Learning Urban Climate Dynamics via Physics-Guided Urban Surface–Atmosphere Interactions

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2026 CESM Winter Working Group Meeting for the Land Model Working Group and Biogeochemistry Working Groups

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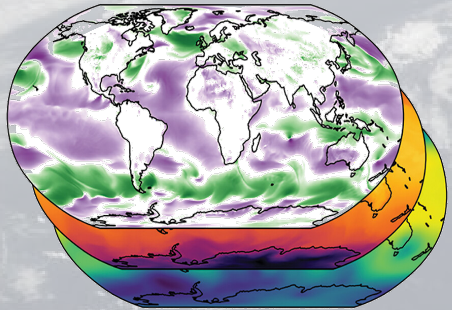
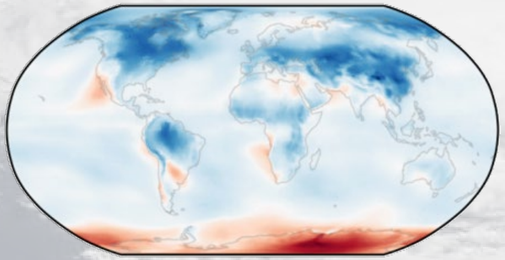
Climate science has gained significant attention in the ML community

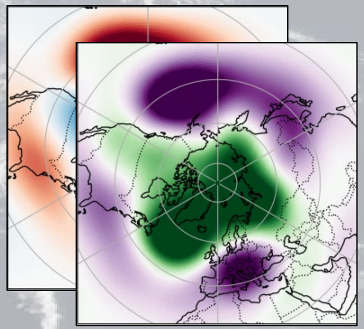
Fully AI-driven weather/climate models



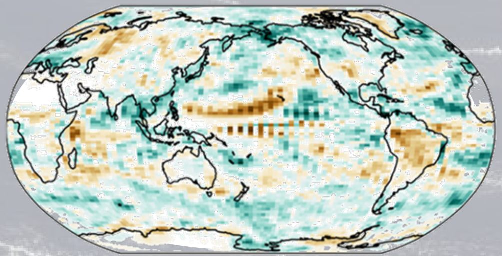
GraphCast
(Lam et al, 2023)



ACE (Ai2 Climate Emulator)
(Watt-Meyer et al, 2023)

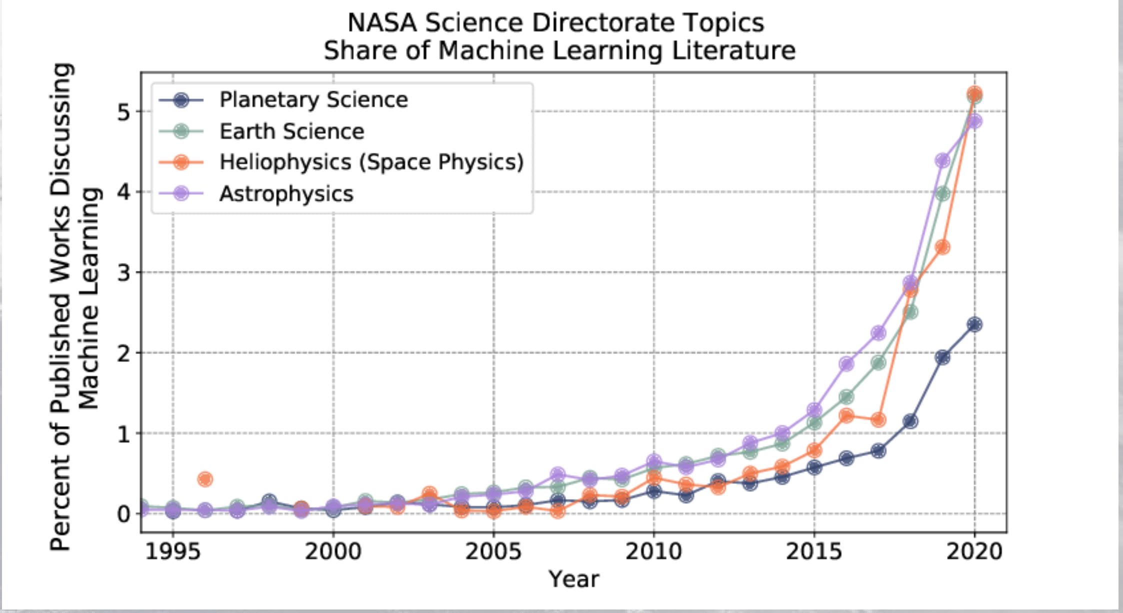


CAMulator
(Chapman *et al, 2025*)



DiffESM
(Bassetti et al, 2024)

A rapidly evolving trend



(Azari et al, 2021)

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Urban areas remain marginalized in most AI-based approaches for climate science

Urban: blind spots in climate artificial intelligence?

climate AI model

under-represented?

systematic bias?

urban

~ 3%

urban areas constitute only 3% of global surface area

> 50%

urban concentrates 50% of the global population

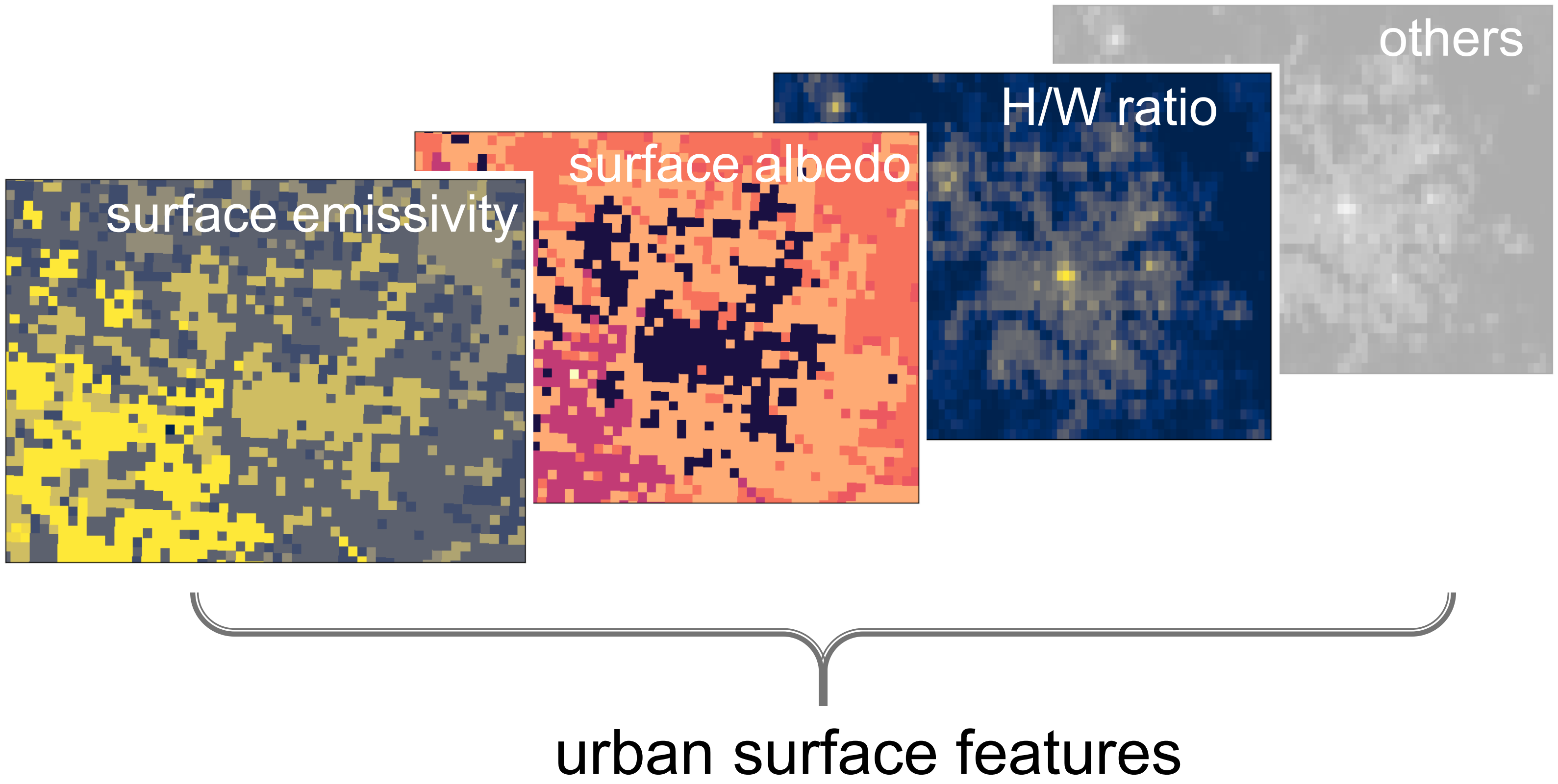
~ 70%

urban emits 70% of greenhouse gas emissions

localized climate pattern

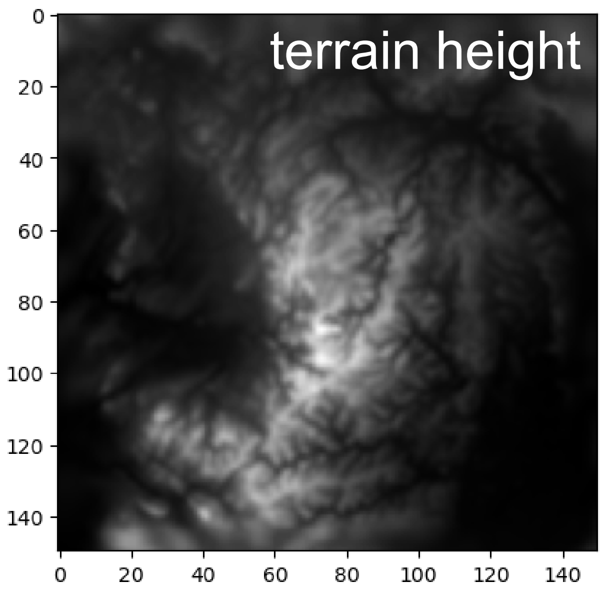
Challenges in learning an urban climate-specific AI model

