Deep Learning and Flux Predictions: A New Frontier for USCCC

Jiquan Chen

Landscape Ecology & Ecosystem Science
Michigan State University
Email: jqchen@msu.edu

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Eddy Covariance (EC) Technology for direct measurement of net exchange of trace gases, momentum, energy, and other materials at **ecosystem level**

- ~2000 EC towers since the first one at the Harvard Forest in 1989
- Lots of experience, tools, maintenance protocols, data process, etc.
- Beyond CO_2: CH_4, N_2O, CO, NOx, aerosols, Albedo, etc.
- Goodwill for data sharing => global synthesis and knowledge development
- Communication and coordinated efforts (e.g., FLUXNET, AmeriFlux, USCCC, etc.)
- Many more

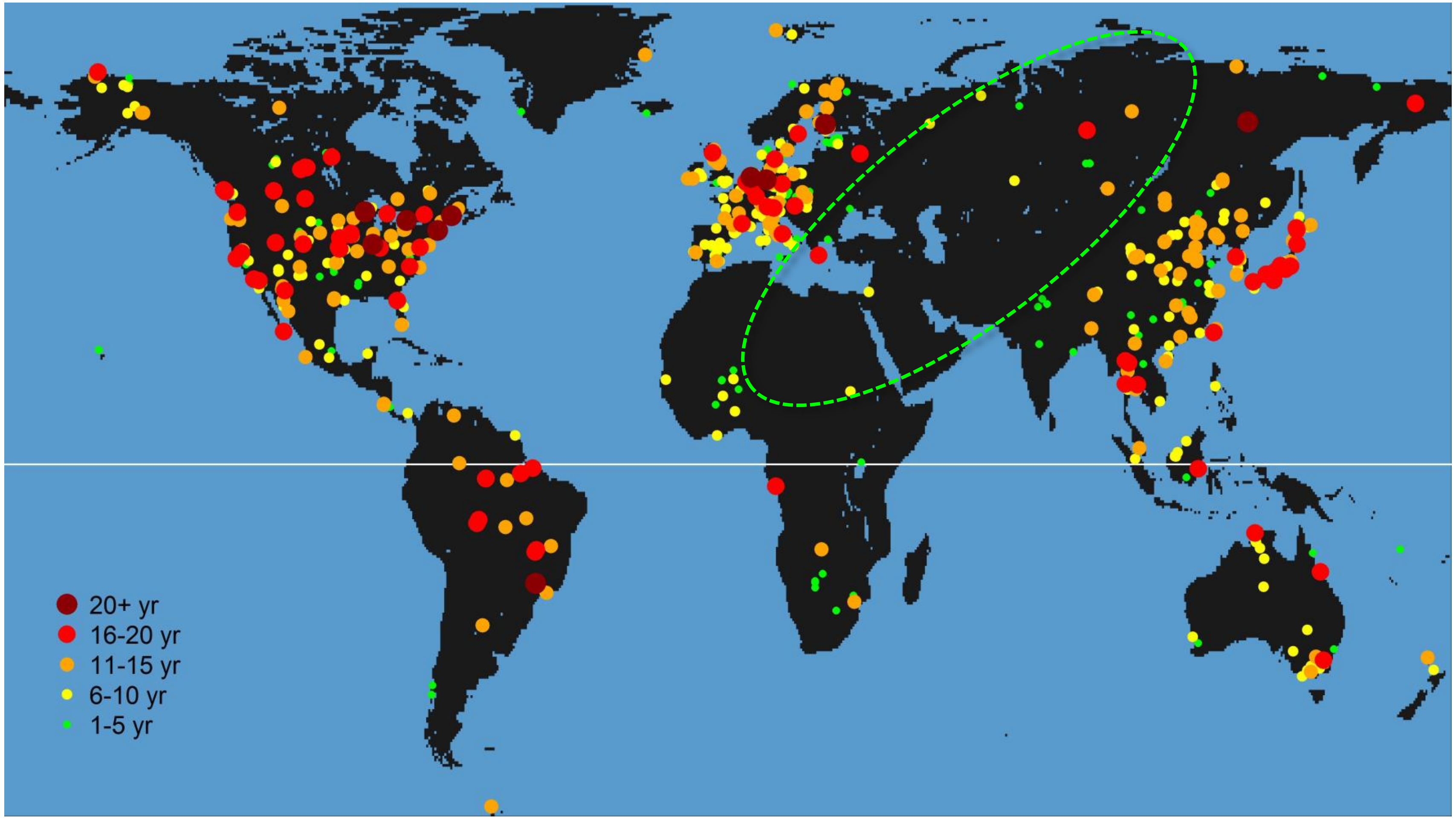
Among the Challenges are

1) 2000^{+} EC towers are not enough to cover all ecosystems, with their distributions seriously skewed
2) Most tower sites are not large enough
3) Our understanding of the regulation mechanisms on C fluxes is based on a few biophysical models, often empirical, such as Q10, Michaellis-Menten, Farquar, Penmen-Monteith, etc.
4) There lack reliable models for CH_4 and N_2O fluxes

