase procedure: first updating only

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the diagnostic head, then unfreezing the full model at a uniform low learning rate (10^{-6}) to mitigate catastrophic forgetting. S5 updates the full model from the start with a uniform learning rate ($5{\times}10^{-5}$) across all components.

Table 2. Fine-tuning strategies.

Strategy	Frozen Components	Trainable Components	Learning Rates	Training Schedule
Diagnostic-only strategies				
S1 (Freeze)	Backbone + prognostic head	Diagnostic head (1 block + projection)	5×10^{-5} (all trainable)	20 epochs, 40K steps
S2 (Deep)	Backbone + prognostic head	Diagnostic head (3 blocks; 2 randomly initialised)	1×10^{-4} (all trainable)	20 epochs, 60K steps
Backbone-adaptive strategies				
S3 (DiffLR)	None	Full model (backbone, prognostic head, diagnostic head)	10^{-7} (backbone + prognostic), 10^{-4} (diagnostic)	20 epochs, 40K steps
S4 (TwoPhase)	Phase 1: Backbone + prognostic head Phase 2: None	Phase 1: Diagnostic head Phase 2: Full model	Phase 1: 5×10^{-5} Phase 2: 10^{-6}	10 + 10 epochs
S5 (FullLR)	None	Full model	5×10^{-5}	20 epochs, 40K steps

2.3 Evaluation tools and metrics

2.3.1 Standard metrics

To evaluate model performance, we use common metrics such as the root-mean-square error (RMSE), the mean absolute error (MAE) and the anomaly correlation coefficient (ACC). The ACC is calculated as the Pearson correlation between predicted and reference anomalies, defined as deviations from the climatology. The climatology is computed from the ecLand dataset over a multi-year reference period (here 1998–2024) using a sliding-window approach. For each 6-hourly timestep, samples are assigned to their hour-of-year bin and to neighbouring bins within a $\pm$3-day window (cyclically), and averaged across all years to obtain a smoothed climatological mean for each timestep, variable, and grid point. All metrics are on the N320 reduced Gaussian grid, with glacier and coastal points excluded throughout.

2.3.2 Data-driven biomes

To test the transferability of aiLand-base, we derive data-driven biomes for cross-biome transfer analysis. Long-term climatological features (2009–2020) were computed from ERA5, including monthly mean and seasonal amplitude of 2 m temperature and precipitation, aridity index, top-layer soil moisture, snow cover fraction, leaf area index (LAI), and Bowen ratio. All features were standardised to zero mean and unit variance prior to analysis to ensure comparable contributions across variables with different units. Biomes were identified using k-means clustering ($k = 7$), with k chosen based on multiple validity metrics.

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One cluster predominantly corresponding to glaciated or ice-covered regions was masked prior to transfer experiments, leaving six effective biomes. Spatial coherence of the biome labels was enforced using a local majority filter to suppress isolated cells while preserving large-scale structure.

We interpret the resulting clusters as climate-vegetation biomes (summarised in Figure 2 and Table 3). The six-cluster partition captures broad climate-vegetation regimes rather than following the usual biome naming conventions: 'temperate continental' includes both grasslands and forests with similar climates, and 'tropical/subtropical humid' is distinguished from 'tropical rainforest' by precipitation and LAI rather than by latitude. The arid/semi-arid and dry-desert clusters are separated by an order-of-magnitude difference in mean precipitation (640 vs. 58 $\mathrm{mm\,yr^{-1}}$) and vegetation cover (LAI 1.2 vs. 0.4), reflecting genuinely different surface energy and water budgets. However, the biomes are not internally homogeneous: hard k-means clustering of continuous climate features inevitably assigns transition-zone grid points to single clusters despite genuinely intermediate characteristics. An internal margin analysis (relative distance to nearest vs. second-nearest centroid) indicates that around 30% of all grid points fall in transition zones (borderline assignments or grid points reassigned by the spatial-coherence filter). The dry desert cluster (B4) is the most internally consistent, with only 11% of its grid points in transition zones, while the tropical/subtropical humid cluster (B0) is the most heterogeneous (40% transition-zone cells). Cross-biome transfer experiments (Sect. 3.1.3) should therefore be interpreted as testing transferability across overlapping climate regimes rather than cleanly separated ecosystems.

For each biome, we extract latitude/longitude coordinates to define training subsets. Pairwise Euclidean distances between cluster centroids in feature space are computed to quantify biome similarity for these transferability analyses.

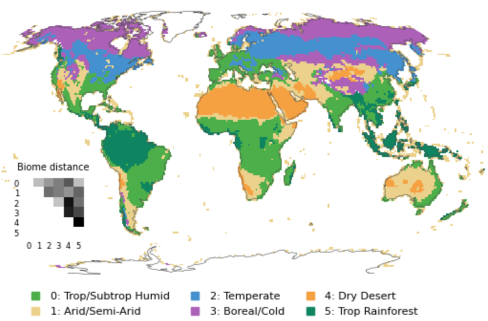

Figure 2. Global distribution of biome classes. Each grid cell is assigned to one of six biome categories. The panel in the bottom left-hand corner shows the Euclidean distance between cluster centroids.

Table 3. Primary characteristics of the different biomes, given as mean annual temperature, total precipitation, leaf area index (LAI), percentage of snow cover, and percentage of land grid points assigned to each cluster.

Biome	Primary Character	Temp (°C)	Precip (mm)	LAI	Snow (%)	Points (%)
0	Tropical/Subtropical Humid	21	1050	4.3	1%	27.7%
1	Arid/Semi-Arid Warm	18	640	1.2	3%	20.7%
2	Temperate Continental	3	780	3.9	37%	14.9%
3	Boreal/Cold Continental	-4	550	2.7	52%	13.4%
4	Dry Desert	24	58	0.4	0%	11.9%
5	Tropical Rainforest	24	2700	6.1	1%	11.4%
6	Glaciers (masked)	–	–	–	–	

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3 Results and discussion

3.1 aiLand-base performance

For the first part of the results, we evaluate how well the aiLand-base emulator reproduces ecLand and how robust it is across lead times, multi-year integrations, ecosystem regimes, and spatial resolutions. A recurring finding is that prognostic state variables—predicted via a residual increment formulation—generalise cleanly, because the increment is small relative to the absolute state and is tightly anchored to the previous timestep, whereas diagnostic variables—predicted as absolute values at each step—are more sensitive to regime and resolution. We establish this asymmetry in the lead-time and stability analysis, then show that it defines the error structure across biomes and grids.

3.1.1 Overall performance and stability

We evaluate aiLand-base in two complementary protocols, both forced by ERA5 atmospheric reanalysis (the same forcing used in the corresponding ecLand simulations) and both initialised from ecLand state at the start time. The first protocol consists of 138 independent 90-day integrations launched every two days from January through early October 2022 (the latest start date allowing a full 90-day window within the evaluation year), used to characterise short-range error growth as aiLand-base and ecLand diverge under identical forcing (Table 4, Fig. 3a). The second consists of continuous autoregressive integrations over 2020 (1 yr) and 2020-2023 (4 yr), used to assess long-range stability and the representation of the seasonal cycle (Table 5, Fig. 3b).

Errors remain well controlled over the 90-day integration horizon (Table 4, Fig. 3a). Surface soil temperature (stl1) RMSE rises by 29% and surface soil moisture (swvl1) by 19%. Deep soil layers have very small day-1 errors (stl3: 0.03 K; swvl3: $0.002\,\mathrm{m}^3\,\mathrm{m}^{-3}$), reflecting long memory timescales, so their apparent growth ratios are large (stl3: 21.7×) despite absolute errors remaining smaller than at the surface throughout the time integration. Snow cover RMSE peaks at intermediate lead times (0.046 at 60 d) before declining slightly, consistent with transition-season timing errors rather than monotonic drift. Diagnostic variables (2 m temperature: 0.69 K; skin temperature: 1.06 K; sensible heat flux: 11.7-12.5 $\mathrm{W\,m^{-2}}$; latent heat flux: 10.1-11.1 $\mathrm{W\,m^{-2}}$) show near-constant RMSE across all lead times, confirming that they are effectively re-diagnosed from the prognostic state at each step rather than accumulating error.

This stability is confirmed over continuous integration (Table 5). While stl1 RMSE gradually increases from 1.47 K (1 yr) to 1.72 K (4 yr), a 17% increase, and stl2 and stl3 grow by 34% and 37%, respectively, correlation coefficients remain high across all soil variables (≥0.993 for temperature; ≥0.993 for moisture), and anomaly correlations stay above 0.93 for all prognostic variables except swvl3, which decreases from 0.888 to 0.855. The stl1 RMSE trace (Fig. 3b) shows a seasonal cycle but no upward trend, confirming stable autoregressive behaviour with no dynamical divergence. Soil moisture RMSE grows more slowly than temperature (14-20% over four years), and snow cover is nearly stable (+4%), indicating negligible drift in non-thermal prognostic variables. Diagnostic variables degrade minimally (2 m temperature: 0.61 to 0.63 K; sensible heat flux: 11.8 to 12.1 $\mathrm{W\,m^{-2}}$; latent heat flux: 9.8 to 10.4 $\mathrm{W\,m^{-2}}$), with correlations remaining near unity (~0.998-0.999) and anomaly correlations above 0.99.

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Table 4. Global RMSE of aiLand-base against ecLand by integration time, averaged over 138 ERA5-forced 90-day integrations initialised throughout 2022. The final column gives the 1 day to 90 day growth ratio. Surface heat flux values (H, LE) are reported as RMSE of the time-averaged flux in W m^{-2} over each 6-hourly timestep. RMSE magnitudes and growth ratios should be interpreted within each variable class rather than across, since native units and dynamic ranges differ (e.g. thermal vs. hydrological).