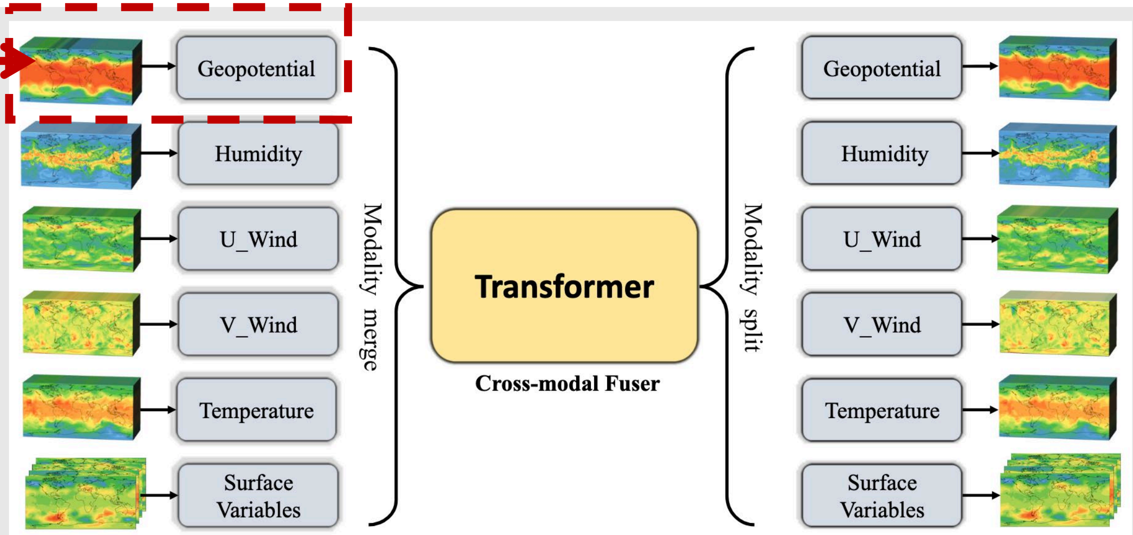
The complexity and variability of urban surface



Challenges in learning an urban climate-specific AI model

- Terrain is one of the few surface data considered in the AI-model approach



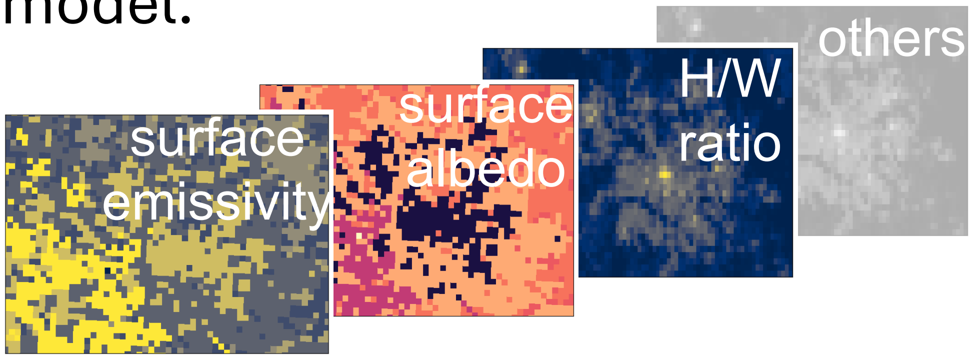


FengWu
(Chen et al, 2023)

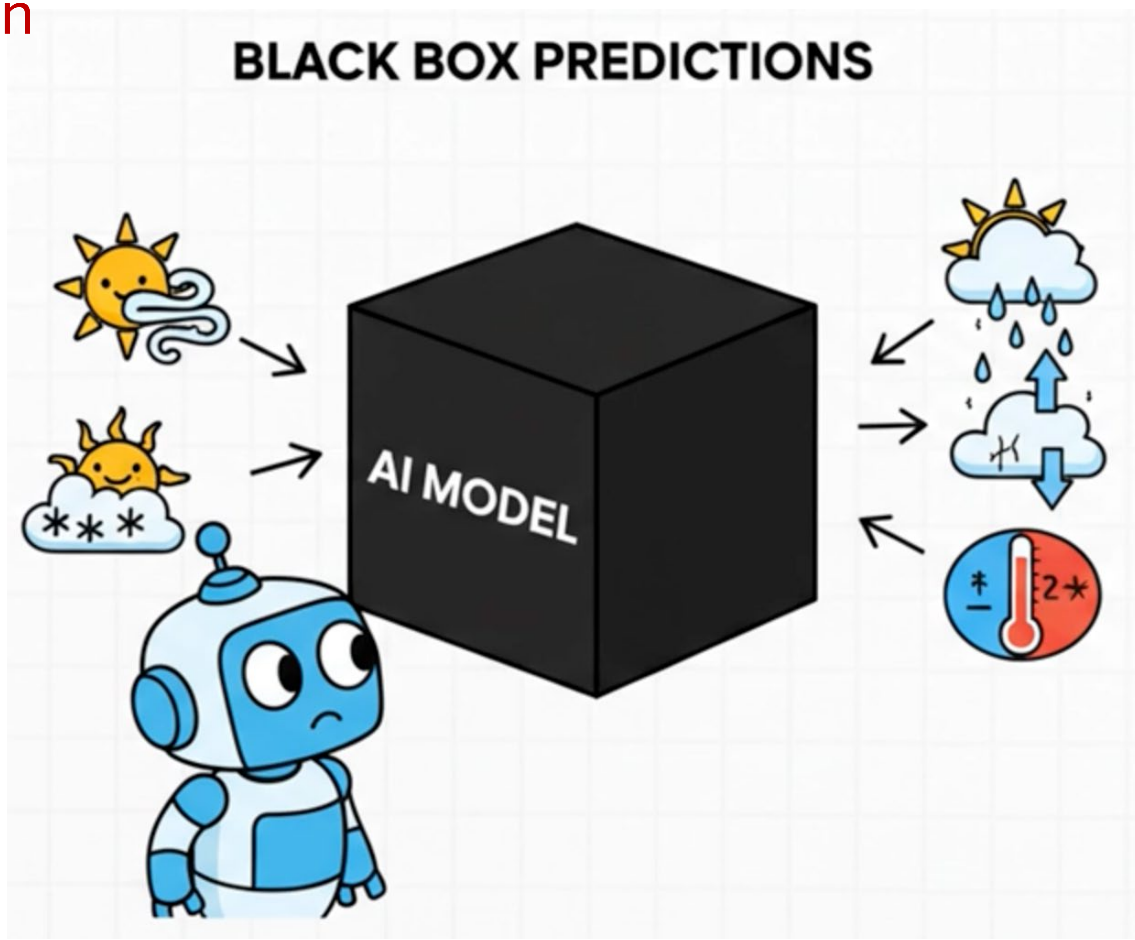
Challenges in learning an urban climate-specific AI model

AI model acts as a black box without domain knowledge:

- urban surfaces are static and feature-rich, which could place burdens on AI model.