Among the Challenges are

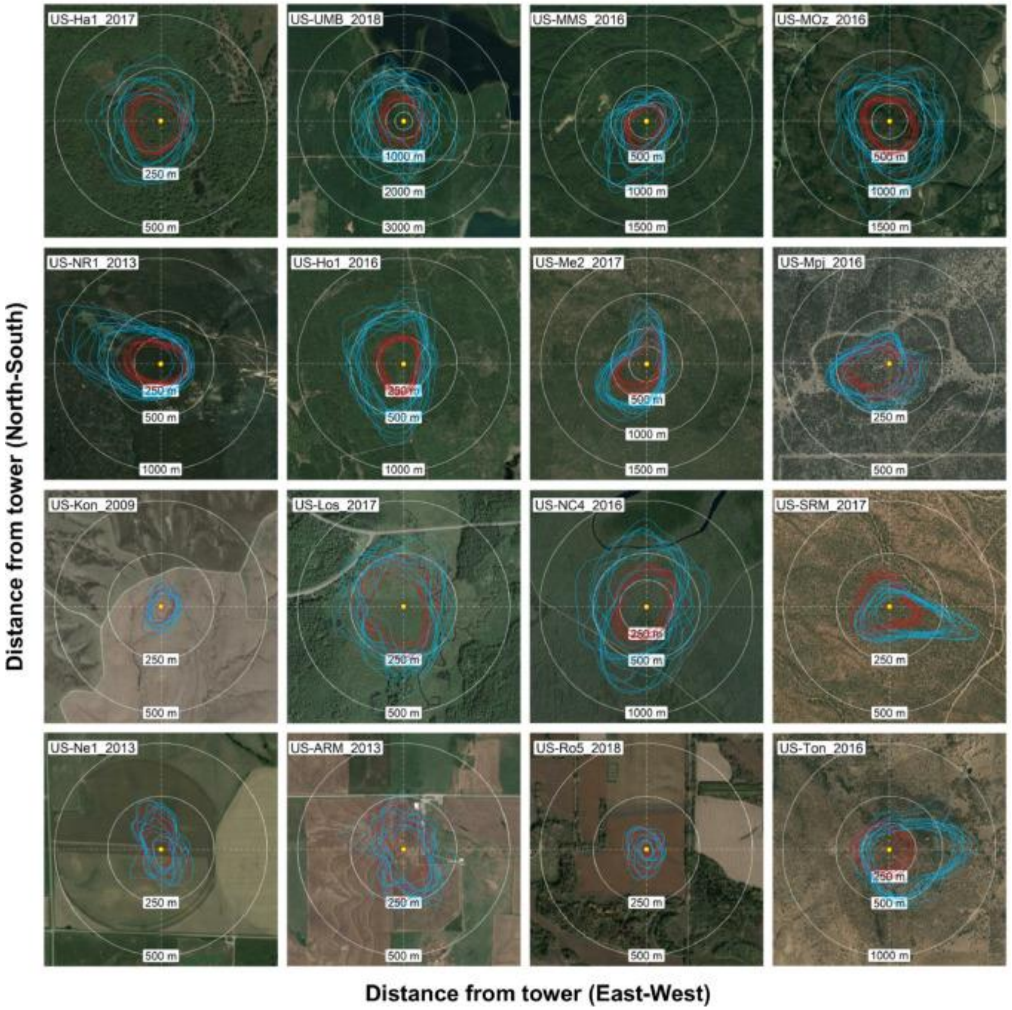
https://fluxnet.org/sites/site-summary/

- 2000^+ EC towers are not enough to cover all ecosystems, with their distributions seriously skewed