Variable	Unit	1 d	7 d	30 d	60 d	90 d	90 d / 1 d
stl1	K	0.92	0.98	1.06	1.13	1.19	1.3×
stl2	K	0.17	0.32	0.52	0.63	0.71	4.2×
stl3	K	0.03	0.17	0.45	0.58	0.65	21.7×
swvl1	m^3 m^{-3}	0.011	0.012	0.013	0.014	0.014	1.3×
swvl2	m^3 m^{-3}	0.004	0.005	0.007	0.008	0.008	2.0×
swvl3	m^3 m^{-3}	0.002	0.005	0.010	0.012	0.013	6.5×
snowc	–	0.016	0.028	0.045	0.046	0.044	2.8×
2t	K	0.69	0.69	0.70	0.69	0.69	1.0×
2d	K	0.95	0.95	0.95	0.95	0.94	1.0×
skt	K	1.06	1.07	1.08	1.07	1.06	1.0×
H	W m^{-2}	11.67	11.90	12.31	12.45	12.50	1.1×
LE	W m^{-2}	10.05	10.23	10.65	10.93	11.06	1.1×

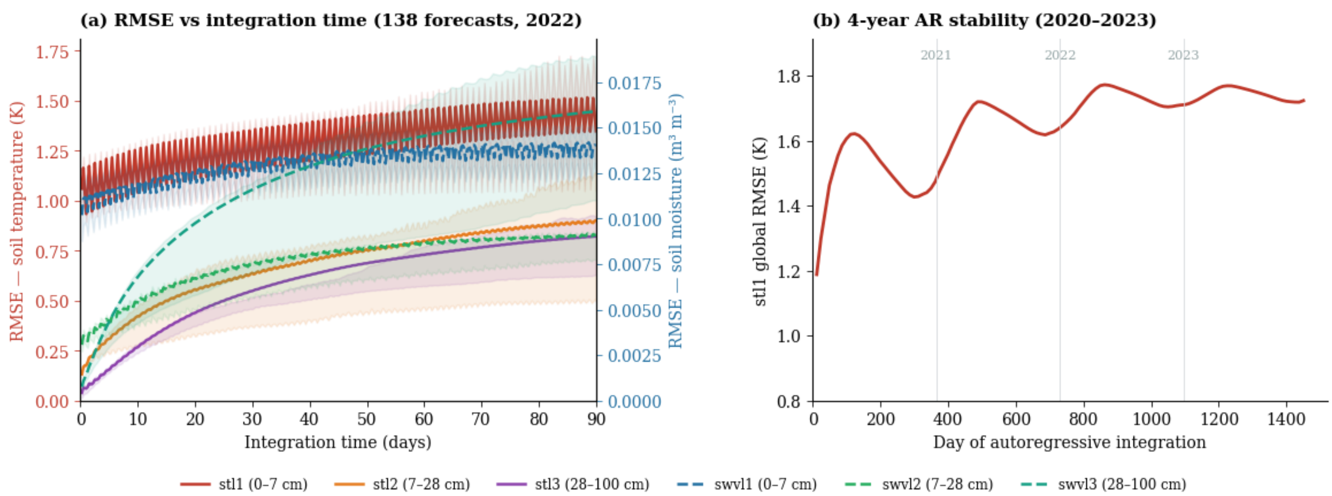

Figure 3. Skill of the emulator for soil temperature (solid lines, left axis) and soil moisture (dashed lines, right axis) at three depth layers, both panels using ERA5-forced offline integrations of aiLand-base. (a) Global RMSE as a function of integration time, averaged over 138 independent 90-day integrations initialised every two days from ecLand state throughout 2022; shading shows the interquartile range across integrations. (b) Global stl1 RMSE during a continuous 4-year autoregressive integration initialised on 1 January 2020 from ecLand state.

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Table 5. Global metrics from continuous autoregressive integrations over 2020 (1 yr) and 2020–2023 (4 yr, approximately 5,800 time steps). Surface heat flux values (H, LE) are reported as RMSE and bias of the time-averaged flux in W m^{-2} over each 6-hourly timestep.

	RMSE		Bias		Corr		ACC	
Variable	1 yr	4 yr	1 yr	4 yr	1 yr	4 yr	1 yr	4 yr
stl1	1.47	1.72	+0.35	+0.40	0.994	0.993	0.970	0.959
stl2	0.99	1.32	+0.06	+0.14	0.997	0.995	0.978	0.962
stl3	0.94	1.29	+0.07	+0.17	0.997	0.994	0.963	0.934
swvl1	0.014	0.016	+0.000	+0.001	0.996	0.995	0.963	0.953
swvl2	0.010	0.012	+0.001	+0.002	0.998	0.997	0.973	0.961
swvl3	0.015	0.018	+0.003	+0.003	0.995	0.993	0.888	0.855
snowc	0.056	0.058	−0.002	−0.001	0.986	0.985	0.948	0.945
2t	0.61	0.63	−0.03	−0.03	0.999	0.999	0.996	0.996
2d	0.77	0.80	−0.01	−0.01	0.998	0.998	0.992	0.992
skt	1.08	1.12	−0.04	−0.04	0.998	0.998	0.991	0.991
H	11.76	12.13	−0.05	−0.14	0.990	0.989	0.979	0.977
LE	9.81	10.42	−0.65	−0.65	0.992	0.991	0.980	0.977

The dominant systematic feature is a +0.40 K warm bias in stl1, present at 89% of land grid points and largely established within the first year of integration. Equivalent integrations within the training period yield comparable biases (+0.44 to +0.47 K), confirming that the offset is an intrinsic property of the learned dynamics rather than distribution shift. The bias is consistent with a conditional-mean offset induced by the Smooth L1 loss under the right-skewed soil-temperature increment distribution (training skewness +0.94 K), with an additional Arctic component reflecting underestimated polar warming. It is confined to soil thermal variables; moisture biases are negligible and diagnostic temperatures show small negative offsets consistent with per-step re-diagnosis.

3.1.2 Error structure and the role of snow cover

The global RMSE values in Sect. 3.1.1 mask strong geographic structures (Fig. 4). At latitudes >60°N the 90-day RMSE reaches 2.42 K for stl1 and 0.018 m^3 m^{-3} for swvl1—roughly three times its tropical value. The soil moisture comparison is harder to interpret directly because hydraulic properties and dynamic ranges differ between regions, and freezing affects the modelled state in cold winters; we therefore focus the analysis on relative spatial patterns rather than absolute magnitudes. A spatial decomposition (Fig. 5a) shows that the high-latitude error amplification is dominated by seasonal snow cover, although freeze-thaw cycling and reduced atmospheric coupling in cold winters likely contribute as well. Grid points with seasonal snow (fractional snow-cover RMSE >0.02; 33% of valid land area) account for 57%, 82%, and 76% of the global stl1, stl2, and stl3 mean squared error at 90-day intergration time. In these zones stl1 RMSE is 1.83 K (2.1× the snow-free value), stl2 is 1.31 K

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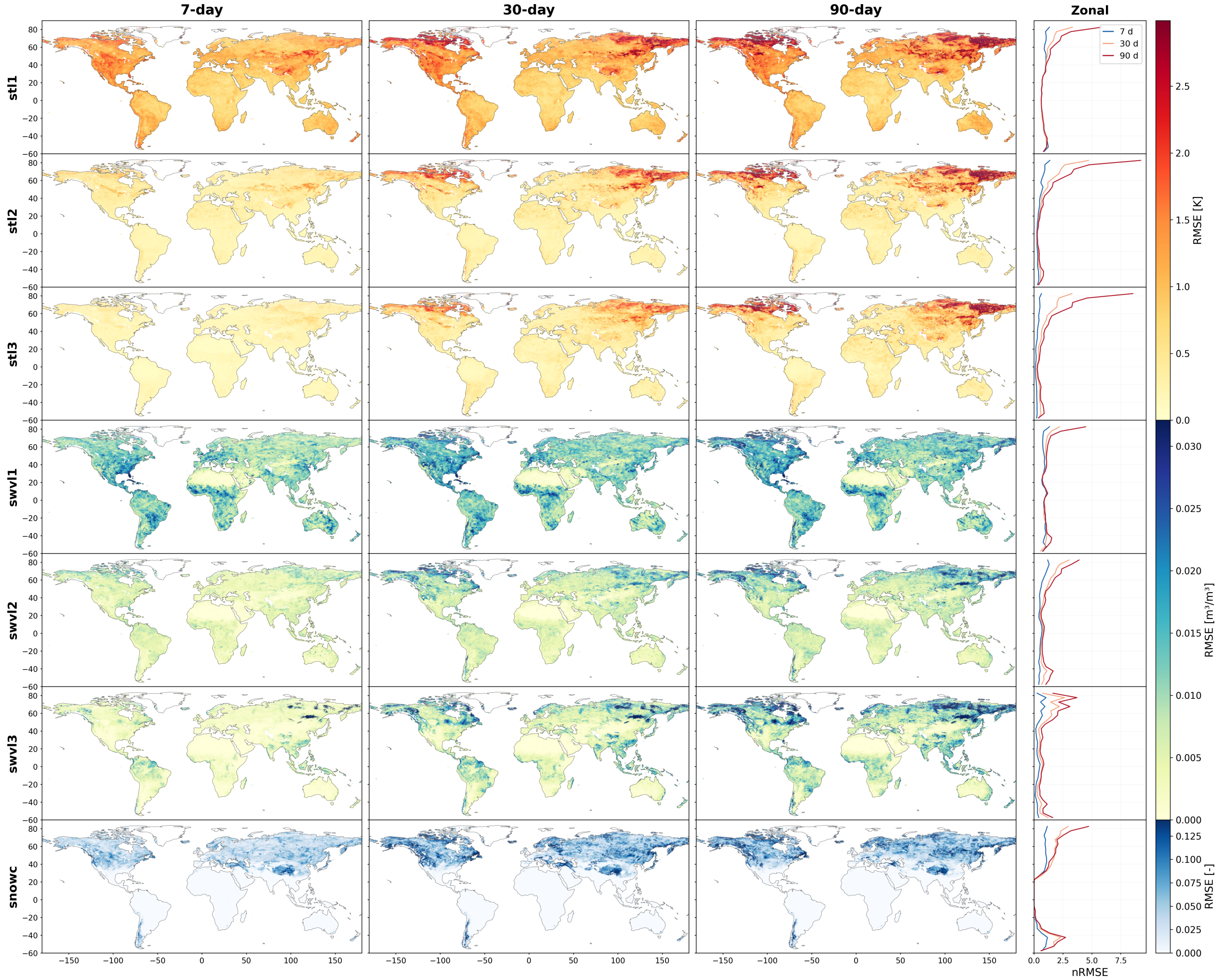

Figure 4. Spatial distribution of prognostic RMSE at 7-day, 30-day, and 90-day integration times (columns 1-3), with normalised zonal profiles (column 4). Each row shows one prognostic variable: soil temperature (stl1-3), soil moisture (swvl1-3), and snow cover (snowc). Zonal profiles are normalised by each variable's global RMSE at 90-day integration time.

(4.3×), and stl3 is 1.16 K (3.5×); swvl3 is 2.9× the snow-free value. Seasonal snow covers 95% of all land poleward of 60°N and 62% of the 30–60°N band but less than 1% of the tropics, explaining the latitudinal error gradient.

Consistent with the diagnostic re-diagnosis pathway established above, diagnostic outputs are largely unaffected by snow regime (Fig. 5b): 2 m temperature RMSE is nearly identical across regimes (0.70 K vs. 0.69 K snow-free), and surface heat fluxes are actually lower under snow cover. This is physically expected: snow's high albedo and the frozen surface state both

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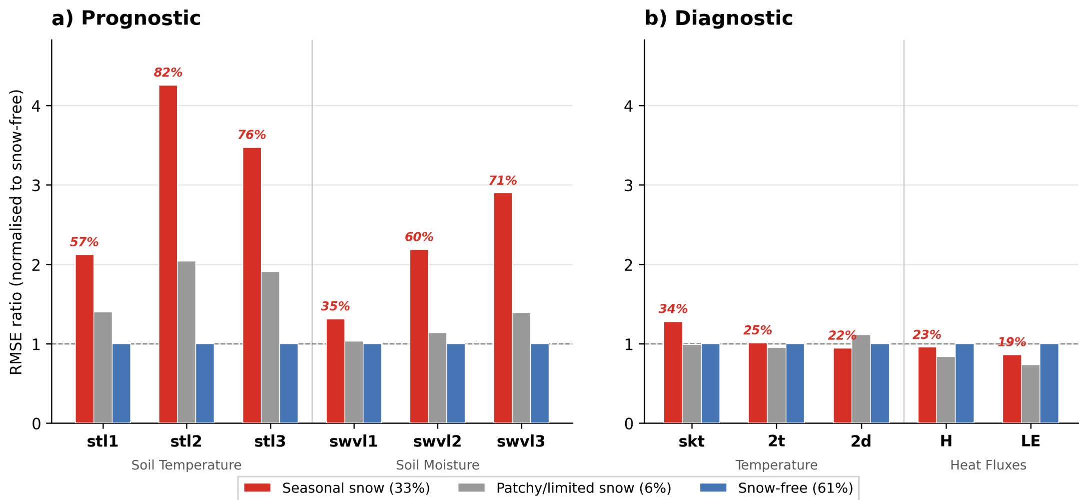

Figure 5. RMSE by snow regime at 90-day integration time, normalised by the snow-free baseline. Land grid points are classified by their 90-day snow cover RMSE into seasonal-snow (snowc RMSE > 0.02, 33% of land; red), patch/limited snow (0.005–0.02, 6%; gray), and snow-free (< 0.005, 61%; blue) regimes. Bars show RMSE for soil temperature (left, K) and soil moisture (right, m^3 m^{-3}) in panel a) and diagnostics in panel b). Italic red numbers show the percentage of global MSE contributed by seasonal-snow zones.

suppress the absolute magnitude of turbulent exchange, so absolute flux errors are smaller in snow-covered conditions. Only skin temperature shows mild amplification (1.3×), reflecting its direct coupling to the prognostic soil state.