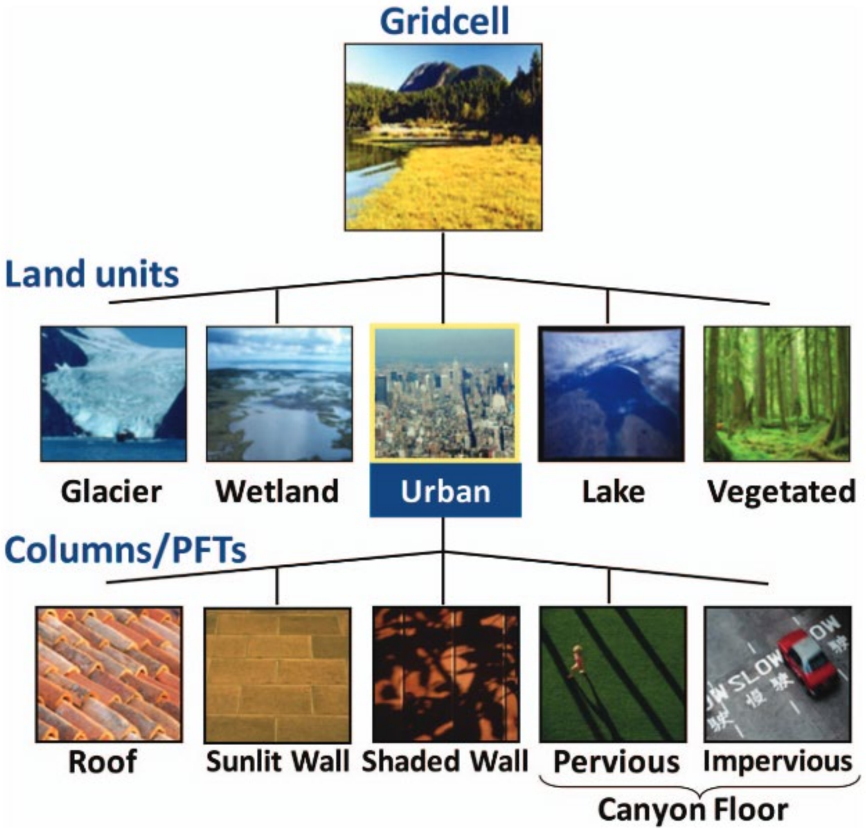


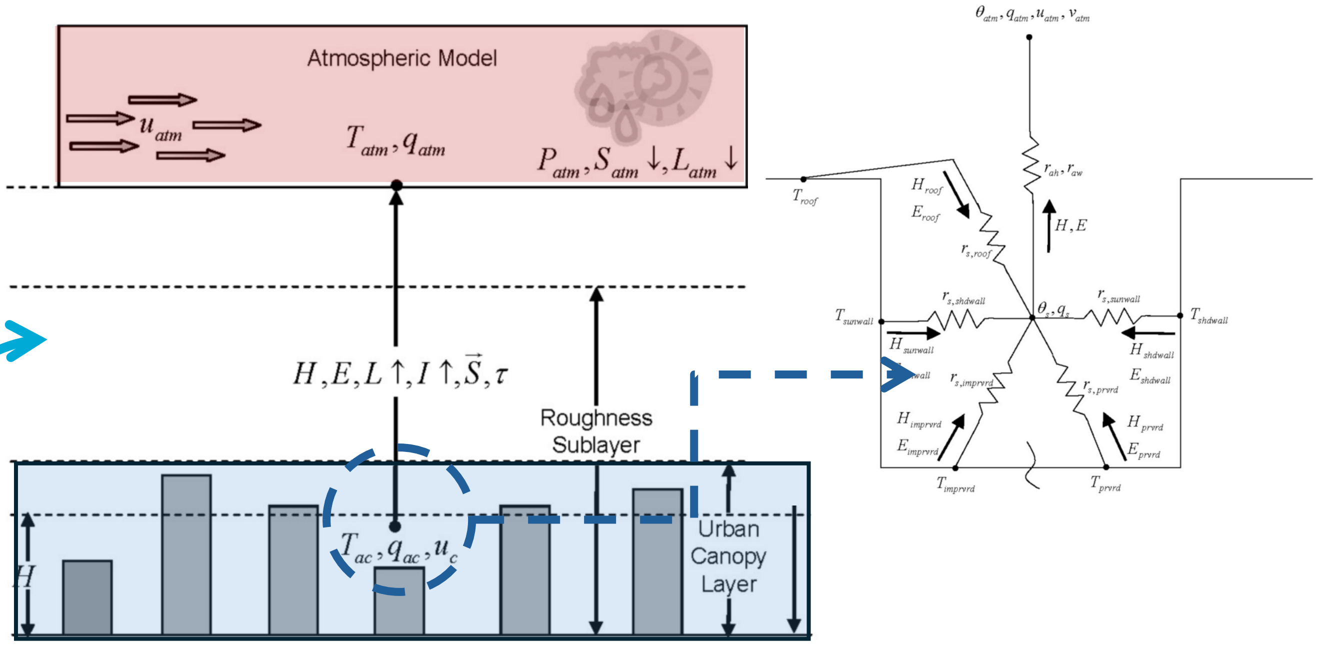
- The model fails to use urban surface information efficiently



Physical-guided deep learning architecture for urban climate

Inspiration & Domain Knowledge Induction



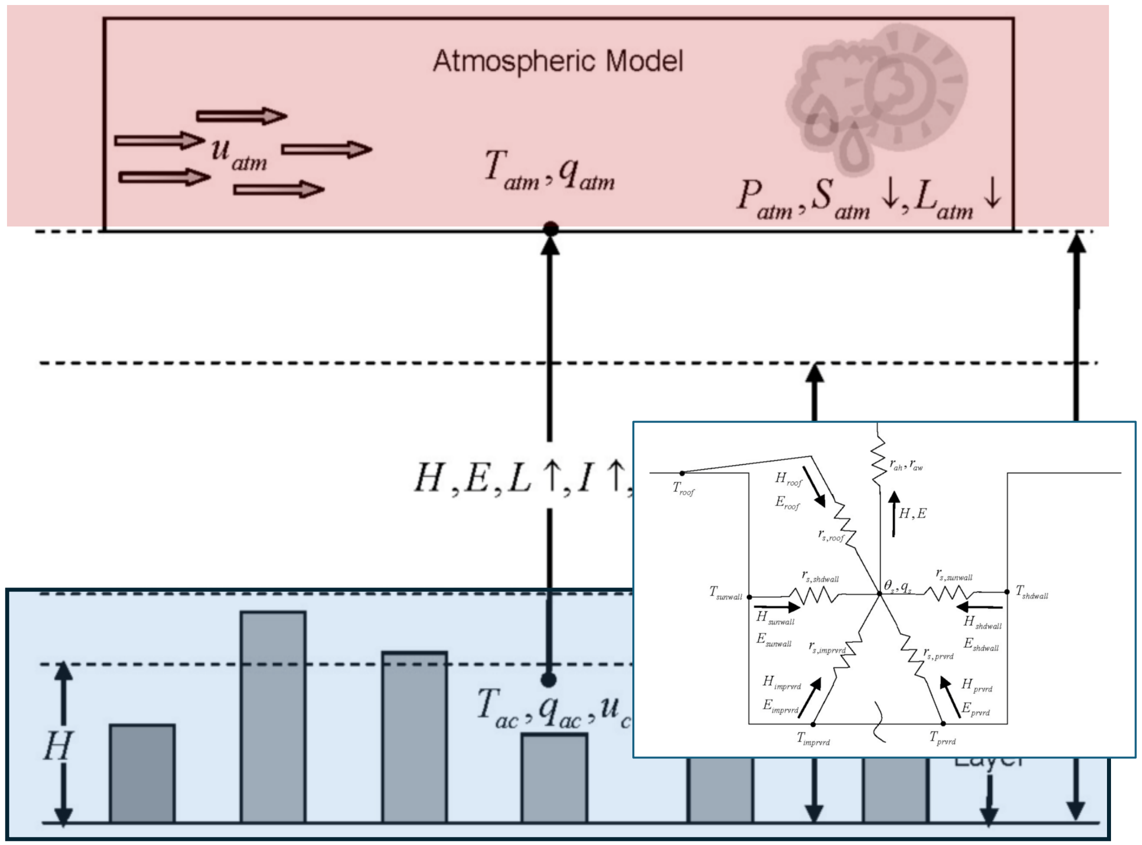


Single-layer urban canyon scheme

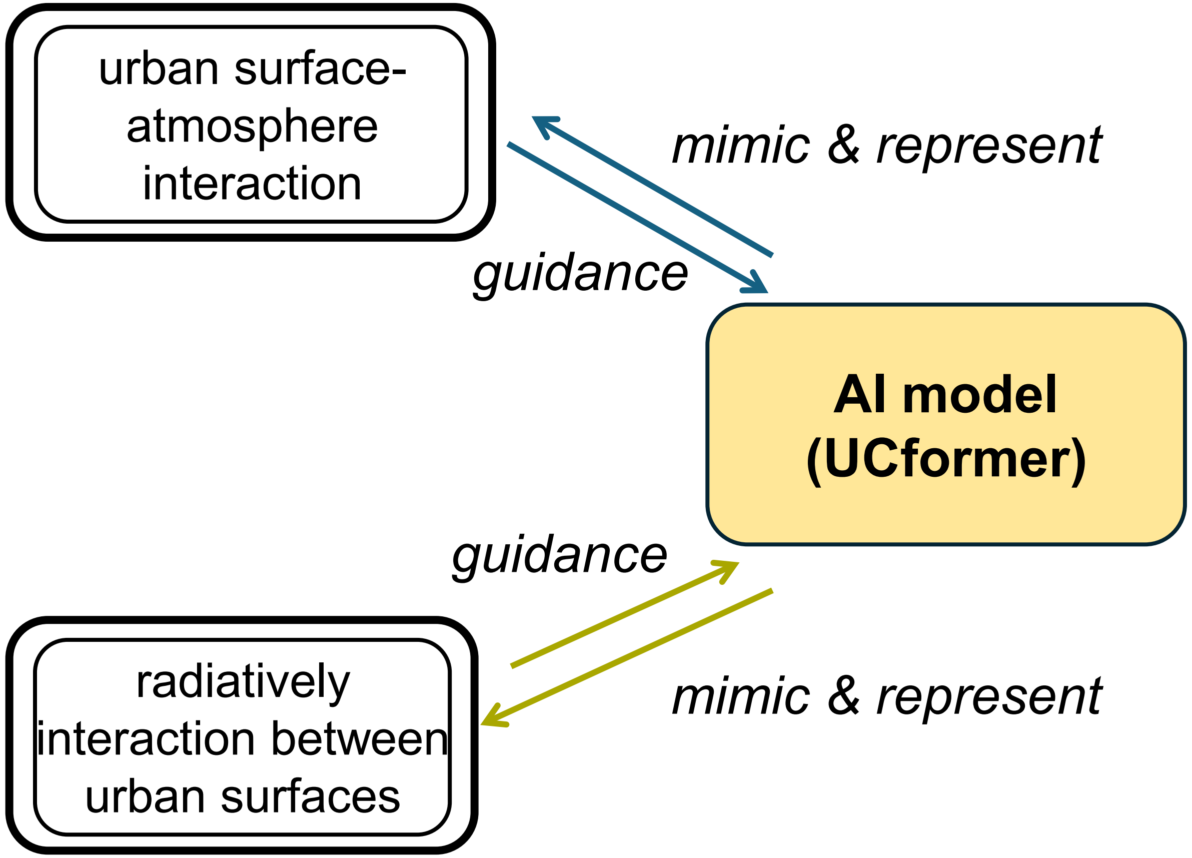
(Oleson et al, 2010)