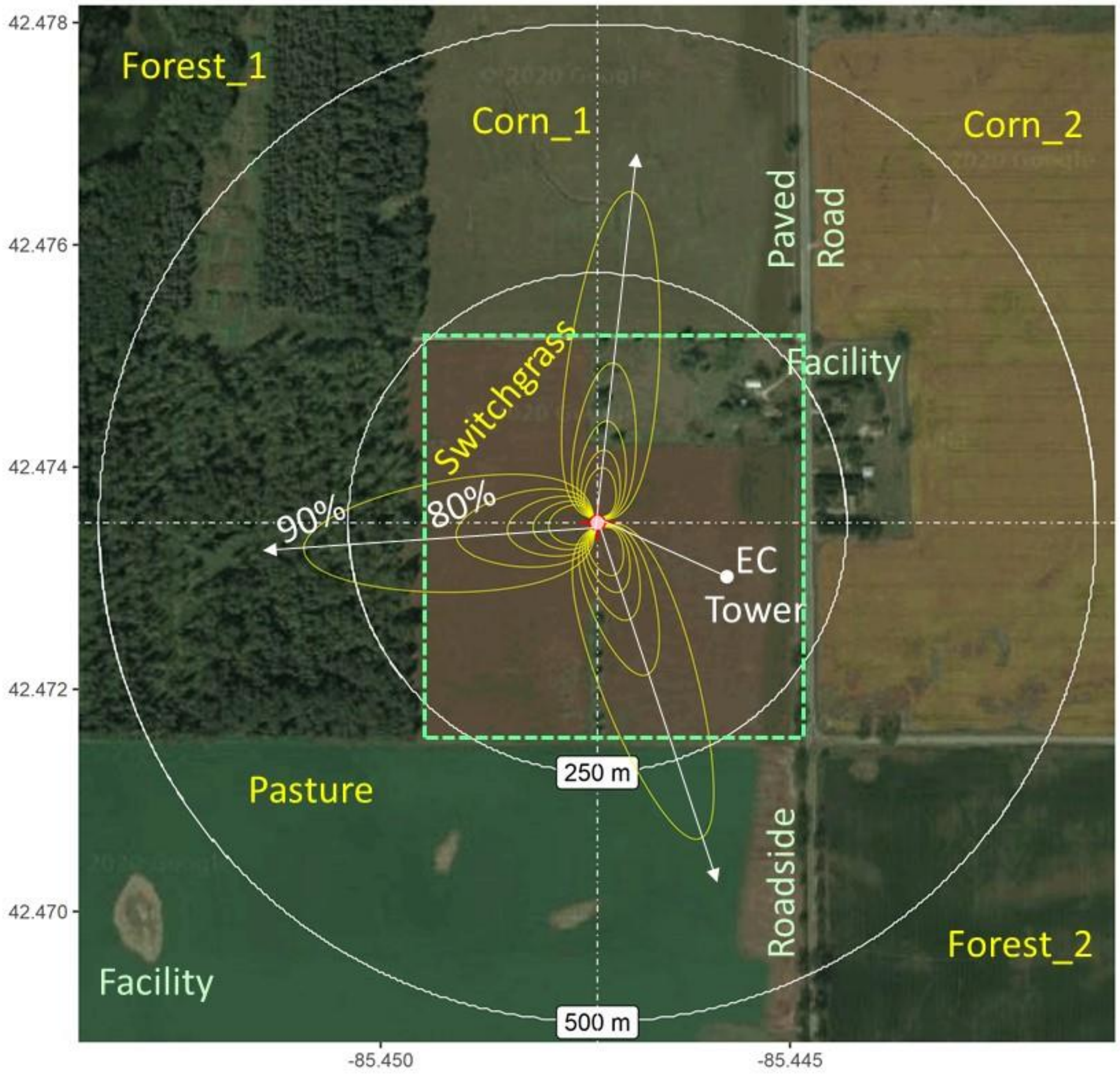
Among the Challenges are

- Most sites are not large enough



Chu et al. 2021. Ag. For. Met.

A switchgrass cropland at the Kellogg Biological Station



Among the Challenges are

- Our understanding of the regulation mechanisms on C fluxes is based on a few biophysical models, often empirically tried, such as Q10, Michaellis-Menten, Farquar, Penmen-Monteith, etc.

$$P_n = \frac{\alpha \cdot PAR \cdot P_m}{\alpha \cdot PAR + P_m} - R_d$$

3 parameters

These are based on PAR & Ta, with many other potential drivers not used!

$$P_n = \frac{2\cdot\alpha\cdot PAR/Pm}{1+\alpha\cdot\frac{PAR}{Pm} + \sqrt{(1+\alpha\cdot\frac{PAR}{Pm})^2-4\cdot\alpha PAR/pm}}$$