Error seasonality at snow-affected sites differs sharply between thermal and hydrological variables, as illustrated by point-level traces from the continuous 4-year integration (Fig. 6). At a representative warm arid site (Fig. 6a), aiLand-base tracks ecLand essentially perfectly year-round, confirming that the residual errors identified above are regime-specific rather than systematic. At the boreal site (Fig. 6b), soil temperature errors concentrate during sustained snow cover rather than at onset or melt transitions: stl2 RMSE under continuous snow is 1.71 K versus 0.37 K in snow-free months (4.6×). Snow acts as an insulating layer that decouples the soil column from atmospheric forcing, weakening the learned mapping from meteorological inputs to soil-state increments; sub-surface variables are disproportionately affected because they are furthest from any remaining surface coupling. Soil moisture exhibits the opposite seasonality: swvl1-3 errors peak after the snow has gone, during the active hydrological season when freeze-thaw cycling and snowmelt-driven rewetting produce complex transient dynamics that are harder for the emulator to track. Under snow cover itself, by contrast, soil moisture is largely frozen and temporally static, so low variability yields low error.

This site-level contrast generalises to the global error field. Grid points with seasonal snow show soil moisture RMSE 1.3-2.7× higher than permanently snow-free regions, and 85% of snow-zone grid points exceed the snow-free median despite the errors occurring primarily outside the snow-covered season. Insulation and freeze–thaw mechanisms therefore act on different variables and in different seasons, but both have a strong impact on the annual error budget of snow-affected regions. Future

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work could improve this regime by extending the emulator to predict surface and sub-surface runoff, allowing it to better account for snowmelt routing and the post-melt soil-moisture dynamics.

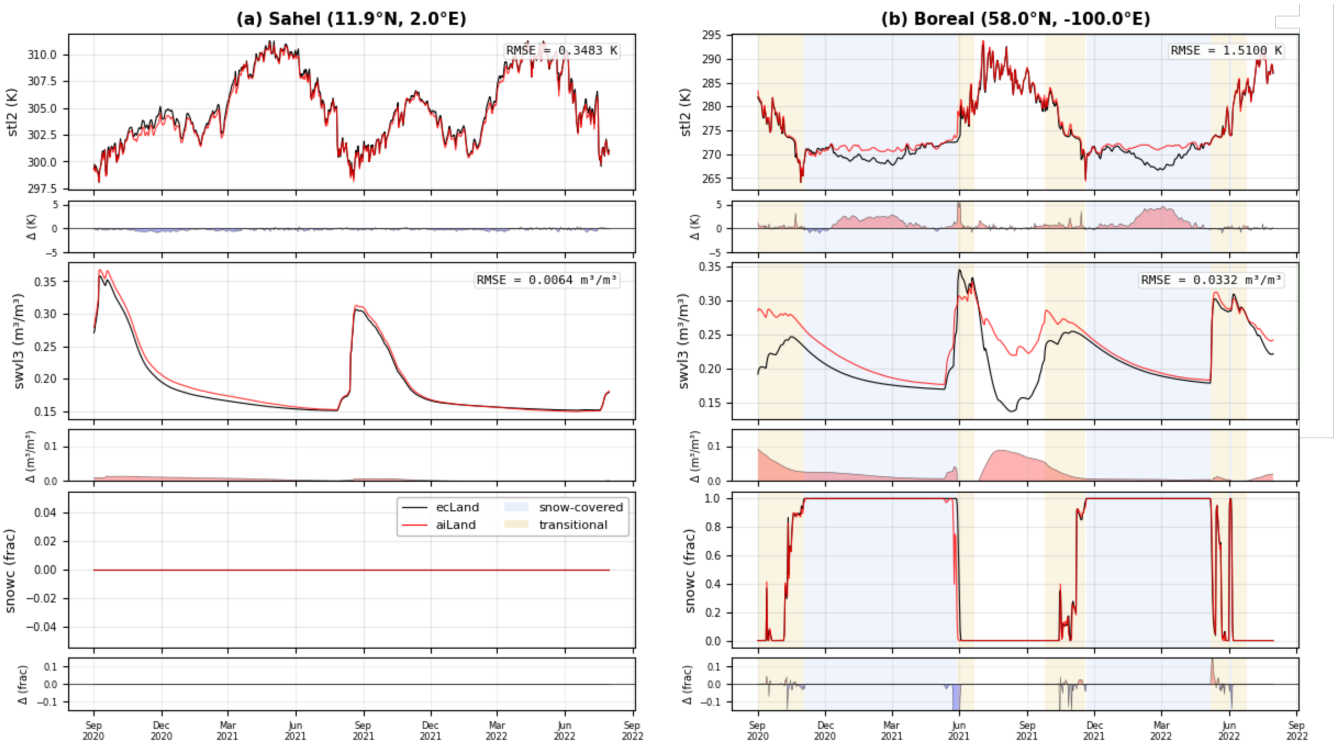

Figure 6. Point-level time series at a snow-free site (Sahel, 13.5°N; left) and a boreal site with seasonal snow cover (60.5°N; right) from a continuous 4-year autoregressive run (Sep 2020–Aug 2022 shown). Rows show soil temperature at layer 2 (stl2), soil moisture at layer 3 (swvl3), and snow cover fraction, each with a residual strip (aiLand-base - ecLand) below. Blue shading marks snow-covered periods (snow cover ≥ 0.99); yellow shading marks transitional periods (fractional snow cover $\pm$ 5-day buffer).

3.1.3 Ecosystem robustness

A key question for ML-based land surface emulators is whether learned input-output mappings remain valid across ecosystem regimes, including extreme climates not well sampled during training. The snow-coupling analysis above predicts that cold-climate biomes should be among the hardest targets, because specialists trained on narrow climate regimes will not encounter enough snow-insulated soil dynamics to learn the distinct forcing-state relationship that applies under a snowpack. To test this and to evaluate broader ecosystem sensitivity, we trained six biome-specialist models on data-driven clusters: tropical/-subtropical humid, warm arid/semi-arid, temperate continental, boreal/cold continental, dry desert, and tropical rainforest (see Table 3 and Fig. 2 for full characterisation). Each specialist was evaluated within its home biome and across all others (Fig. 7a), alongside the globally trained model evaluated under the same protocol.

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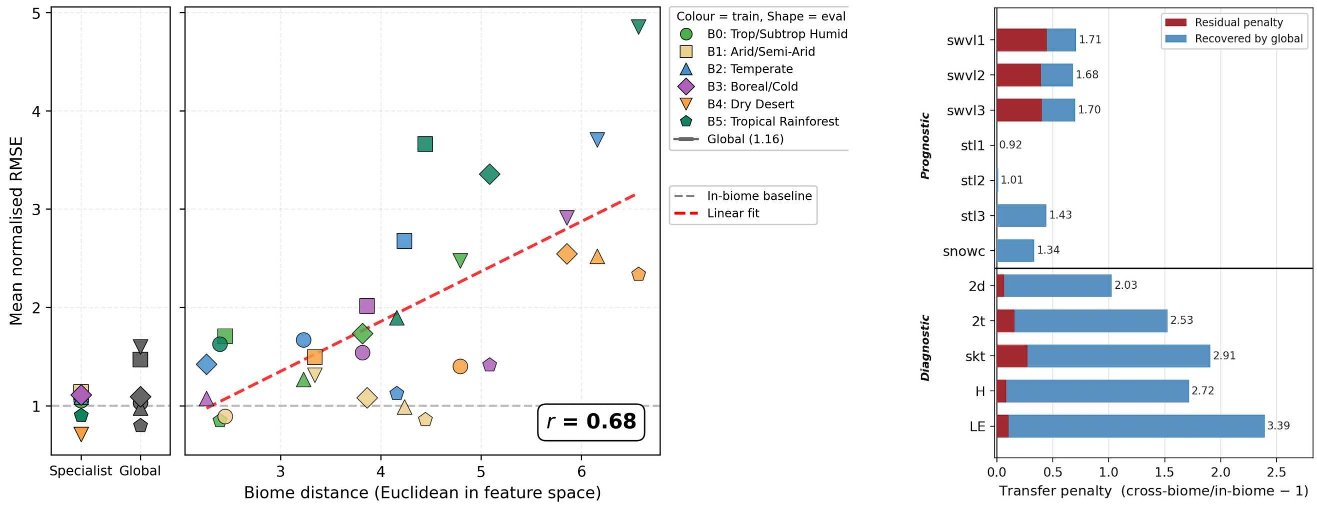

(a) (b)

Figure 7. Cross-biome transfer skill. (a) In-biome specialist performance (left; coloured markers) and the global model (grey) evaluated on each biome, alongside cross-biome transfer skill as a function of biome dissimilarity (right). Each point represents a specialist trained on one biome and evaluated on another; marker colour indicates training biome, marker shape the evaluation biome. RMSE is normalised by the mean in-biome specialist RMSE (averaged across all 12 output variables), so 1.0 corresponds to average specialist performance (dashed line). (b) Mean transfer penalty per variable, defined as cross-biome RMSE divided by in-biome RMSE minus one. The red portion shows the residual penalty under global training; the blue portion shows the penalty recovered by the global model. Numbers indicate the total cross-biome ratio.

Biomes are not uniformly learnable (Fig. 7a, left panel). Tropical and desert regimes are the most easily fitted by their respective specialists, consistent with their relatively clean cluster definitions (B4 desert: only 11% transition-zone cells; B5 rainforest: 24%; see Sect. 2.3.2). Temperate (B2) and boreal (B3) biomes show above-average in-biome errors reflecting a combination of greater internal process heterogeneity and substantial transition-zone content (~26–28%). Against this in-biome baseline, generalisation error scales with ecological distance in the training feature space (r=0.68; Fig. 7a, right panel). Transfers between similar biomes remain close to parity, while extreme shifts degrade strongly: rainforest-to-desert transfer reaches 4.9× the in-biome baseline. Desert emerges as the most challenging target overall (mean 3.1×), consistent with its outlier climatology (Table 3), although this is partly amplified by near-zero in-biome variability for several variables.