Physical-guided deep learning architecture for urban climate

Domain Knowledge Induction



(Oleson et al, 2010)



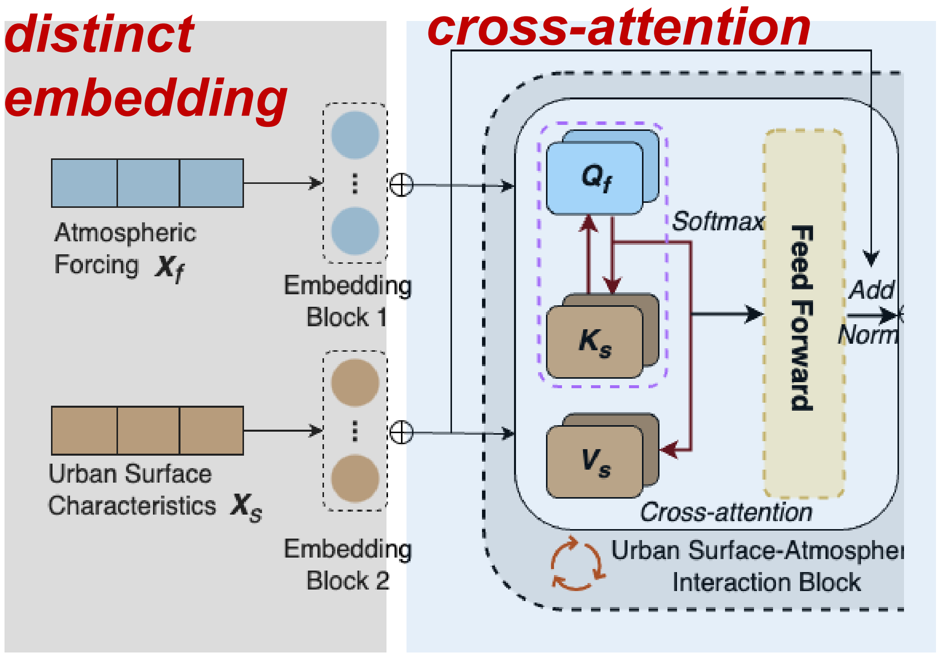
Physical-guided deep learning architecture for urban climate

mapping between the model components and the elements of the inference scheme.

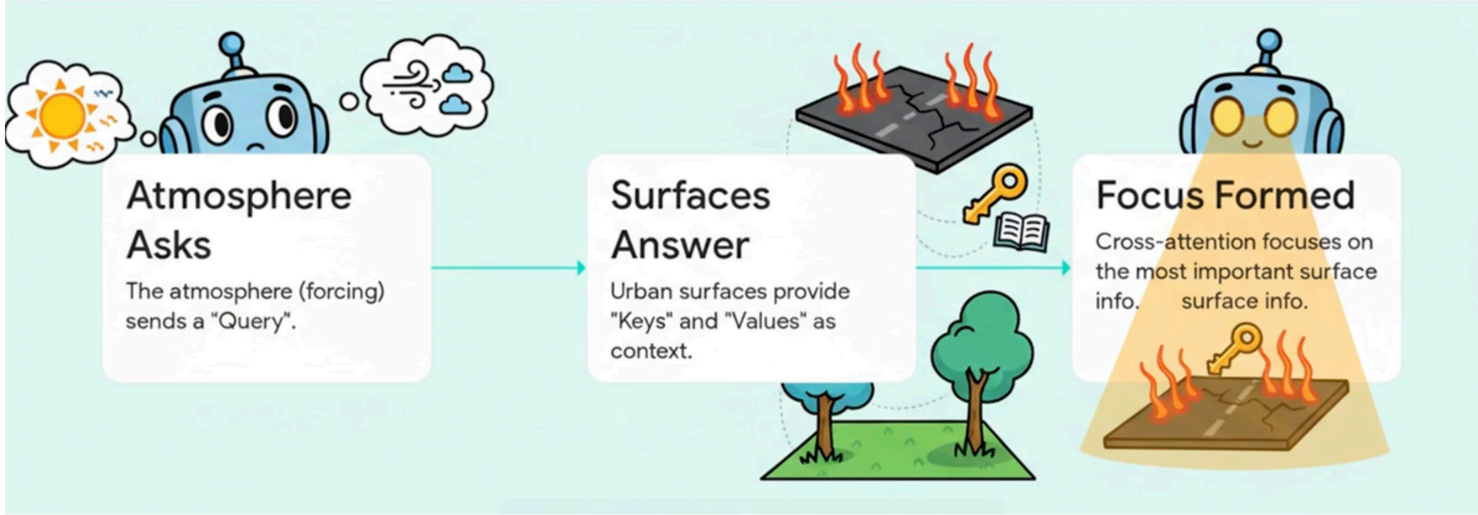
Model Component	Role in Inference Scheme	Input(s)	Output(s)
forcing embedding layer	encodes atmospheric forcing characteristics	atmospheric forcing features	forcing tokens
urban surface embedding layer	encodes urban surface feature characteristics	urban surface features	urban surface tokens
urban surface-atmosphere interaction block	learns interactions between urban surfaces and atmosphere	forcing query tokens, urban surface key tokens, urban surface value tokens	interaction-encoded tokens
surface fluxes interaction block	learns urban surface-surface radiatively interaction	updated interaction-encoded tokens	intermediate features tokens
decoder branch 1	T (temperature) estimation	intermediate T query tokens, concatenated q and t tokens (as keys and values)	esitmated T
decoder branch 2	q (specific humidity) estimation	intermediate q query tokens, concatenated T and t tokens (as keys and values)	esitmated q
decoder branch 3	t (dew point temperature) estimation	intermediate t query tokens, concatenated T and q tokens (as keys and values)	esitmated t

Physical-guided deep learning architecture for urban climate

Block A:



represent urban surface-atmosphere interaction

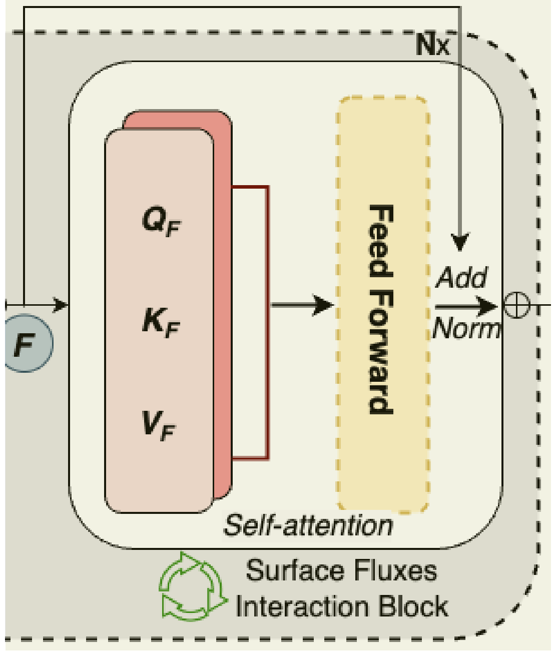


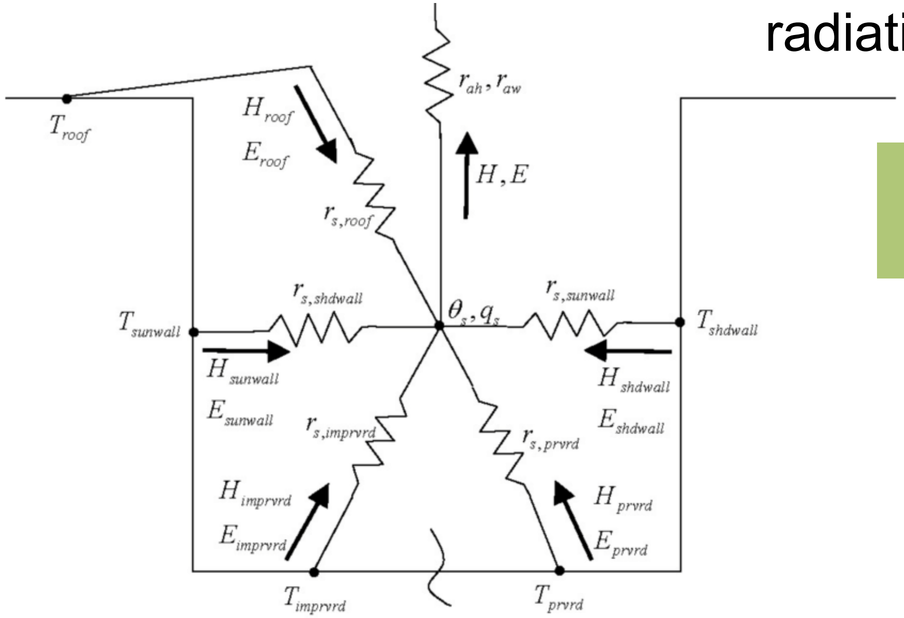
Radiation	Focus →	Albedo/Emissivity
Wind	Focus →	Morphology
......	Focus →	......