4 parameters

Yet, we have dozens of other variables collected at an EC tower, but not used

AGR-C-FC - Excel

F5 | -0.753518547938533

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
1	CO2	H2O	FC	LE	H	USTAR	WD	WS	ZL	U_SIGMA	V_SIGMA	W_SIGMA	PA	T_SONIC	SW_IN	TA	RH	VPD	SWC	TS_1_1_1	TS_1_2_1	TS_1_3_1	G_1_1_1	G_2_1_
2	-1.33163	-1.08039	0.20826	-0.65045	-0.3864	-0.71644	1.01033	0.13426	0.02564	-0.55868	-0.45544	-0.53	0.06022	-1.51739	-0.49113	-1.15501	0.69957	-1.51E-12	-1.65883	-1.15294	-1.20357	-1.20294	#######	5.53E-1
3	-1.31099	-1.08093	0.21274	-0.64188	-0.39044	-0.64415	0.89945	0.14395	0.02393	-0.38259	-0.44898	-0.4245	0.06743	-1.5163	-0.49113	-1.15792	0.82335	-1.51E-12	-1.65908	-1.15338	-1.2036	-1.20384	#######	5.53E-1
4	-1.31823	-1.07857	0.19566	-0.69279	-0.38757	-0.59779	0.91271	0.13965	0.02192	-0.06104	-0.25988	-0.30364	0.0835	-1.5123	-0.49113	-1.15789	0.88849	-1.51E-12	-1.65921	-1.15386	-1.20366	-1.20485	#######	5.53E-1
5	-1.32445	-1.07636	0.2114	-0.66502	-0.39211	-0.75352	0.87764	-0.04149	0.02913	-0.48234	-0.49185	-0.44475	0.08776	-1.51423	-0.49113	-1.15474	0.91455	-1.51E-12	-1.65955	-1.15429	-1.20372	-1.20583	#######	5.53E-1
6	-1.27446	-1.10439	0.20259	-0.65006	-0.36522	-0.81379	0.94443	-0.18645	0.02274	-0.67411	-0.56458	-0.58614	0.11651	-1.50978	-0.49113	-1.15613	0.96016	-1.51E-12	-1.65992	-1.15472	-1.2038	-1.20676	#######	5.53E-1
7	-1.27609	-1.08608	0.24342	-0.67469	-0.3704	-0.65298	0.82224	-0.12988	0.01969	-0.46047	-0.65562	-0.61652	0.13264	-1.50491	-0.49113	-1.15424	1.05788	-1.51E-12	-1.66028	-1.1551	-1.20388	-1.2076	#######	5.53E-1
8	-1.28577	-1.07156	0.21735	-0.65968	-0.36709	-0.77267	0.87341	-0.21379	0.02199	-0.56477	-0.63283	-0.57762	0.165	-1.48634	-0.49113	-1.15047	1.08394	-1.51E-12	-1.66016	-1.15543	-1.20397	-1.20843	#######	5.53E-1
9	-1.28181	-1.06418	0.25623	-0.659	-0.35861	-0.69098	0.85382	-0.18887	0.01756	-0.59138	-0.66928	-0.76986	0.16329	-1.47289	-0.49113	-1.13273	1.12954	-1.51E-12	-1.66027	-1.15571	-1.20406	-1.20918	#######	5.53E-1
10	-1.26209	-1.05564	0.23526	-0.67033	-0.38786	-0.73949	0.90857	-0.06476	0.02713	-0.32829	-0.63789	-0.70622	0.16278	-1.45627	-0.49113	-1.11646	1.12303	-1.51E-12	-1.65999	-1.15592	-1.20414	-1.20983	#######	5.53E-1
11	-1.17878	-1.07217	0.31781	-0.70222	-0.36054	-0.75823	1.11139	0.31262	0.01938	-0.4805	-0.26807	-0.53684	0.1772	-1.43119	-0.49113	-1.09998	1.11651	-1.51E-12	-1.65981	-1.15609	-1.20423	-1.21034	#######	5.53E-1
12	-1.23975	-1.05215	0.21834	-0.65902	-0.42384	-0.62297	1.19547	0.41911	0.03011	-0.5623	-0.53115	-0.56948	0.19072	-1.41414	-0.49113	-1.0777	1.12303	-1.51E-12	-1.65979	-1.15629	-1.20436	-1.21082	#######	5.53E-1
13	-1.27862	-1.0419	0.21982	-0.67107	-0.45694	-0.72255	1.27272	0.15033	0.0455	-0.81087	-0.58894	-0.77831	0.20237	-1.41311	-0.49113	-1.05952	1.06439	-1.51E-12	-1.66048	-1.15642	-1.20447	-1.21123	#######	5.53E-1
14	-1.28725	-1.04351	0.20295	-0.66739	-0.44479	-0.80909	1.26473	0.10227	0.05171	-0.92246	-0.59163	-0.85413	0.23618	-1.41715	-0.49113	-1.05676	1.00576	-1.51E-12	-1.66107	-1.15655	-1.20458	-1.21159	#######	5.53E-1
15	-1.28508	-1.04378	0.22771	-0.65918	-0.44638	-0.73147	1.26653	0.23771	0.04334	-0.71002	-0.65186	-0.72204	0.26977	-1.41735	-0.49113	-1.06016	0.94713	-1.51E-12	-1.66131	-1.15675	-1.20466	-1.21191	#######	5.53E-1
16	-1.27218	-1.05027	0.16516	-0.64335	-0.41652	-0.48184	1.31002	0.37729	0.02348	-0.5401	-0.30199	-0.63455	0.29389	-1.40745	-0.49113	-1.06045	0.90152	-1.51E-12	-1.66206	-1.15694	-1.20475	-1.21228	#######	5.53E-1
17	-1.31637	-1.0421	0.2256	-0.66848	-0.48327	-0.30275	1.37553	0.30931	0.02601	-0.48656	0.11689	-0.38497	0.30109	-1.40863	-0.49113	-1.04987	0.95364	-1.51E-12	-1.6621	-1.15711	-1.20486	-1.21264	#######	5.53E-1