The prognostic-diagnostic asymmetry identified in Sect. 3.1.2 persists across biomes (Fig. 7b). Prognostic variables incur moderate transfer penalties (mean ratios 0.92-0.71), with soil temperature layers transferring almost perfectly (stl1: 0.92; stl2: 1.01) and soil moisture and snow cover showing larger penalties (1.34-1.71). Diagnostic variables are substantially more sensitive (median 2.0× vs. 1.1× for prognostics), with latent heat flux (3.4×) and skin temperature (2.9×) the most affected.

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The stacked decomposition in Fig. 7b shows that global training recovers the majority of the diagnostic cross-biome penalty, indicating that training over diverse climate samples largely compensates for biome-specific surface-atmosphere coupling.

The globally trained model achieves a mean normalised RMSE of 1.16—only 16% above the specialist in-biome baseline. Its largest penalties occur in dry biomes (1.47 for B1; 1.60 for B4), reflecting different mechanisms in each case. B1 makes up 21% of land grid points—not under-sampled—but has substantial transition-zone content (~31% borderline or reassigned cells; Sect. 2.3.2), so its representation is diluted into neighbouring clusters during global training. B4 is internally consistent (only 11% transition-zone cells) but combines outlier climatology (58 mm yr^{-1} precipitation vs. 550-2700 in other biomes, LAI 0.4 vs. 1.2-6.1) with a small sample share (12% of land points), so the global training distribution provides limited explicit coverage of its distinctive surface energy and water budget. Notably, the global model outperforms cross-biome specialist transfers for the temperate (B2) and rainforest (B5) regimes. These are regimes where the specialists themselves face challenging training distributions: B2 spans grasslands and forests with similar climates but distinct surface physics, and B5 cells appear partly in B0 due to the continuous precipitation-LAI gradient (Sect. 2.3.2). The global model benefits from having seen the full climate continuum without enforced cluster boundaries.

Overall, a single global model provides the most robust performance across regimes, while biome specialists offer an advantage primarily for diagnostic variables within climatically well-defined environments. Beyond cross-biome transfer, we also tested whether the same prognostic-diagnostic asymmetry holds across spatial resolutions by training a second global aiLand-base instance on an O96 (~125 km) ecLand simulation. Prognostic state predictions transfer cleanly between the two grids in both directions, while diagnostic outputs—particularly 2 m temperature and surface fluxes—remain sensitive to the training grid's spatial characteristics (Appendix B). For operational applications targeting screen-level scores, this sensitivity could be mitigated by training directly at the target resolution, by multi-resolution training to encourage resolution-invariant features, or by diagnostic-only post-hoc bias correction. We plan to investigate these options systematically in future work.

3.1.4 Summary of aiLand-base performance

Across Sects. 3.1.1–3.1.3, aiLand-base reproduces ecLand's prognostic dynamics with high fidelity, remains stable over multi-year integrations, and generalises cleanly across ecosystem regimes and spatial resolutions (Appendix B). Diagnostic variables are consistently more sensitive to regime changes than prognostic ones, reflecting their absolute-value prediction pathway versus the residual formulation used for prognostic states.

Two physically distinct error sources stand out: *snow-soil coupled dynamics*, where the insulating snowpack decouples the soil column from atmospheric forcing and weakens the learned increment mapping, and *extreme aridity*, where the desert biome's surface energy balance differs sufficiently from vegetated training environments to degrade cross-biome transfer by up to ~5×. Both align with known limitations of ecLand and land surface models more broadly. In cold regions, uncertainties in snow insulation, freeze-thaw processes, and soil thermal coupling lead to systematic errors in sub-surface temperature and moisture. In arid environments, surface fluxes are highly sensitive to soil moisture thresholds and sparse vegetation, making models calibrated on humid conditions difficult to transfer to water-limited regimes. The spatial and regime-dependent error patterns exposed by aiLand-base provide a structured diagnostic of where ecLand's input-output relationships are hardest to

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learn, and therefore where process representations may benefit most from targeted development. In this sense the emulator serves not only as a surrogate for ecLand but as an interpretive tool for identifying priority areas for physical model improvement.

3.2 Fine-tuning on flux observations

Section 3.1 identified two distinct error regimes in the pretrained emulator: snow-soil coupled dynamics, which degrade subsurface soil temperature and moisture in cold biomes; and extreme aridity, which challenges cross-biome transfer in desert environments. Of these, fine-tuning on in situ flux observations can plausibly address the subset that manifests in the diagnostic outputs—specifically the biome-dependent sensitivity of latent heat flux (median cross-biome degradation of $3.4\times$) and, relatedly, the aridity regime where evapotranspiration is strongly water-limited.

Furthermore, ecLand itself exhibits known structural biases in surface fluxes, as highlighted in large model intercomparisons (e.g., Abramowitz et al., 2024). As the emulator is pretrained on synthetic LSM data, it inherits these biases by construction. Fine-tuning on observations therefore provides a mechanism to retain the physically consistent dynamics learned from the LSM while correcting systematic errors using real-world constraints, consistent with the two-stage learning strategy outlined in the introduction.

Here, we test five fine-tuning strategies (Table 2) and evaluate whether we can learn from observations to improve the diagnostic fluxes without degrading predictions of the prognostic states.

3.2.1 Predictive performance and validation

All five strategies substantially reduce flux RMSE relative to aiLand-base at both training and validation sites (Table 6). LE improvements exceed those for H: validation LE RMSE decreases by 17-32%, while H decreases by 8-17%. This asymmetry reflects the structure of the inherited bias. ecLand carries a large systematic LE bias (+8.8 $\mathrm{W\,m^{-2}}$ at validation sites) that fine-tuning readily corrects, whereas H bias is significantly smaller (+4.6 $\mathrm{W\,m^{-2}}$), leaving a less correctable signal. LE also exhibits a strong seasonal cycle linked to soil moisture and vegetation—inputs well represented in the model—while H depends more strongly on boundary-layer processes and the surface-air temperature gradient, making it sensitive to atmospheric conditions not provided as inputs. Fine-tuning largely removes the inherited LE bias: at training sites, $|\text{bias}| < 1\ \mathrm{W\,m^{-2}}$ across all strategies; at validation sites, residual biases range from -1.7 to -4.5 $\mathrm{W\,m^{-2}}$, with aiLand-S4 the smallest.

The strategies differ most in how well gains transfer to unseen sites and unseen years. Spatially, the training-validation RMSE gap ranges from 2.9 $\mathrm{W\,m^{-2}}$ (aiLand-S5) to 9.8 $\mathrm{W\,m^{-2}}$ (aiLand-S2) for LE, and from -0.5 to 5.3 $\mathrm{W\,m^{-2}}$ for H. aiLand-S2 achieves the lowest training RMSE but the largest gap, indicating that its randomly initialised diagnostic blocks overfit training-site patterns. aiLand-S4 combines a small spatial gap with the best validation LE correlation (r=0.786, up from 0.722 for aiLand) and validation H correlation (r=0.719, up from 0.657).

Temporal generalisation reinforces this pattern. Comparing validation-site LE improvements between the training period (2000-2019) and the out-of-sample evaluation period (2020–2023), aiLand-S4 is essentially stable (30.2% vs. 29.6%) and aiLand-S1 shows only mild attenuation (29.7% vs. 28.2%), whereas aiLand-S2 drops markedly (24.2% vs. 16.5%). aiLand-

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Table 6. Surface energy flux performance over the out-of-sample evaluation period 2020-2023. RMSE and bias are in $W\,m^{-2}$; Corr is the Pearson correlation coefficient. Metrics are computed on daily means at sites with valid FLUXNET observations. Validation values (bold) are from 17 held-out sites; training values are from 84 sites.

	LE						H					
	RMSE		Corr		Bias		RMSE		Corr		Bias	
	Train	**Val**	Train	**Val**	Train	**Val**	Train	**Val**	Train	**Val**	Train	**Val**
ecLand	30.7	**32.0**	0.734	**0.718**	+12.7	**+8.8**	28.4	**28.1**	0.693	**0.659**	−0.6	**+4.6**
aiLand-base	31.0	**31.9**	0.736	**0.722**	+12.7	**+9.7**	28.1	**27.2**	0.689	**0.657**	−0.4	**+4.0**
aiLand-S1 (Freeze)	18.0	**22.5**	0.809	**0.785**	+0.1	**−2.3**	21.4	**22.3**	0.784	**0.713**	+1.7	**−0.6**
aiLand-S2 (Deep)	14.7	**24.5**	0.853	**0.777**	−0.4	**−4.5**	17.5	**22.8**	0.843	**0.704**	+3.1	**+1.0**
aiLand-S3 (DiffLR)	17.4	**22.9**	0.819	**0.780**	+0.3	**−2.5**	20.5	**23.1**	0.792	**0.708**	+1.3	**−0.5**
aiLand-S4 (TwoPhase)	18.4	**22.3**	0.805	**0.786**	−0.0	**−1.7**	20.9	**21.8**	0.783	**0.719**	+0.9	**−0.5**
aiLand-S5 (FullLR)	20.2	**23.1**	0.787	**0.768**	−0.2	**−2.2**	22.1	**21.6**	0.770	**0.717**	+0.9	**+2.1**

S5 is the one case where validation-site improvement strengthens in the evaluation period (27.9% to 31.9% for LE; 19.7% to 15.8% for H), suggesting that full-model fine-tuning with a low learning rate learns a structural correction rather than memorising site-specific patterns, though at some cost to training-site skill.

To illustrate site-level behaviour, we focus on aiLand-S4 as a representative fine-tuning strategy and delivers the best flux RMSE and correlations across validation sites (Table 6). At the site level, aiLand-S4 improves LE at 14 of 17 validation sites and H at 14 of 17; 11 sites improve in both fluxes simultaneously, while no site degrades in both (Fig. 8). The largest LE gains occur at water-limited sites (IT-Lsn, -60.6%; US-xGR, -56.4%) and extend across temperate wetland (US-ALQ, -57.2%) and Mediterranean (IT-Tor, -53.9%) biomes. Three sites show LE degradation: US-NC4 (coastal wetland, +45.2%), CH-Dav (+13.8%), and US-xCP (+0.3%), though all three improve in H. Conversely, three sites with strong LE improvement degrade in H—IT-Tor (+21.9%), US-Me1 (+36.5%), and CH-Cha (+44.2%)—predominantly high-altitude or complex-terrain locations where the ~60 km grid cannot resolve topographic variability. Figure 9 illustrates these improvements at few validation sites of varying climates and vegetation. We see that ecLand systematically overestimates LE during the growing season. Fine-tuning pulls the model toward the observed flux magnitude while preserving the seasonal phase and inter-annual variability.