Physical-guided deep learning architecture for urban climate

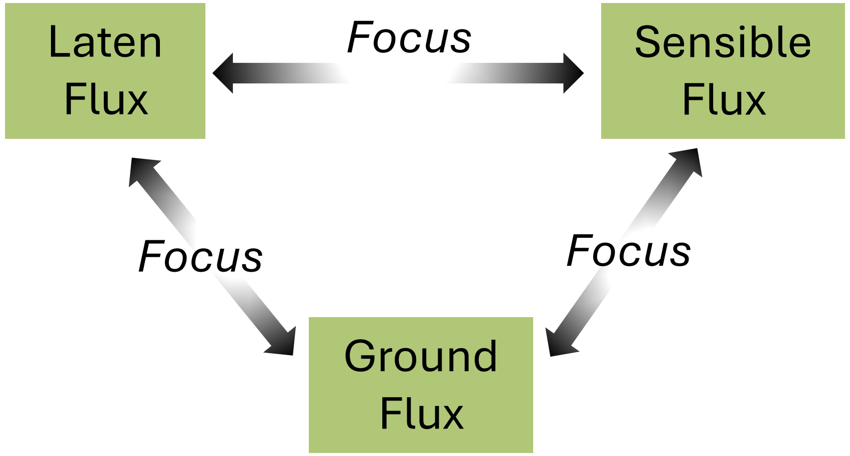
Block B

self-attention





radiatively cross-talk between urban surfaces



represent surface fluxes interaction

Physical-guided deep learning architecture for urban climate

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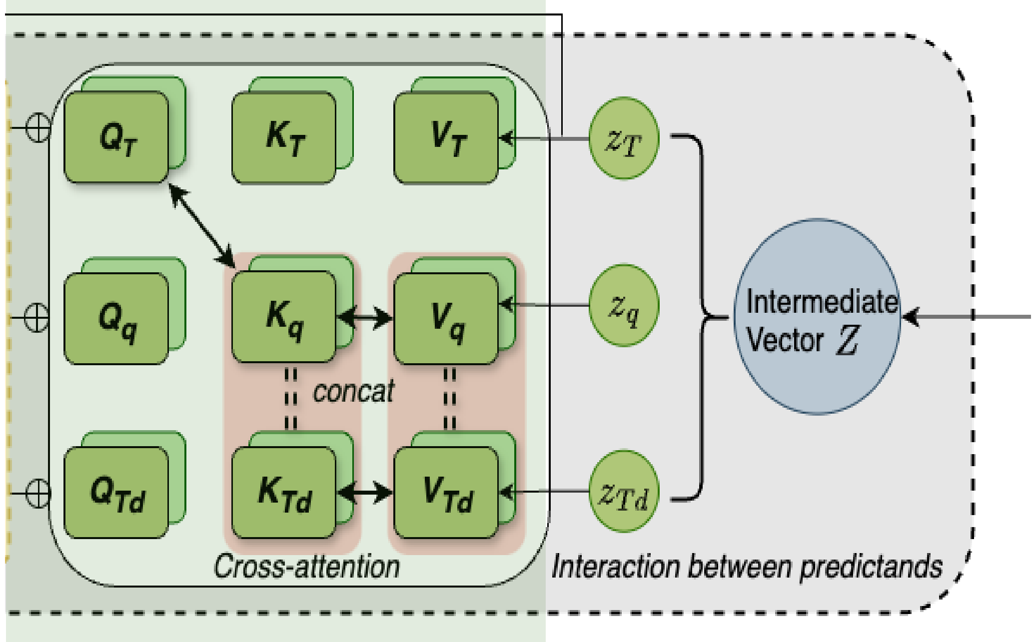
Block C:

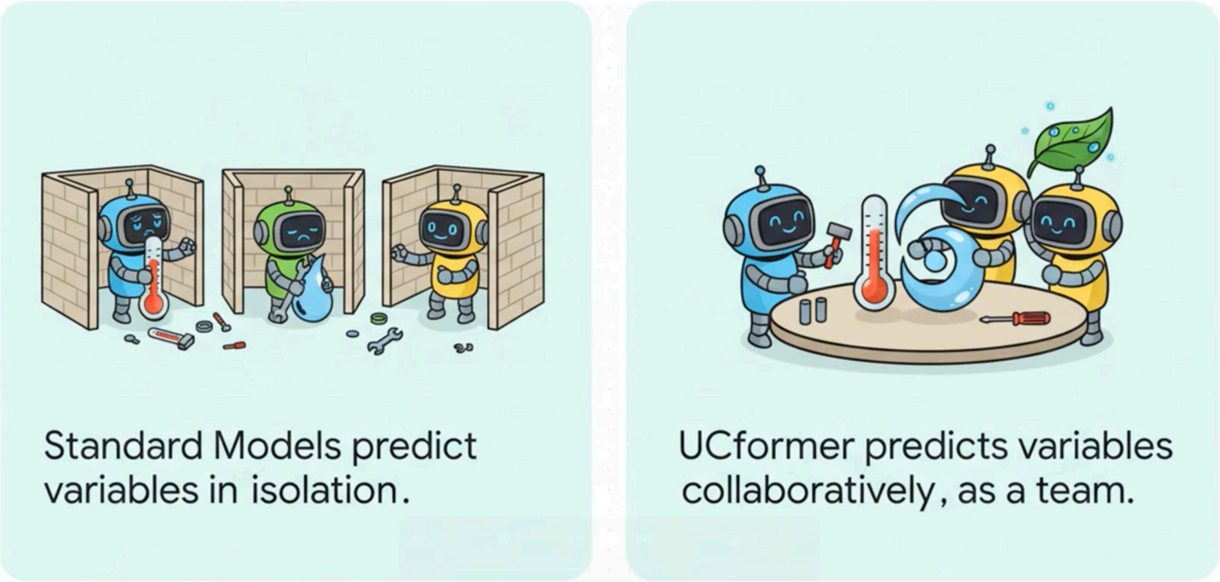
Modeling Target:

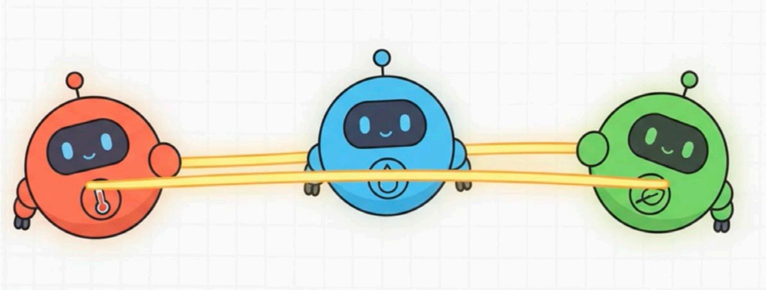
T: urban 2-m air temperature

T_d: urban dew point temperature

q: urban specific humidity





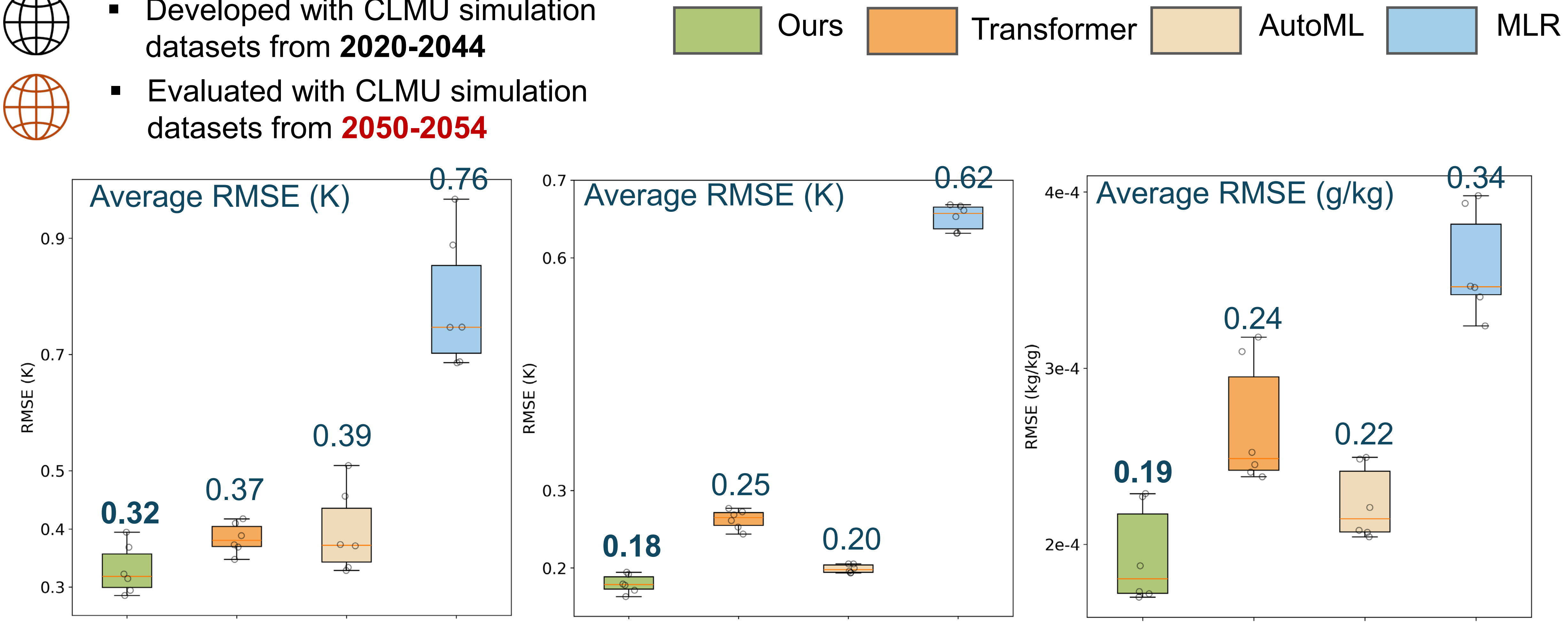


Modeling the physical interdependence as an emergent property

Multi-task modeling performances

Skillful urban climate estimations

- Developed with CLMU simulation datasets from **2020-2044**
- Evaluated with CLMU simulation datasets from **2050-2054**



(a) T (b) T_d (c) q

Fine-tuning model adaptation to real-world data

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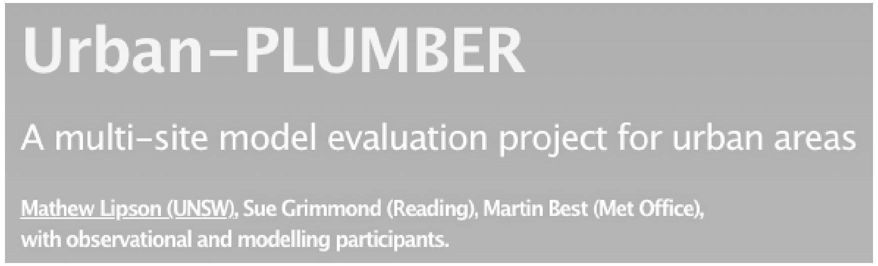

Urban-PLUMBER

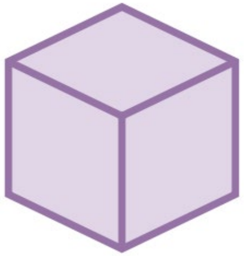
A multi-site model evaluation project for urban areas

Mathew Lipson (UNSW), Sue Grimmond (Reading), Martin Best (Met Office), with observational and modelling participants.

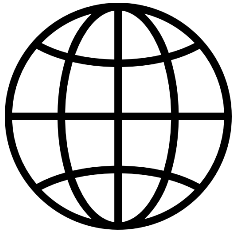
real-world data

drive

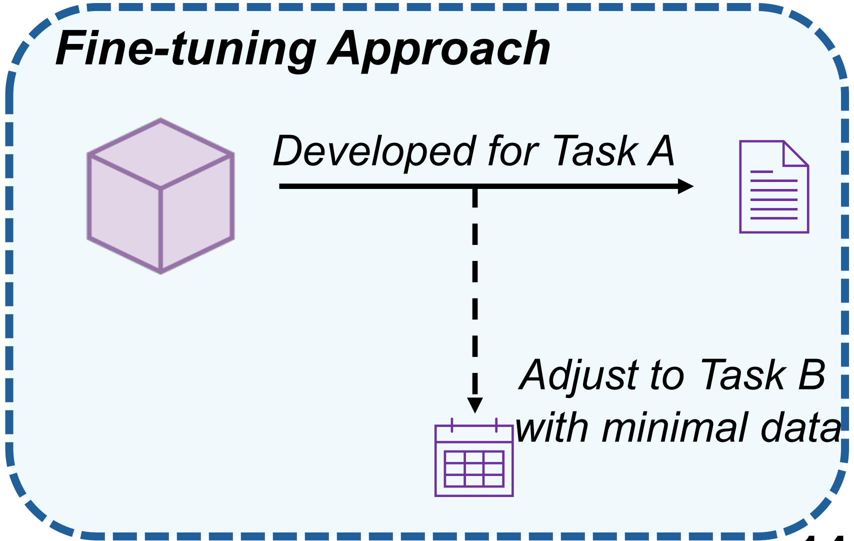
***fine-tuned** with 20% of a station dataset*
(the remaining 80% are tests)



our UCformer model



Community Land Model Urban (CLMU)



Fine-tuning model adaptation to real-world data

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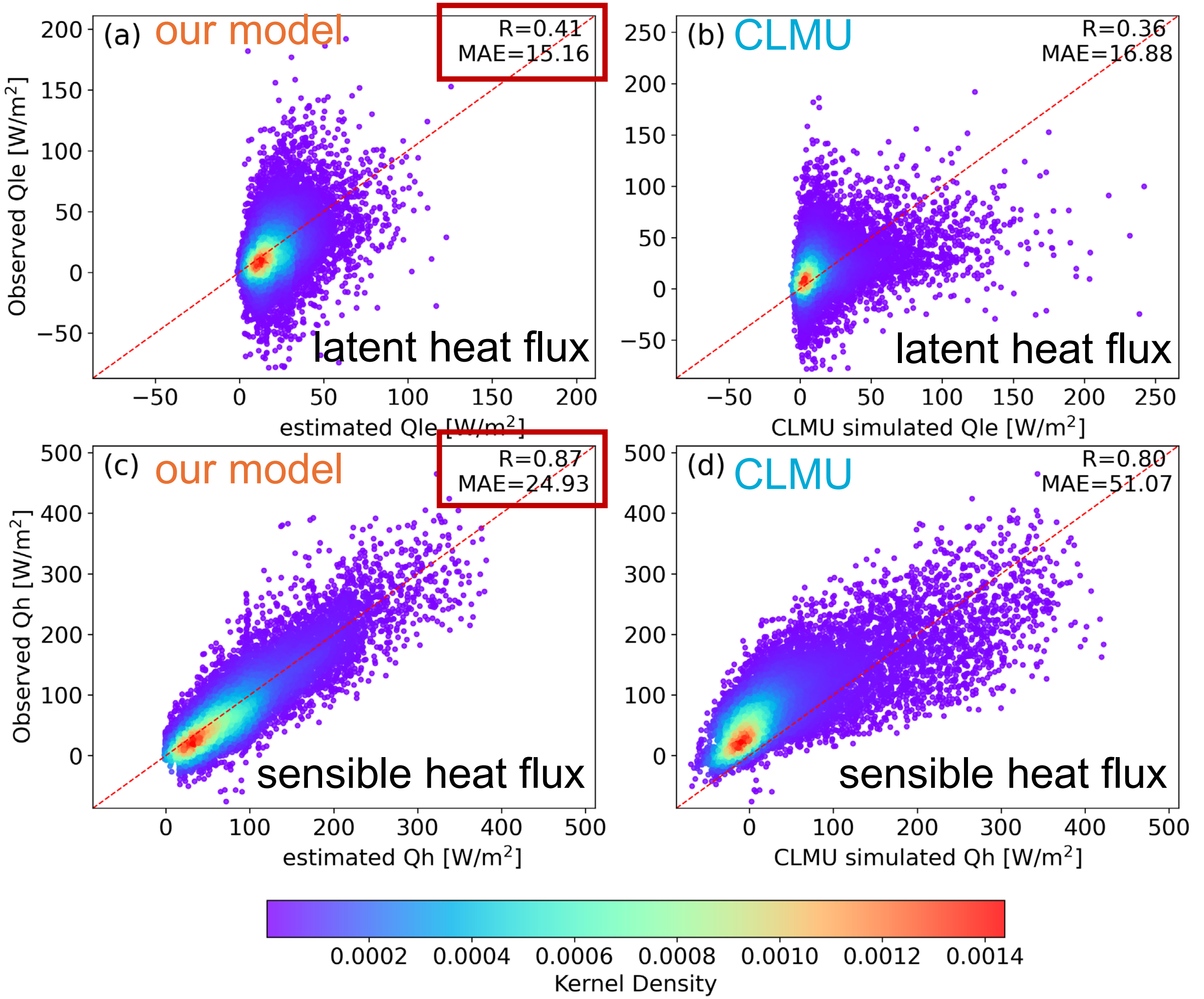

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NEURAL INFORMATION PROCESSING SYSTEMS

Learning Urban Climate Dynamics via Physics-Guided Urban Surface-Atmosphere Interactions