18	-1.33857	-1.04641	0.17993	-0.66207	-0.48748	-0.19239	1.37229	0.35325	0.02346	-0.45403	-0.00321	-0.41794	0.32639	-1.41097	-0.47562	-1.05005	0.82335	-1.51E-12	-1.66207	-1.15729	-1.20495	-1.2129	#######	5.53E-1
19	-1.34727	-1.0468	0.17327	-0.65797	-0.43722	-0.15511	1.38836	0.28219	0.01909	-0.54159	0.08863	-0.42697	0.35104	-1.41337	-0.39411	-1.05155	0.6279	-1.51E-12	-1.66229	-1.15744	-1.20503	-1.2132	#######	5.53E-1
20	-1.35412	-1.05012	0.15515	-0.64495	-0.42323	-0.18622	1.39377	0.41873	0.01846	-0.19716	0.27733	-0.20373	0.39025	-1.41066	-0.19692	-1.04494	0.52367	-1.51E-12	-1.66182	-1.15749	-1.20511	-1.21324	#######	5.53E-1
21	-1.36204	-1.05128	0.24916	-0.61292	-0.39604	0.06939	1.38584	0.46948	0.01473	0.00847	0.19154	-0.20621	0.41984	-1.40214	-0.09917	-1.03303	0.46503	-1.51E-12	-1.66128	-1.15744	-1.20516	-1.21313	#######	5.53E-1
22	-1.36195	-1.05314	0.23441	-0.6272	-0.3207	-0.14396	1.46961	0.02468	0.01079	-0.24341	0.34729	-0.21697	0.46194	-1.38789	0.03712	-1.01694	0.31519	-1.51E-12	-1.66036	-1.1572	-1.2052	-1.21271	#######	5.53E-1
23	-1.35814	-1.06204	0.20793	-0.56398	-0.31871	0.2657	1.52937	0.48406	0.0113	0.46439	0.92893	0.20107	0.4869	-1.37552	0.37781	-0.98144	0.12627	-1.51E-12	-1.65941	-1.15673	-1.20519	-1.21181	#######	5.53E-1
24	-1.34225	-1.06619	0.15699	-0.55845	-0.27413	-0.29881	1.60125	0.2855	0.0059	0.27927	0.44585	0.50036	0.47142	-1.36744	0.63316	-0.95876	-0.09524	-1.51E-12	-1.65886	-1.15609	-1.20514	-1.21062	#######	5.53E-1
25	-1.32857	-1.06819	0.17355	-0.54997	-0.29903	-0.03121	1.49601	0.45565	0.00978	0.31139	0.97223	0.22582	0.46352	-1.36657	0.5235	-0.9347	-0.1669	-1.51E-12	-1.65895	-1.15539	-1.20495	-1.20937	#######	5.53E-1
26	-1.34652	-1.08868	0.03577	-0.59923	-0.46241	-0.94188	-2.21564	-0.09443	0.08642	0.1246	0.37294	0.40987	0.44319	-1.3805	1.31642	-0.92233	-0.48612	-1.51E-12	-1.65831	-1.15463	-1.20492	-1.20803	#######	5.53E-1
27	-1.37105	-1.10663	0.00824	-0.56096	-0.44678	0.36578	1.47152	0.39606	0.01521	0.01566	0.84687	0.2423	0.40708	-1.38217	0.9495	-0.90059	-0.66202	-1.51E-12	-1.65844	-1.15394	-1.20487	-1.20684	#######	5.53E-1
28	-1.35299	-1.11808	0.06543	-0.57017	-0.39693	-0.09566	1.654	0.17115	0.01577	0.21209	0.6099	0.42011	0.38112	-1.37521	1.66561	-0.86454	-0.90958	-1.51E-12	-1.65859	-1.15309	-1.20479	-1.20561	#######	5.53E-1
29	-1.35201	-1.12382	0.08855	-0.61062	-0.53396	-0.61455	1.63344	-0.03029	0.05224	0.13983	0.57094	0.17522	0.36045	-1.3606	1.33536	-0.86691	-1.11154	-1.51E-12	-1.65881	-1.15235	-1.20466	-1.20443	#######	5.53E-1
30	-1.34951	-1.1335	0.08594	-0.5607	-0.4916	-0.23099	1.52991	0.26576	0.02475	0.15061	0.83253	0.17194	0.36158	-1.34984	0.84756	-0.81974	-1.24184	-1.51E-12	-1.65895	-1.15173	-1.20455	-1.20354	#######	5.53E-1
31	-1.36669	-1.143	0.11758	-0.4494	-0.49695	0.7041	1.45944	1.2324	0.01491	0.76157	1.67316	0.60429	0.39043	-1.3646	0.82323	-0.87892	-1.20926	-1.51E-12	-1.65978	-1.15117	-1.20427	-1.20266	#######	5.53E-1
32	-1.36998	-1.14371	0.22882	-0.48948	-0.54118	0.79775	1.42781	1.27964	0.01532	0.69606	1.16249	0.44256	0.4094	-1.36999	0.46369	-0.90837	-1.09851	-1.51E-12	-1.66074	-1.15074	-1.20397	-1.20209	#######	5.53E-1
33	-1.39546	-1.22231	0.53891	-0.52415	0.33388	0.5442	1.46024	0.73799	-0.00378	0.29895	0.67454	0.20887	0.4362	-1.37612	0.03096	-0.94812	-1.04639	-1.51E-12	-1.66153	-1.15055	-1.20423	-1.20179	#######	5.53E-1
34	-1.38444	-1.15088	0.16286	-0.47496	-0.4803	0.29755	1.47776	0.6703	0.01663	0.08857	0.7855	0.27023	0.46301	-1.39106	-0.12386	-0.97878	-0.88352	-1.51E-12	-1.66226	-1.15047	-1.2041	-1.20146	#######	5.53E-1