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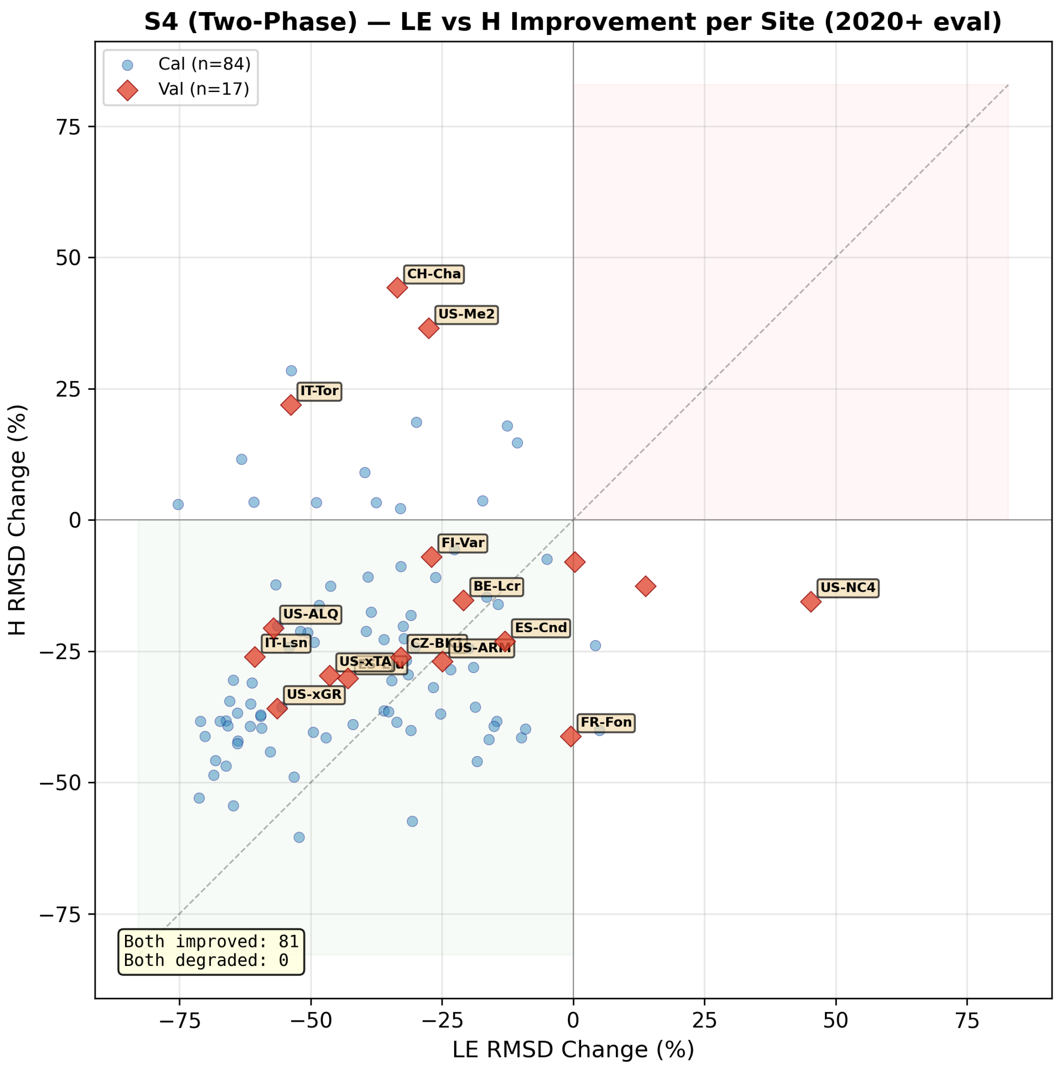

Figure 8. Per-site percentage change in RMSE for aiLand-S4 (TwoPhase) relative to aiLand-base during the evaluation period (2020-2023), for LE (x-axis) and H (y-axis). Each marker represents one FLUXNET site; circles are training sites ($n = 84$) and triangles are validation sites ($n = 17$). Points in the lower-left quadrant indicate improvement in both fluxes simultaneously. Site labels are shown for the largest improvements and degradations.

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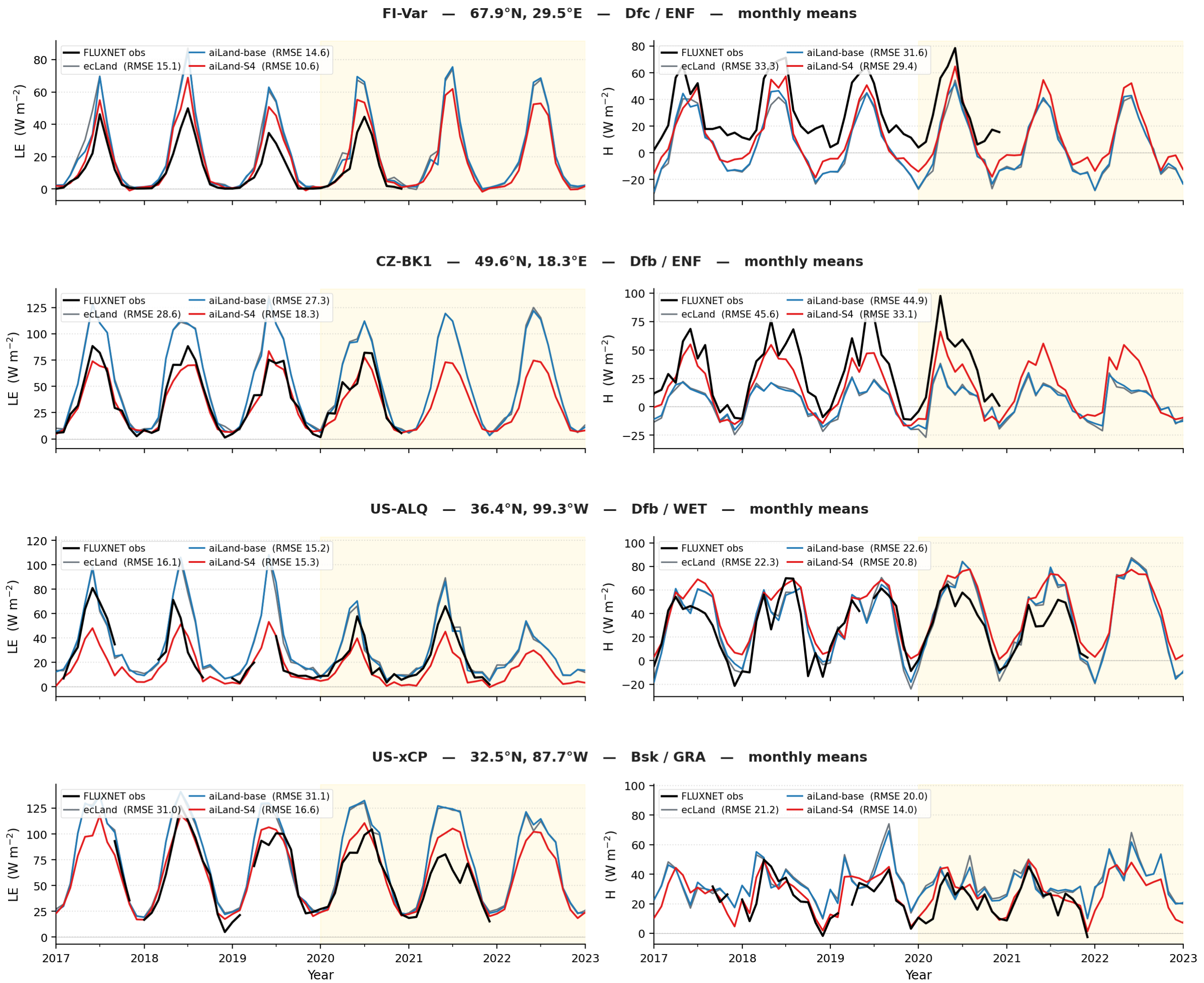

Figure 9. LE and H at range of validation sites. Black: FLUXNET observations; grey: ecLand; blue: aiLand-base (pretrained emulator); purple: aiLand-S4 (two-phase fine-tuned). The gold shaded area represents the out-of-sample evaluation period.

3.2.2 Energy partitioning and balance closure

Reductions in LE and H RMSE can, in principle, be achieved either by improving the emulator's energy partitioning or by damping flux magnitudes toward zero. To distinguish these mechanisms, we evaluate two physical-consistency metrics at the FLUXNET sites: the Bowen ratio (BR = H/LE), which measures how surface available energy is partitioned between sensible and latent fluxes, and the total turbulent energy balance (H+LE error relative to observations), which tests whether any gains come at the cost of closure. ecLand's median Bowen ratio at validation sites is 0.44 against an observed median

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of 0.53 (Table 7), reflecting a systematic tendency to partition too much available energy into latent heat relative to sensible heat—consistent with the LE overestimation identified in Sect. 3.2.1 and with analogous biases reported for other LSMs in PLUMBER2 (Abramowitz et al., 2024). All fine-tuned strategies correct this partitioning bias: per-site Bowen ratio MedAE drops from 0.26 (aiLand-base) and 0.22 (ecLand) to between 0.15 and 0.20 across strategies, with aiLand-S4 achieving the lowest value (0.15, a 42% reduction relative to aiLand-base). Notably, aiLand-S5 recovers the observed median BR exactly but has a higher MedAE (0.20) than aiLand-S4, indicating that a correct bulk ratio does not guarantee correct site-level partitioning. This confirms that the flux RMSE improvements in Sect. 3.2.1 reflect genuine energy-partitioning corrections rather than magnitude damping.

Table 7. Energy partitioning and balance closure metrics evaluated over the full observational period (2000–2023) at the 42 validation sites using daily means. BR: Bowen ratio (H/LE, computed only when LE > 5 $\mathrm{W\,m^{-2}}$, clipped to $[-20, 20]$). Median BR: median of per-site median daily BR. BR MedAE: median of per-site median absolute difference between modelled and observed daily BR (median statistics chosen for robustness to the skewed H/LE distribution at low LE, where RMSE is dominated by rare outliers). Bias and energy balance residual: mean of per-site time-mean difference (model − obs), reported in $\mathrm{W\,m^{-2}}$; positive values indicate model overestimation of upward fluxes. All fluxes follow meteorological sign convention (positive upward). Observations (Obs) are from FluxDataKit's energy-balance-closed variant.

Model	Median BR	BR MedAE	E-bal residual ($\mathrm{W\,m^{-2}}$)	Bias H ($\mathrm{W\,m^{-2}}$)	Bias LE
Obs	0.53	—	—	—	—
ecLand	0.44	0.22	+13.38	+4.54	+8.84
aiLand-base	0.40	0.26	+13.60	+3.91	+9.69
aiLand-S1	0.51	0.19	−2.90	−0.57	−2.33
aiLand-S2	0.58	0.18	−3.42	+1.05	−4.47
aiLand-S3	0.50	0.20	−2.94	−0.48	−2.46
aiLand-S4	0.48	0.15	−2.24	−0.55	−1.68
aiLand-S5	0.53	0.20	−0.10	+2.06	−2.17

Energy balance closure provides a stricter test. ecLand overestimates both fluxes at validation sites (+8.84 $\mathrm{W\,m^{-2}}$ for LE, +4.54 $\mathrm{W\,m^{-2}}$ for H; time-averaged per site), producing a compounding closure offset of +13.38 $\mathrm{W\,m^{-2}}$. Fine-tuning reverses this bias: all strategies slightly underestimate the turbulent flux sum, with aiLand-S5 achieving near-perfect closure (-0.10 $\mathrm{W\,m^{-2}}$) and aiLand-S4 second-best (-2.24 $\mathrm{W\,m^{-2}}$). aiLand-S2 retains the largest offset among fine-tuned models (-3.42 $\mathrm{W\,m^{-2}}$), consistent with its tendency to overcorrect LE (-4.47 $\mathrm{W\,m^{-2}}$). Because the observational target used here is an energy-balance-closed flux budget, these results indicate that fine-tuning recovers a physically consistent surface energy balance at the tower scale.