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Abstract

Urban warming differs markedly from regional background trends, highlighting the unique behavior of urban climates and the challenges they present. Accurately predicting local urban climate necessitates modeling the interactions between urban surfaces and atmospheric forcing. Although off-the-shelf machine learning (ML) algorithms offer considerable accuracy for climate prediction, they often function as black boxes, learning data mappings rather than capturing physical evolution. As a result, they struggle to capture key land-atmosphere interactions and may produce physically inconsistent predictions. To address these limitations, we propose UCformer, a novel multi-task, physics-guided Transformer architecture designed to emulate nonlinear urban climate processes. UCformer jointly estimates 2-m air temperature (T), specific humidity (q), and dew point temperature (t) in urban areas, while embedding domain and physical priors into its learning structure. Experimental results demonstrate that incorporating domain and physical knowledge leads to significant improvements in emulation accuracy and generalizability under future urban climate scenarios. Further analysis reveals that learning shared correlations across cities enables the model to capture transferable urban surface–atmosphere interaction patterns, resulting in improved accuracy in urban climate emulation. Finally, UCformer shows strong potential to fit real-world data: when fine-tuned with limited observational data, it achieves competitive performance in estimating urban heat fluxes compared to a physics-based model. [1]

Google Scholar

Top publications

Categories > Engineering & Computer Science > Artificial Intelligence

	Publication	h5-index	h5-median
1.	Neural Information Processing Systems	371	637
2.	International Conference on Learning Representations	362	652
3.	International Conference on Machine Learning	272	471
4.	AAAI Conference on Artificial Intelligence	232	358
5.	Expert Systems with Applications	183	268
6.	IEEE Transactions on Neural Networks and Learning Systems	165	242
7.	IEEE Transactions On Systems, Man And Cybernetics Part B, Cybernetics	157	213
8.	Neurocomputing	148	211
9.	Artificial Intelligence Review	147	272

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paper

code

Summary

- We introduce a **UCformer** that integrates domain and physical knowledge to **learn** urban climate **efficiently.**

- The model features a **domain-aware encoder** and a soft **physics-constrained decoder**, enabling **accurate** and **generalizable** urban climate estimations.

- It performs well on **multi-task learning**, adapts to **sparse real-world data**, and this physics-guided design presents a **transferable concept** for broader Earth system sciences

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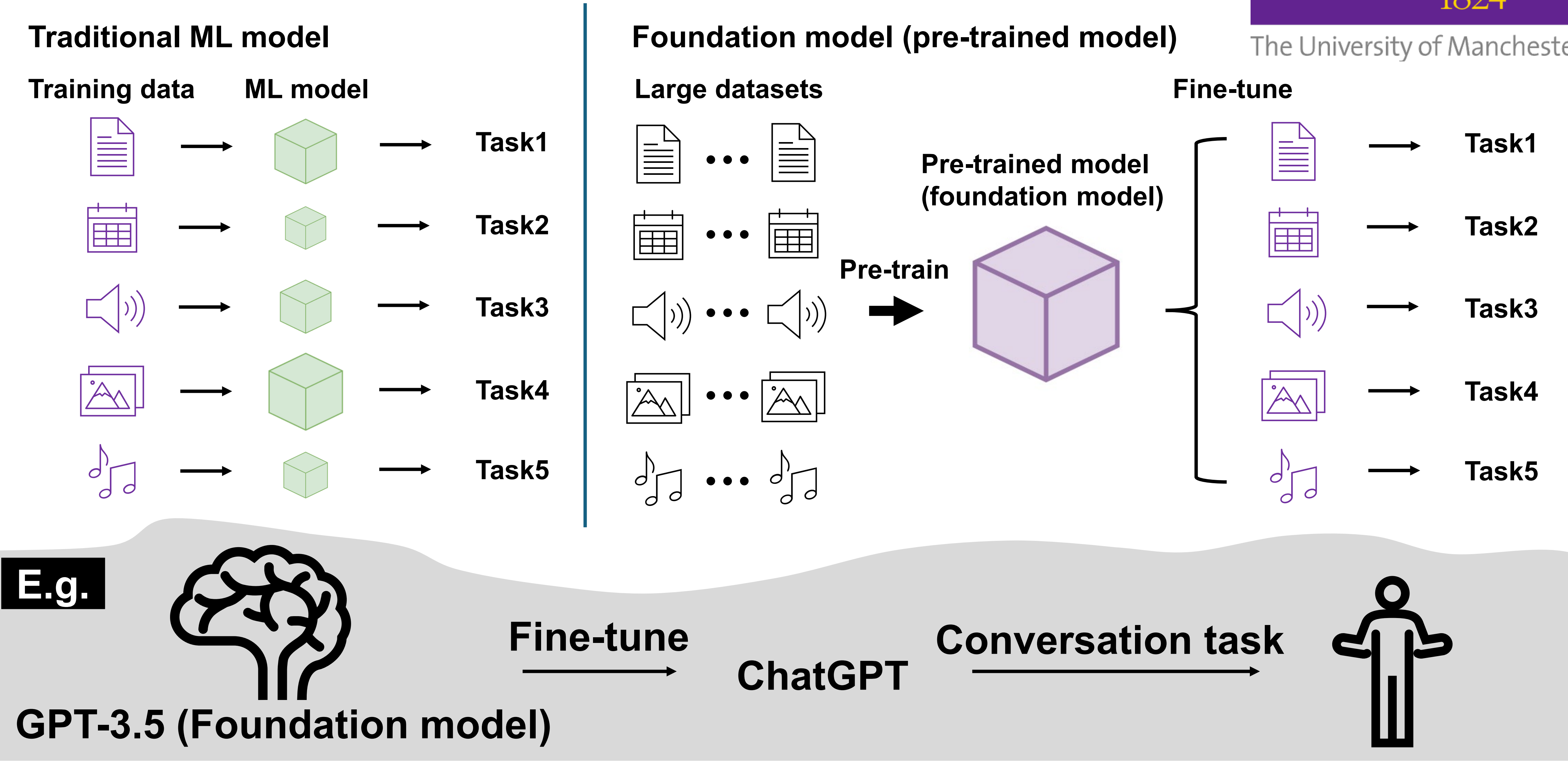
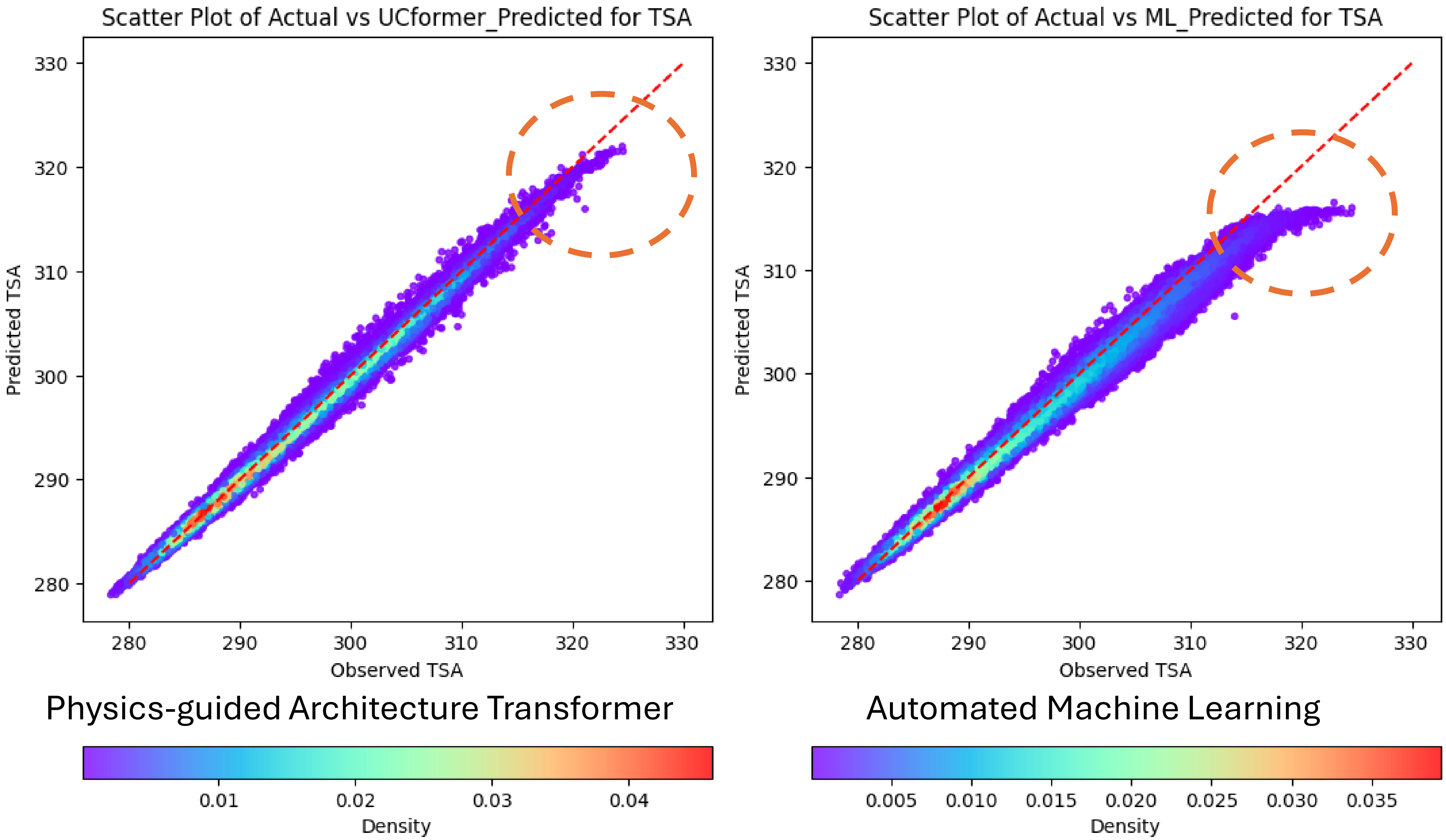
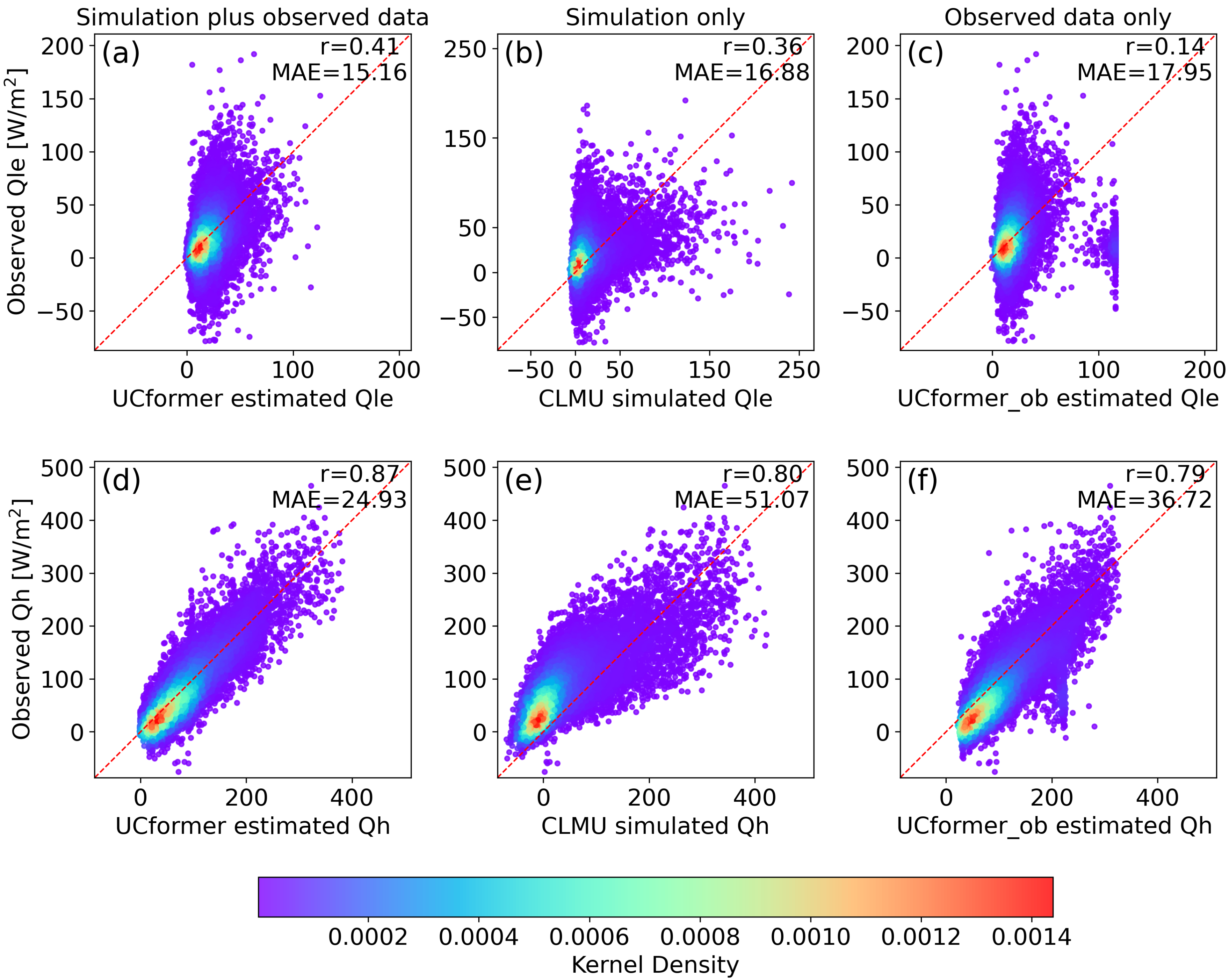
Fine-tuning Approach