AGR-C-FC

Among the Challenges are

- There lack reliable models for CH_4 and N_2O fluxes

Knox et al. 2019; Delwiche et al. 2021). The growth in available CH_4 data can help improve bottom-up estimates of regional-to-global wetland CH_4 sources (Treat et al. 2018; Peltola et al. 2019; Rosentreter et al. 2021) but this requires data processing standards that ensure eddy covariance CH_4 flux data products are of the same quality and provenance as carbon dioxide (CO_2) and energy fluxes (e.g., FLUXNET2015; Pastorello et al. 2020). Gap-filling is a particularly

Irvin et al. 2021. https://doi.org/10.1016/j.agrformet.2021.108528

Opportunities

1. Rich data

EC Towers	Biometric	RS
Ta, VDP, Soil, turbulence, …	LAI, height, species, density, …	EVI, cover, spatial Ms, DEM, …

All contribute to the magnitude and dynamics of fluxes

2. Evolving analytical tools

Mechanistic models	Computing Power	Machine Learning

Mechanistic and/or empirical explorations

Accurate predictions of fluxes and underline regulations

Machine Learning in flux studies?

Speech Recognition

Human **expertise** does not exist

Personalized Medicine

Models must be **customized**

Genomics

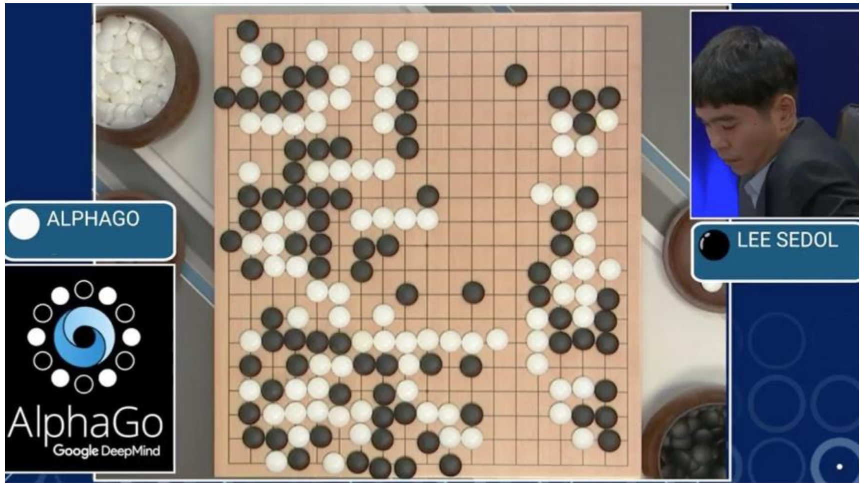
Huge amounts of data

Credit: Dr. Jiliang Tang

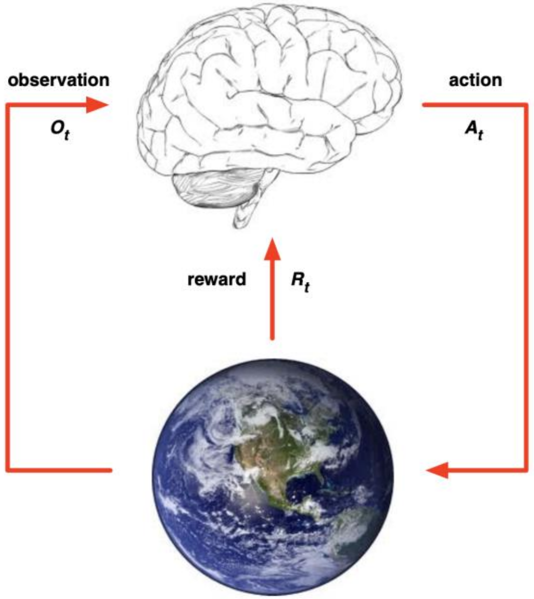
The fundamental concept of Machine Learning (ML) in flux studies

All bio-physical variables are responsible, at various degrees, for the magnitude and dynamics of fluxes, with known or unknown mechanisms.