Fine-tuning also produces physically consistent changes in the screen-level diagnostic variables (2 m temperature, 2 m dew point, skin temperature; Fig. 10). Across strategies (excluding aiLand-S2), reduced evaporative cooling at the surface produces a modest warming of skin temperature (+0.02 to +0.05 K) and 2 m temperature (+0.03 to +0.05 K) relative to aiLand-base,

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while 2 m dew point decreases slightly (−0.01 to −0.04 K), consistent with reduced moisture flux into the boundary layer. aiLand-S4 is notable for near-zero annual temperature change (Δ2t = 0.00 K, Δskt = −0.01 K), reflecting its more conservative two-phase training schedule. The seasonal partitioning of this response is informative: skin temperature warming peaks in MAM (+0.06 to +0.12 K all strategies excluding aiLand-S2) and remains positive in DJF and SON for most strategies (+0.02 to +0.06 K), but is near-neutral in JJA (-0.02 to -0.00 K, excluding aiLand-S4). aiLand-S4 shows slight cooling in all seasons outside MAM (-0.02 to -0.07 K), reflecting its two-phase schedule. Despite the largest absolute LE correction occurring in summer ($\sim$17 W m^{-2} in JJA, where aiLand-base overestimates the total upward turbulent flux), fine-tuning corrects this primarily through LE reduction while H changes remain an order of magnitude smaller (<2 W m^{-2}), leaving surface temperature near its baseline value. aiLand-S2 is an exception—its deep diagnostic head produces a cooler skin temperature (-0.18 K annually) and 2 m temperature (-0.08 K) despite similar LE reductions, indicating that an over-parameterised diagnostic-only architecture can decouple the temperature prediction from the surface energy balance.

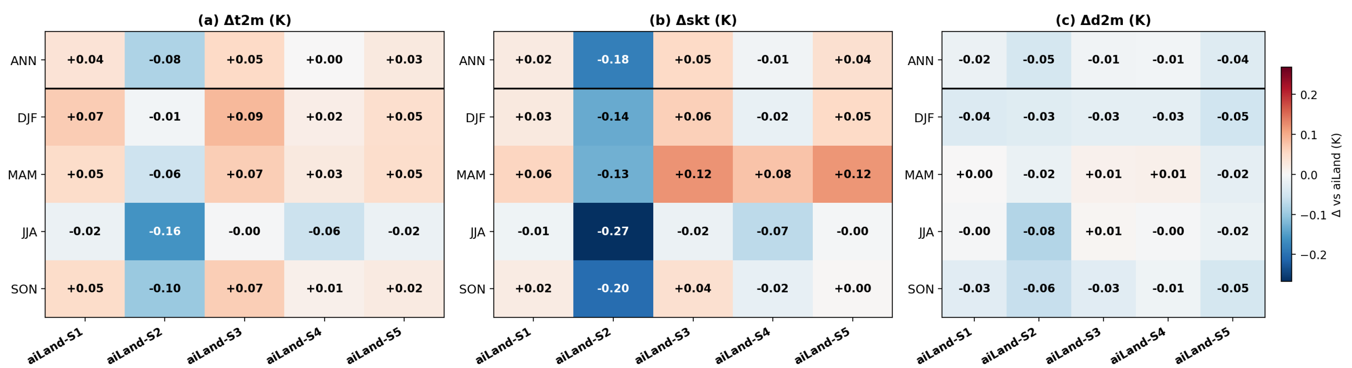

Figure 10. Seasonal mean differences (fine-tuned variant − aiLand-base) in screen-level temperature variables across fine-tuning strategies, evaluated at 42 validation sites for 2000–2023. (a) 2 m air temperature, (b) skin temperature, (c) 2 m dew point. Top row of each panel shows annual means; remaining rows show DJF, MAM, JJA, SON. Warm colours indicate model warming relative to aiLand-base; cool colours indicate cooling.

3.2.3 Prognostic state stability

Strategies aiLand-S1 and aiLand-S2 freeze the prognostic backbone, so their state trajectories are identical to aiLand-base by construction. The backbone-adaptive strategies (aiLand-S3, aiLand-S4, aiLand-S5) modify the backbone and could, in principle, improve flux predictions at the expense of degraded soil moisture or temperature. To assess this, we compare the free-running prognostic trajectories of each fine-tuned model against aiLand-base over the full 24-year period (2000–2023), with focus on the out-of-sample evaluation period (Table 8).

Across the backbone-adaptive strategies, soil moisture is slightly wetter than aiLand-base by 0.3–1.8$\times 10^{-3}$ m^3 m^{-3} and soil temperatures are marginally cooler by 0.02–0.16 K. These offsets are consistent between training and validation sites, indicating a genuine equilibrium shift rather than overfitting. Within-evaluation-period drift is small: soil moisture trends remain below

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Table 8. Prognostic state deviations from aiLand-base during the out-of-sample period 2020-2023. Bias is the time-mean difference (strategy-aiLand-base); Drift is the change over the evaluation window (2023-2020 annual mean). Soil moisture values are given as $\times10^{-3}$ m^3 m^{-3}, soil temperatures in K, and snow cover as $\times10^{-3}$ fraction, all pre-scaled. These metrics compare model against model (no observations required) therefore computed at all sites with valid predictions: 199 training sites and 42 validation sites.

	aiLand-S3 (DiffLR)				aiLand-S4 (TwoPhase)				aiLand-S5 (FullLR)			
	Bias		Drift		Bias		Drift		Bias		Drift	
	Train	**Val**	Train	**Val**	Train	**Val**	Train	**Val**	Train	**Val**	Train	**Val**
swvl1 ($\times10^{-3}$ m^{3}m^{-3})	+1.8	**+1.8**	−0.1	**+0.1**	+1.3	**+0.8**	−0.5	**+2.7**	+1.5	**+1.0**	−0.4	**+3.2**
swvl2 ($\times10^{-3}$ m^{3}m^{-3})	+1.1	**+1.2**	−0.2	**+0.1**	+0.6	**+0.4**	−0.4	**+2.9**	+0.7	**+0.4**	−0.5	**+2.9**
swvl3 ($\times10^{-3}$ m^{3}m^{-3})	+1.3	**+1.0**	−0.3	**+0.1**	+0.3	**−0.2**	−0.6	**+3.4**	+0.7	**+0.0**	−0.8	**+3.2**
stl1 (K)	−0.09	**−0.07**	−0.02	**−0.03**	−0.09	**−0.02**	−0.05	**−0.14**	−0.16	**−0.06**	+0.01	**−0.15**
stl2 (K)	−0.04	**−0.02**	−0.02	**−0.04**	−0.06	**+0.01**	−0.06	**−0.14**	−0.09	**−0.00**	+0.01	**−0.15**
stl3 (K)	−0.08	**−0.06**	−0.03	**−0.04**	−0.10	**−0.04**	−0.07	**−0.13**	−0.13	**−0.05**	−0.00	**−0.13**
snowc ($\times10^{-3}$)	+0.4	**+0.1**	−0.2	**+1.1**	−2.9	**−5.0**	−2.3	**+13.9**	−2.6	**−5.0**	−2.5	**+13.5**

1 $\times10^{-3}$ m^3 m^{-3} over four years at training sites, rising to ~3 $\times10^{-3}$m^3 m^{-3} at validation sites—an order of magnitude smaller than the soil moisture range across biomes, but indicating somewhat more equilibrium shift at unseen locations. Soil temperature trends stay within 0.15 K across both site sets. Snow cover shows a comparable pattern, with validation-site drift of ∼0.014 in fractional cover over four years—small relative to the ~0.06 snow-cover RMSE already present in the pretrained model (Table 5) and unlikely to materially interact with the snow-coupled error regime identified in Sect. 3.1.2.

The sign of these changes is physically consistent with the flux corrections: the fine-tuned models reduce LE magnitude relative to aiLand-base (correcting a systematic overestimation of evapotranspiration), which is qualitatively consistent with the slight wetting of the soil profile, while the associated reduction in evaporative cooling is consistent with the marginal temperature decrease.

3.2.4 Strategy selection and limitations

Comparing strategies on their combined flux skill and state integrity, aiLand-S3 achieves the smallest prognostic biases and near-zero drift in all variables, while aiLand-S4 and aiLand-S5 show comparable biases but slightly larger variability at validation sites—particularly in soil moisture drift (~3$\times10^{-3}$ m^3 m^{-3} over 4 years) and snow cover. Constraining the backbone learning rate (aiLand-S3) or freezing it entirely (aiLand-S1, aiLand-S2) therefore provides the most robust guard against prognostic instability, while aiLand-S4 and aiLand-S5 trade marginally more state uncertainty for comparable or better flux skill, with downstream effects on screen-level diagnostics consistent with this flux–state tradeoff.

Bringing together the different metrics, aiLand-S4 (two-phase) and aiLand-S5 (full low LR) emerge as the top-performing strategies, with the choice between them depending on application priorities. aiLand-S4 achieves the best flux RMSE, correlations, and per-site Bowen ratio skill (MedAE 0.15) at validation sites, making it preferable when flux prediction accuracy

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is the primary target. aiLand-S5 achieves near-perfect energy balance closure at validation sites (-0.10 W m^{-2}), recovers the observed median Bowen ratio exactly (0.53), and shows the smallest training–validation generalisation gap, at some cost to training-site flux skill and per-site Bowen ratio accuracy. It is therefore preferable for coupled applications where bulk physical consistency of the surface energy budget matters most. Between the two, aiLand-S5 is also easier to implement since it requires only one phase of fine-tuning.

Relating these results to the two error regimes identified in Sect. 3.1.1: fine-tuning on flux observations effectively addresses the diagnostic-variable weaknesses in biome and aridity regimes, with the largest validation improvements at water-limited sites (IT-Lsn -60.6%, US-xGR -56.4%) and robust gains across boreal, temperate, and Mediterranean biomes. Snow-coupled errors are not addressed by diagnostic-head fine-tuning, as both originate in the prognostic increment function. Correcting these prognostic-level errors would require updating the state-evolution network itself, for example through fine-tuning on snow-specific observational data or online bias correction, which we leave to future work.

A consideration in interpreting these results is the scale mismatch between FLUXNET tower footprints (~100 m) and the N320 reduced Gaussian grid (~31 km at the equator, ~60 km at mid-latitudes). The model represents grid-cell-averaged fluxes, whereas tower observations capture local conditions that may not be representative of the surrounding landscape—particularly at sites with heterogeneous land cover, complex terrain, or coastal boundaries. This mismatch contributes to irreducible representation error in the metrics and likely explains some of the site-level degradations observed at high-altitude (CH-Cha, US-Me1) and coastal (US-NC4) locations, where sub-grid variability is largest.

Similarly, while we use energy-balance-closed FLUXNET observations, some caveats remain. The closure correction distributes the residual energy proportionally between H and LE, preserving the observed Bowen ratio but making absolute flux magnitudes conditional on this convention rather than uniquely determined. Net radiation and ground heat flux measurements used in the correction have their own ~10–15% uncertainty (Mauder et al., 2020), which propagates into the closed fluxes. Bowen ratio as a metric is also disproportionately sensitive to low-LE conditions where the ratio diverges.