Physics-guided Architecture Transformer is more robust for extreme temperature estimation

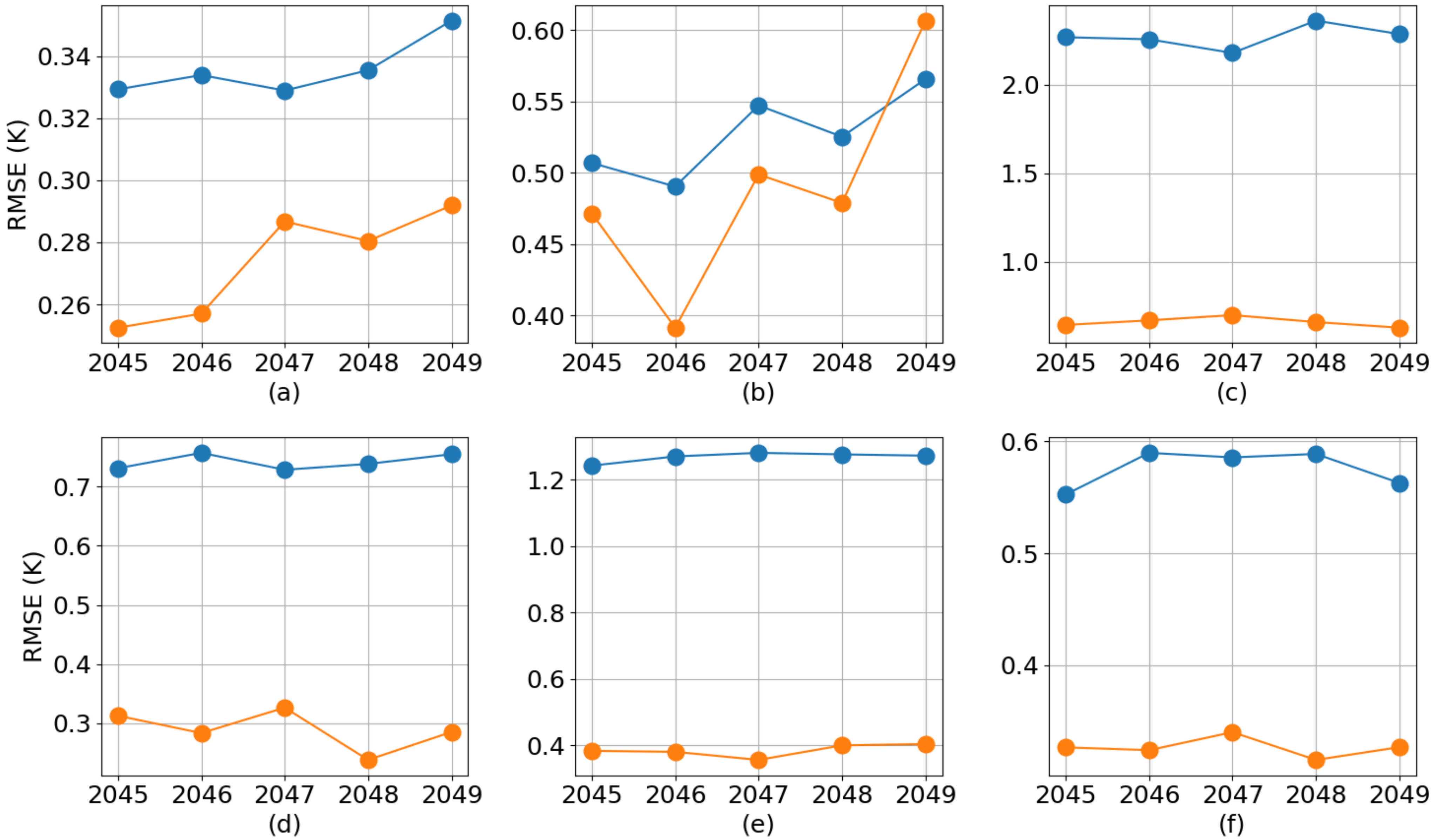
Testing (2070-2074)





Simulation plus observed data
Simulation only
Observed data only
(a) r=0.41 MAE=15.16
(b) r=0.36 MAE=16.88
(c) r=0.14 MAE=17.95
Observed Qle [W/m2]
UCformer estimated Qle
CLMU simulated Qle
UCformer_ob estimated Qle
(d) r=0.87 MAE=24.93
(e) r=0.80 MAE=51.07
(f) r=0.79 MAE=36.72
Observed Qh [W/m2]
UCformer estimated Qh
CLMU simulated Qh
UCformer_ob estimated Qh
0.0002 0.0004 0.0006 0.0008 0.0010 0.0012 0.0014
Kernel Density

Time interdependency



Time interdependency