Complex tasks

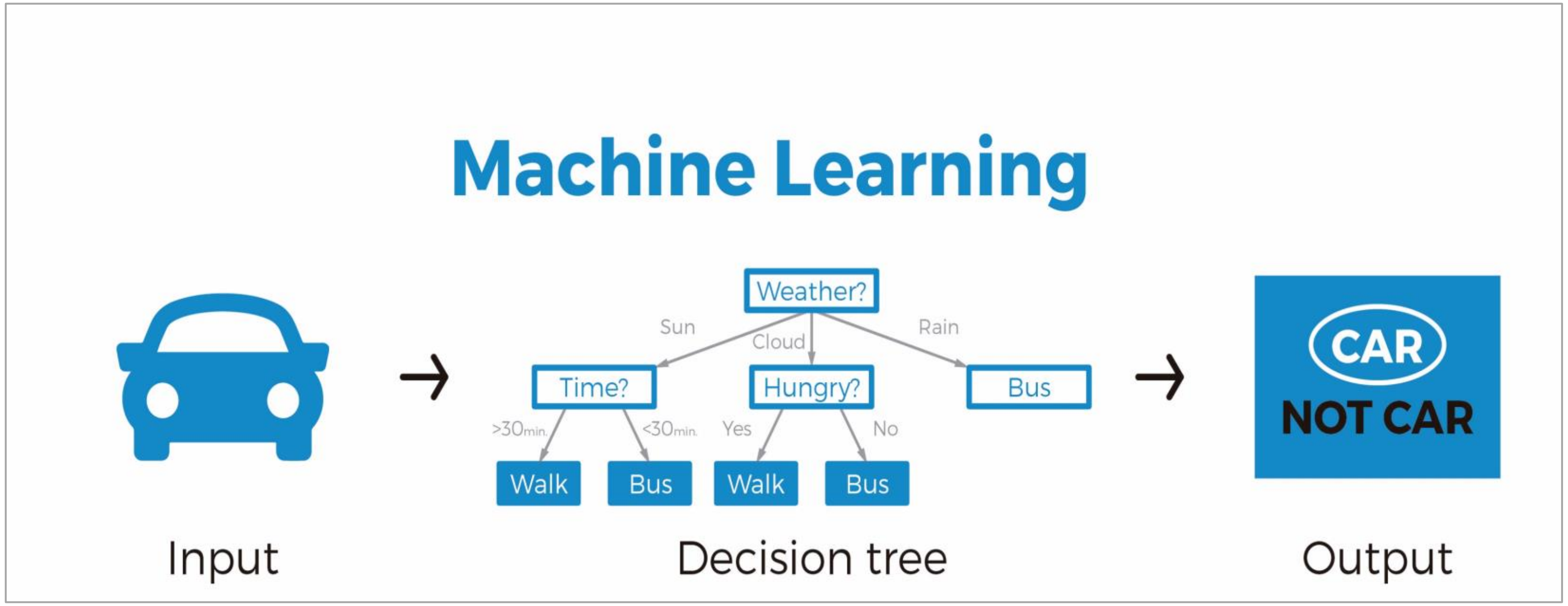


Continuously updated



Credit: Dr. Jiliang Tang

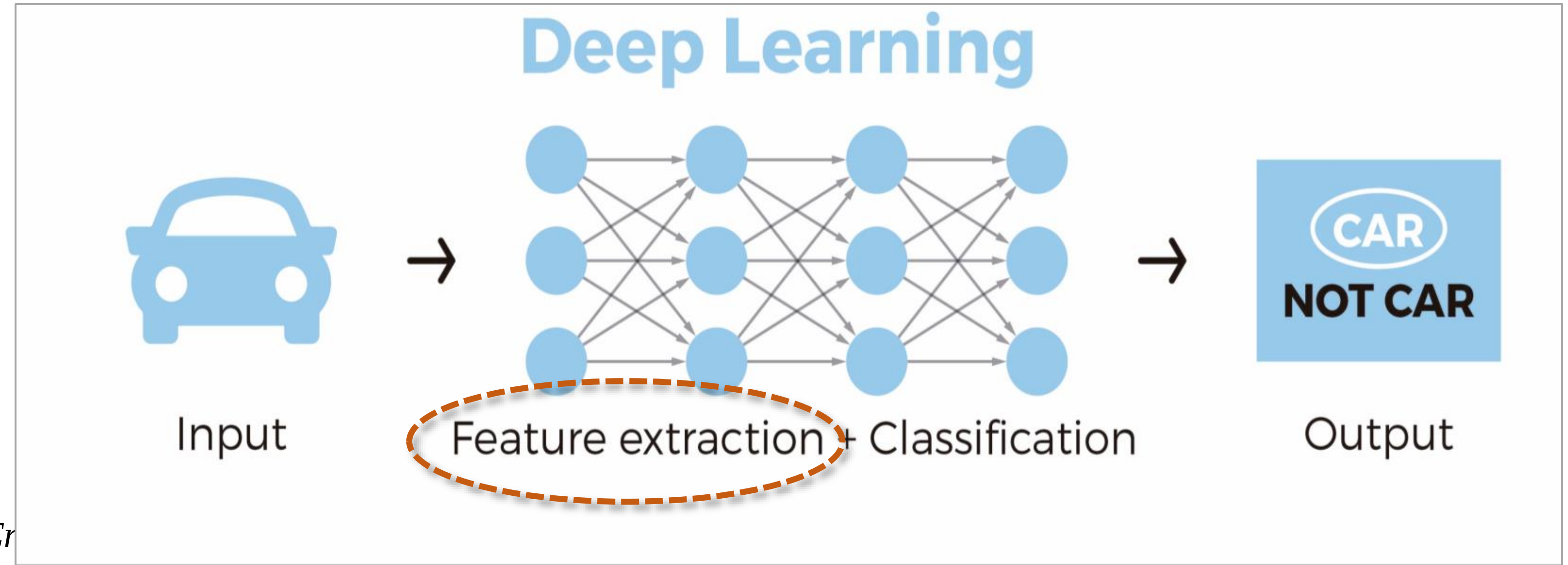
Deep Learning vs Traditional Machine Learning