4 Perspectives and next steps

4.1 Towards a data-driven Earth System Model

This work is part of the broader Destination Earth effort to develop a fully data-driven Earth System Model (see https://destine.ecmwf.int/ml-earth-system-components/). It is also embedded within the Copernicus Climate Change Service Evolution (CERISE) project, which aims to develop next-generation climate and land reanalyses—a context in which fast, differentiable land surface emulators offer particular value. In its current configuration, aiLand emulates a core set of land surface variables from ecLand, including soil moisture, soil temperature, snow cover, latent and sensible heat fluxes, skin temperature, as well as near-surface atmospheric diagnostics such as 2 m temperature and 2 m dew point. These variables represent key components of the land–atmosphere exchange of water and energy and constitute a first step towards a data-driven representation of land surface processes suitable for coupling within an Earth system context.

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A natural next extension is the inclusion of runoff and related hydrological fluxes. Runoff provides the primary interface between the land surface and hydrological routing and streamflow models, and its accurate representation is essential for coupling land surface processes to river discharge, flood forecasting, and freshwater budgets. Emulating runoff alongside soil and snow states would enable aiLand to interact more directly with streamflow and routing models, supporting experiments on land–hydrology coupling and the propagation of land surface uncertainties into river discharge.

Beyond runoff, future developments may extend emulation to a broader range of land surface variables, including both observed quantities—such as leaf area index (LAI), vegetation phenology, or satellite-derived soil moisture—and internal model states that are not directly observable but are critical for coupling with other Earth system components. Expanding the set of emulated variables would strengthen the role of aiLand as an intermediate layer between observations and the physical land surface model, enabling richer diagnostics, calibration, and process-level evaluation.

More generally, a central open question concerns how ML-based land surface emulators, such as the aiLand model explored here, should be coupled with other Earth system components, including the atmosphere (Lang et al., 2024), ocean (Hahner et al., 2026), and hydrological routing and streamflow models (Taccari et al., 2026), to create a full data-driven Earth System Model. Ensuring stability and physical consistency across component interfaces remains an active area of research. Notably, several land variables, including soil moisture, soil temperature, runoff, and snow, are already successfully integrated within ECMWF's Artificial Intelligence Forecasting System (AIFS, Moldovan et al., 2025; Raoult et al., 2025b). In that system, these variables are learned jointly within a single end-to-end ML framework, allowing cross-variable dependencies and feedbacks to be captured implicitly during training rather than imposed through a posteriori coupling. aiLand's differentiability also makes it a candidate for hybrid configurations, where it could replace selected ecLand parameterisations while the surrounding physics enforces conservation. Looking forward, ongoing work is migrating aiLand training fully into the anemoi framework—the same stack used for the AIFS—providing a shared codebase that improves traceability and maintanance, and structurally simplifies future coupling experiments across ECMWF's ML-based Earth system components.

4.2 Data assimilation and parameter estimation

Machine-learning emulators of land surface models offer new perspectives for data assimilation (DA) and parameter estimation, particularly when trained to reproduce an existing physical scheme. In this study, aiLand is trained to emulate ECMWF's land surface model ecLand, ensuring that the learned relationships remain physically informed by process-consistent simulations. Fine-tuning is demonstrated using FLUXNET eddy-covariance observations as an illustrative example, rather than as a comprehensive observational assimilation. The methodology, however, is fully extensible and could incorporate a wider range of observational datasets—from in situ networks to satellite derived products—in future studies.

A first and immediate application of such emulators is rapid offline experimentation. Parameter estimation and sensitivity analysis in land surface models are computationally expensive, particularly in ensemble-based DA settings and high-dimensional parameter spaces (Raoult et al., 2025a). aiLand evaluations are orders of magnitude faster than ecLand, enabling systematic offline testing of parameter sensitivities, regime-dependent behaviour, and observation–model mismatches. This allows efficient narrowing of parameter spaces and targeted exploration of model deficiencies.

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The differentiability of MLP-based emulators further enables gradient-based parameter optimisation and observation-constrained learning without requiring explicit tangent-linear or adjoint formulations of ecLand. Fine-tuning aiLand against FLUXNET surface fluxes demonstrates how observational constraints can be incorporated efficiently while retaining the dynamics learned from ecLand simulations. From a DA perspective, this serves as an offline analogue to variational calibration, providing insights into parameter sensitivities under observational constraints without directly modifying operational DA systems.

The complementary case of gradient-based parameter optimisation has clearer limits in the current configuration. Although several physically meaningful parameters enter the emulator through static physiographic input fields—including soil hydraulic properties such as permanent wilting point and field capacity, which vary spatially across soil texture classes—the broader set of tunable ecLand process parameters (e.g., skin thermal conductivities, stomatal resistance and conductance) is not exposed as input controls. Preliminary experiments have shown that perturbing the existing static input fields produces physically consistent responses in prognostic states such as soil moisture, suggesting a pathway toward parameter sensitivity analysis within the emulator framework. The model has so far only seen these parameters in their natural co-variation with other inputs (vegetation type, climate, soil descriptors), so robust isolated parameter perturbation experiments would require additional targeted ecLand simulations spanning the parameter space independently of the other input variables. Future developments could therefore extend the input set to include further ecLand process parameters as controlled input dimensions, enabling gradient-based calibration and sensitivity analysis of land-surface characteristics while retaining the computational efficiency of the emulator.

In addition, such emulators can reduce computational cost in coupled or weakly coupled land–atmosphere DA (de Rosnay et al., 2022). In ensemble-based systems, repeated evaluation of the land surface model across ensemble members contributes substantially to computational demand (Fairbairn et al., 2019). Fast emulators could act as surrogate forward models in selected components of the DA workflow—for example, for ensemble generation, sensitivity experiments, or observation operators—potentially enabling larger ensembles or more frequent cycling at lower computational cost. Operational integration of ML surrogates into DA systems will require systematic investigation of stability, error propagation, and controllability, which is outside the scope of the present study.

Beyond DA itself, fast and differentiable land surface emulators are also relevant to the production of high-resolution, multi-decadal land reanalyses. The computational cost of multi-decadal ecLand integrations limits how finely current and future land reanalyses can be resolved, and the stability of aiLand over multi-year forced integrations (Sect. 3.1.1) suggests it could enable higher-resolution or larger-ensemble reanalysis production—particularly relevant for Copernicus Climate Change Service users within the broader CERISE objectives.

Finally, aiLand provides a diagnostic framework for physical model development. Systematic corrections learned during fine-tuning against FLUXNET fluxes can reveal compensating errors, missing processes, or regime-dependent biases in ecLand, guiding targeted improvements to parameterisations. In this sense, ML acts as a complementary tool to traditional process-based evaluation, rather than a replacement for the physical model (Abramowitz et al., 2024; Reichstein et al., 2019) ensuring physical consistency, rather than data-driven correlations between states. Future work could expand the observational base, allowing broader evaluation and calibration across climates, land covers, and surface processes. Within this broader per-

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spective, physically informed ML emulators such as aiLand offer a practical pathway to accelerate model development while preserving consistency with established land surface physics.

5 Conclusions

We have presented aiLand, a stand-alone MLP-based, limited processes, emulator of ECMWF's ecLand land surface scheme, trained in a two-stage framework that combines pretraining on ecLand outputs with fine-tuning on FLUXNET eddy-covariance observations. The pretrained emulator reproduces ecLand's prognostic and diagnostic states with high skill at short lead times, remains stable over continuous 4-year autoregressive integrations, with a small intrinsic warm bias (+0.40 K in stl1) arising from the interaction between the Smooth L1 loss and the right-skewed soil-temperature increment distribution. The emulator generalises cleanly across ecosystem regimes: a single globally trained model achieves performance close to biome-specialist baselines in-biome (mean normalised RMSE 1.16, 16% above the specialist average), and outperforms specialists in cross-biome transfer for temperate and rainforest regimes. Complementary experiments indicate that the residual architecture also transfers between spatial resolutions (Appendix B). Residual errors concentrate in snow-insulated cold biomes, where the insulating snowpack decouples the soil column from atmospheric forcing, and in extreme aridity regimes where the surface energy balance differs sharply from vegetated training environments. Both error regimes correspond to long-standing limitations of ecLand and land surface models more broadly—cold-region snow and freeze-thaw representation, and arid-region surface flux sensitivity to soil moisture thresholds—so the spatial and regime-dependent error patterns exposed by these robustness tests provide a structured diagnostic of where ecLand's input–output relationships are hardest to learn, supporting the use of the emulator not only as a surrogate but as an interpretive tool for prioritising physical model development.

Fine-tuning on flux observations reduces validation-site latent heat flux RMSE by 30% and sensible heat flux by 20% while preserving prognostic state integrity, and simultaneously recovers a physically consistent surface energy budget at the tower scale:per-site Bowen ratio error drops by 42% (MedAE; best in aiLand-S4) and the energy balance closure residual is reduced from +13.4 W m^{-2} (pretrained) to within 0.1 W m^{-2} at validation sites (aiLand-S5). The snow-coupled errors identified in the pretrained model are not addressed by this form of fine-tuning, as they originate in the prognostic increment function rather than the diagnostic mapping; correcting them will require observational constraints on the state evolution itself.

Several broader limitations apply to this work. Fine-tuning on a single observational network does not guarantee robustness across regions or climates, and there is a risk that learned corrections compensate for structural model errors rather than resolving them. Relatedly, both pretraining and fine-tuning here sample predominantly typical conditions, so the emulator's behaviour under rare or unprecedented extremes—precisely the regime where purely data-driven systems are most prone to extrapolation failure (Zhang et al., 2026; Cranko Page et al., 2026)—remains largely untested. Deliberately enriching the training distribution with extreme events, or up-weighting them in the loss, is therefore a promising direction for improving robustness in exactly the conditions of greatest societal relevance. The effectiveness of both training and evaluation depends critically on the availability of high-quality, long-term observational records: sustained investment in in-situ measurement networks and satellite missions is therefore essential to ensure that the capacity to constrain, validate, and improve both physical

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models and their ML surrogates is not fundamentally limited. These results should be interpreted as a proof of concept, illustrating how physically informed ML emulators can support offline experimentation, methodological development, and preparatory work for broader data assimilation applications.

Future work will extend fine-tuning to additional observational streams —including satellite-derived soil moisture, surface temperature, and vegetation dynamics observables such as solar-induced fluorescence—explore coupling to the atmospheric component of the IFS, and exploit aiLand's differentiability for gradient-based land surface parameter estimation and data assimilation.

Code and data availability. Code for training, inference, and analysis, together with the aiLand-base checkpoint, can be found at https://doi.org/10.5281/zenodo.20764680 (Raoult and Pinnington, 2026). Training data are published at https://doi.org/10.21957/0f6t-7f73 (n320; Raoult et al., 2026a) and https://doi.org/10.21957/fs25-c406 (o96; Raoult et al., 2026b). FLUXNET observations were obtained from the FluxDataKit harmonised dataset (Hufkens and Stocker, 2025), which compiles openly available eddy-covariance data from the FLUXNET2015 (Pastorello et al., 2020), PLUMBER-2 (Abramowitz et al., 2024), AmeriFlux (Novick et al., 2018), and ICOS (Winter, 2022) networks.

Appendix A: FLUXNET sites

The FluxDataKit (Hufkens and Stocker, 2025) provides eddy-covariance observations from 339 FLUXNET sites worldwide (Pastorello et al., 2020). We apply a two-stage filtering process. First, quality-control filtering removes 93 sites with excessive stuck-sensor values or insufficient valid latent and sensible heat flux observations, leaving 246 sites. Second, because multiple FLUXNET sites can fall within a single grid cell of the N320 reduced Gaussian grid, we retain only one representative site per grid cell—the site with the highest data-quality score—removing a further 5 co-located sites and leaving 241 sites in total. The sites are split into 199 training sites used for fine-tuning and 42 independent validation sites held out for evaluation. The split is stratified by IGBP vegetation type so that the relative proportion of each land-cover class is preserved in both subsets (approximately 82%/18% training/validation), ensuring that the validation set is representative of the same vegetation and climate diversity as the training set (Figure A1). Of the 42 validation sites, 17 have flux observations in the post-2020 hold-out period (Table A1), enabling a fully out-of-sample temporal evaluation.

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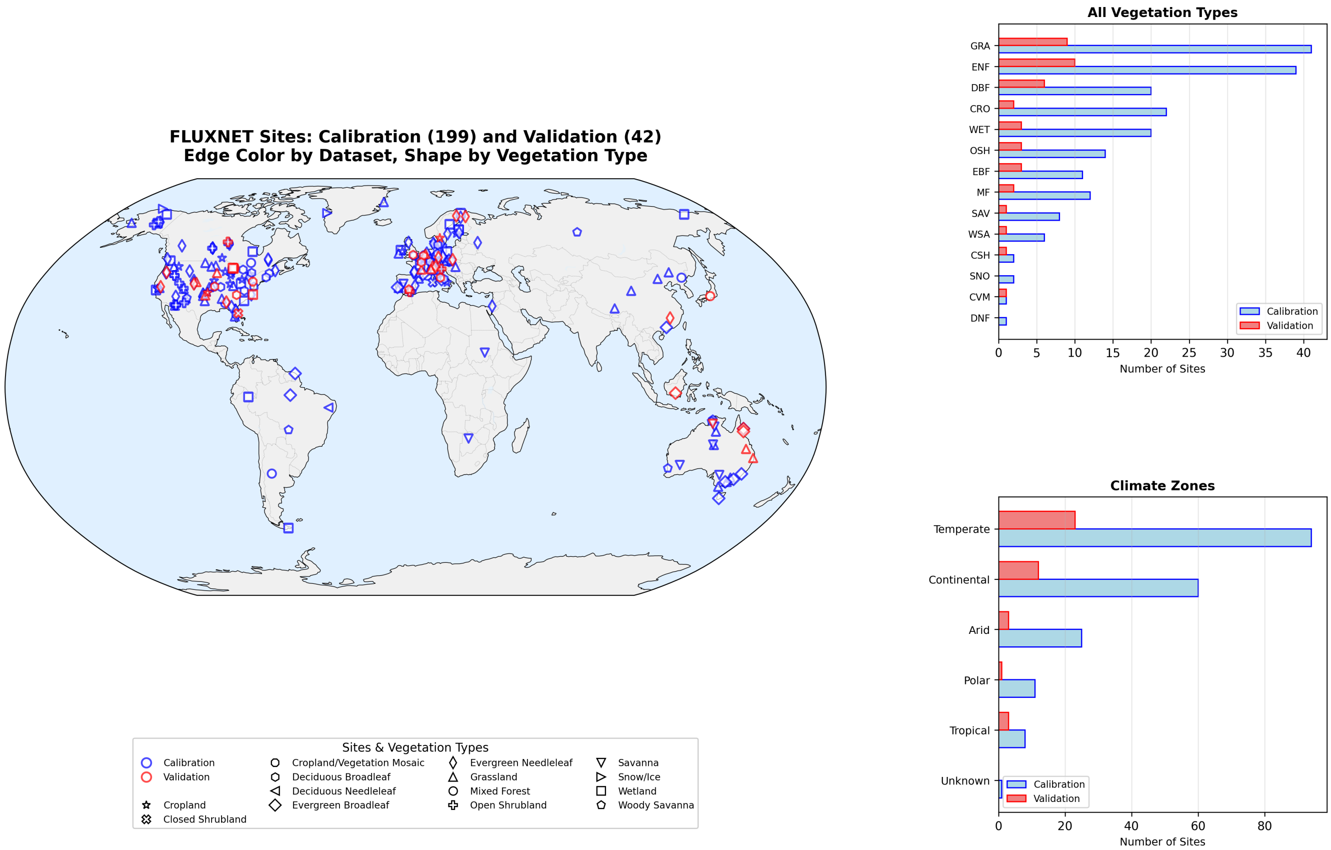

Figure A1. Geographic distribution of the 241 FLUXNET sites used in this study, split into 199 training (blue) and 42 validation (red) sites. Marker shapes denote IGBP vegetation type. The split is stratified by vegetation class so that both subsets span the same range of land-cover and climate conditions. Right panels show the distribution of vegetation types (top) and Köppen–Geiger climate zones (bottom) for each subset. FLUXNET data courtesy of the FLUXNET network (Pastorello et al., 2020).

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Table A1. Validation sites with flux observations in the 2020+ hold-out period (17 of 42 held-out sites). Vegetation type follows the IGBP land-use classification; climate zone follows the Köppen–Geiger scheme.

Site	Country	Lat	Lon	Vegetation	Climate	Start	End
BE-Lcr	Belgium	51.10	3.85	DBF	Cfb	2019	2020
CH-Cha	Switzerland	47.21	8.41	GRA	Cfb	2005	2020
CH-Dav	Switzerland	46.82	9.86	ENF	ET	1997	2020
CZ-BK1	Czechia	49.50	18.54	ENF	Dfb	2004	2020
ES-Cnd	Spain	37.91	−3.23	WSA	Bsk	2014	2020
ES-LJu	Spain	36.93	−2.75	OSH	Csa	2004	2020
FI-Var	Finland	67.75	29.61	ENF	Dfc	2016	2020
FR-Fon	France	48.48	2.78	DBF	Cfb	2005	2020
IT-Lsn	Italy	45.74	12.75	OSH	Cfa	2016	2020
IT-Tor	Italy	45.84	7.58	GRA	Dfc	2008	2020
US-ALQ	USA	46.03	−89.61	WET	Dfb	2015	2023
US-ARM	USA	36.61	−97.49	CRO	Cfa	2003	2023
US-Me2	USA	44.45	−121.56	ENF	Csb	2002	2023
US-NC4	USA	35.79	−75.90	WET	Cfa	2009	2021
US-xCP	USA	40.82	−104.75	GRA	Bsk	2016	2022
US-xGR	USA	35.69	−83.50	DBF	Cfa	2017	2022
US-xTA	USA	32.95	−87.39	ENF	Cfa	2017	2022

Appendix B: Resolution agnosticism

The cross-biome experiments in Sect. 3.1.3 showed that prognostic state predictions transfer cleanly across ecosystem regimes while diagnostic outputs are more sensitive to the training distribution. A complementary question is whether the same asymmetry holds across spatial resolutions: does a model trained on one grid generalise to another, and does the prognostic–diagnostic split persist? To answer this, we trained an additional aiLand instance on an O96 ecLand simulation ($\sim$125 km resolution), using the same setup as the N320 model. Each model was evaluated on its native grid and on the alternative resolution (Table B1).

For same-resolution evaluation, the two models achieve comparable prognostic RMSE. O96 is marginally better for deep soil layers (stl3: 0.068 K for O96 vs. 0.078 K for N320) and snow cover, while N320 is better for near-surface diagnostics (2 m temperature: 0.616 K for N320 vs. 0.876 K for O96) and surface fluxes (sensible heat: 11.01 W m^{-2} for N320 vs. 11.57 W m^{-2} for O96), likely reflecting the richer spatial heterogeneity captured at higher resolution.

Cross-resolution transfer is asymmetric. The O96 model transfers to N320 with modest prognostic degradation (mean ratio 1.057) and near-neutral diagnostic performance (mean ratio 1.018). The N320 model evaluated on O96 shows improved prognostic skill (mean ratio 0.959) but substantially degraded diagnostics (mean ratio 1.289), particularly for 2 m temperature (ratio

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1.737). The N320 model, having learned fine-scale surface–atmosphere coupling, struggles to reproduce the smoother diagnostic fields of the coarser grid, while its prognostic predictions—which depend mainly on local forcing and static descriptors—generalise well or even improve. The N320 grid sits near the threshold at which some mesoscale processes (e.g. organised convection, mountain–valley flows) are partially resolved in ERA5 forcing, whereas at O96 these are firmly subgrid; the asymmetric diagnostic degradation may therefore reflect, in part, the loss of mesoscale variability that the high-resolution model has implicitly used as a predictor.

These results confirm that the point-wise MLP architecture is largely resolution-agnostic for prognostic states. Diagnostic outputs—especially 2 m temperature and surface fluxes—remain sensitive to the spatial characteristics of the training grid, consistent with the diagnostic sensitivity observed in the cross-biome analysis. For operational applications, a model trained at one resolution can therefore provide reliable state predictions at alternative grids, though diagnostic outputs may benefit from resolution-specific training. RMSE values reported correspond to single-timestep predictions; autoregressive rollouts up to 10 days (40 steps) show negligible additional error accumulation, with cross-resolution transfer ratios remaining stable across all lead times.

Table B1. Prognostic and diagnostic RMSE for models trained at O96 and N320 resolutions for single-timestep predictions. Each cell reports either the same-resolution RMSE (shaded) or the RMSE for the alternative resolution together with the ratio relative to the corresponding same-resolution RMSE. Mean and median ratios summarise cross-resolution changes. Surface heat fluxes (H, LE) are reported in W m^{-2} as time-averaged power over each 6-hourly timestep.

	Trained on O96 (~125 km)		Trained on N320 (~31 km)	
Variable	O96	N320	O96	N320
swvl1	0.010400	0.010808 (1.039)	0.010439 (0.976)	0.010693
swvl2	0.003115	0.003341 (1.073)	0.003118 (0.949)	0.003286
swvl3	0.000746	0.000845 (1.132)	0.000745 (0.911)	0.000817
stl1	1.056	1.116 (1.057)	1.094 (1.037)	1.055
stl2	0.138	0.155 (1.121)	0.157 (1.152)	0.136
stl3	0.032	0.054 (1.691)	0.038 (0.891)	0.042
snowc	0.01462	0.01685 (1.153)	0.01477 (0.898)	0.01644
Mean (prognostic ratio)		1.181	0.974	
Median (prognostic ratio)		1.121	0.949	
2d	0.857	0.874 (1.019)	0.940 (1.165)	0.807
2t	0.876	0.724 (0.826)	1.070 (1.737)	0.616
skt	1.081	1.147 (1.061)	1.194 (1.150)	1.038
H	11.57	12.76 (1.103)	13.63 (1.238)	11.01
LE	9.68	10.44 (1.079)	10.59 (1.153)	9.18
Mean (diagnostic ratio)		1.018	1.289	
Median (diagnostic ratio)		1.061	1.165	

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Author contributions. NR and EP conceptualised the study. EP built the first prototype of aiLand, NR extended the framework to interface with anemoi and the ability to fine-tune against observations. NR ran the analysis and generated the figures, with strong support from EP. MSC provided technical support on the anemoi, and FP, BR and NZ on specifically on anemoi-datasets. GA, GB and SB are key developers of ecLand and provided knowledge on the physical model. PdR and CR provided further expertise on the physical modelling side, and MC and PD on the ML side. All authors contributed to the writing of the manuscript.

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