Common Knowledge
In flux studies

Ta, VPD, Ms, PAR,
Rn, DOY, G, Ts, …

Fc



Partial knowns & unknowns
In flux studies

WD, WS, U*, CO_2,
RH, …

Fc

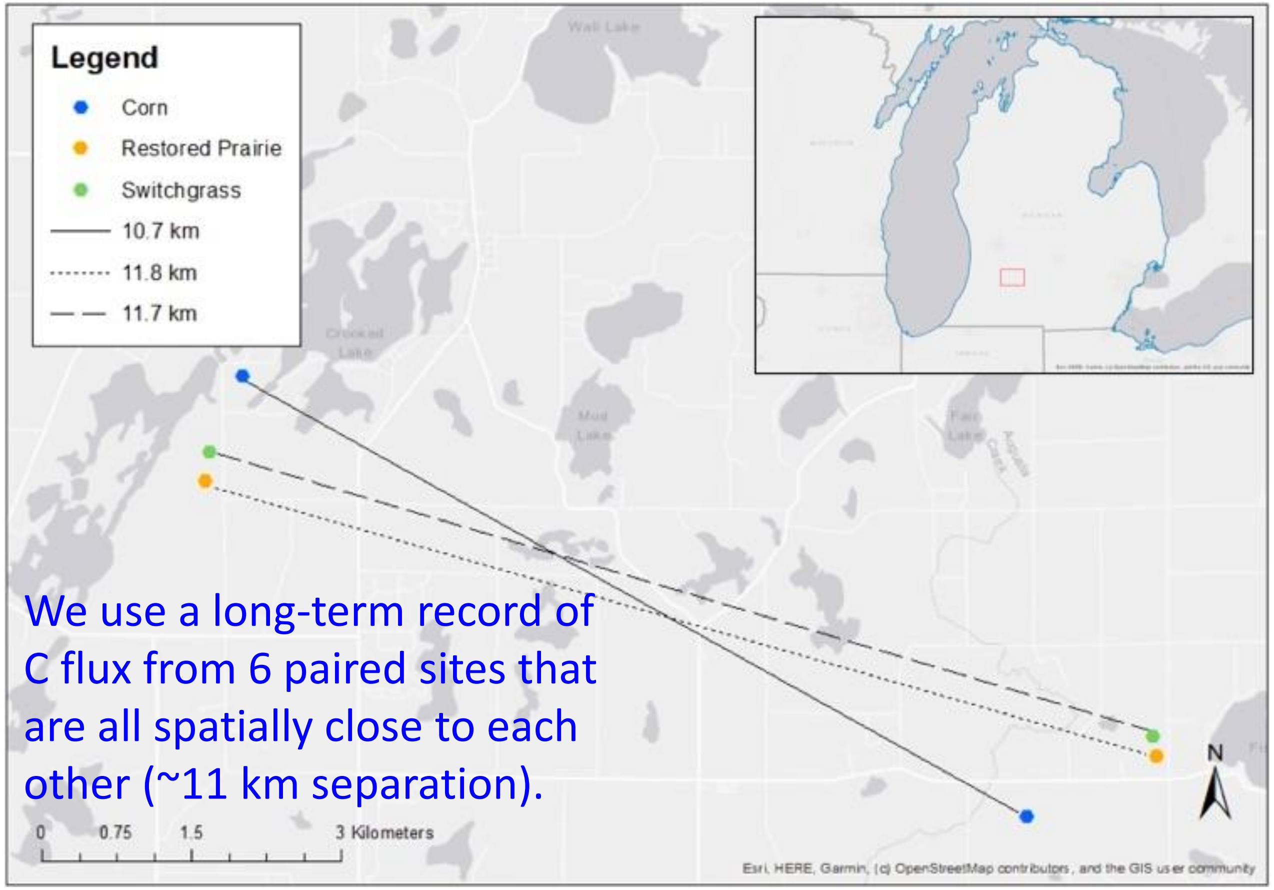
Cr

Reed, D.E., J. Poe, M. Abraha, K. M. Dahlin, and J. Chen. Modeled Surface-Atmosphere Fluxes from Paired Sites in the Upper Great Lakes Region Using Neural Networks. *Journal of Geophysical Research – Biogeosciences (accepted)*

Map of 3-paired EC sites; color coded by land-cover type, showing distance between paired EC sites at the Kellogg Biological Station, Michigan

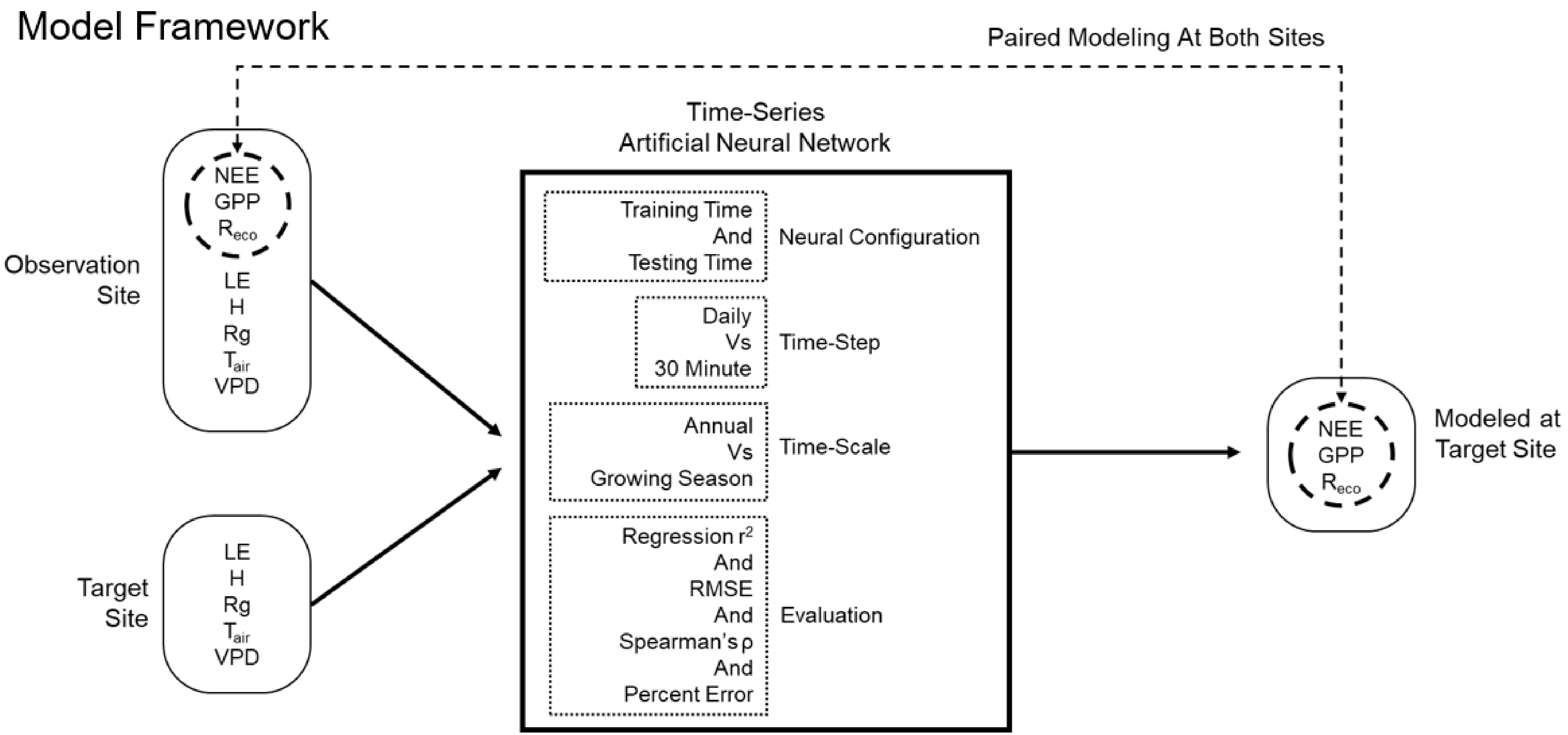
- Can we use the knowledge built from one EC site to predict others using a small set of *in situ* measurements (5 key ancillary variables)?

- Artificial Neural Network (ANN)



We use a long-term record of C flux from 6 paired sites that are all spatially close to each other (~11 km separation).

Conceptual framework of experimental design, showing model input data used from the observation and target sites that is used to model carbon fluxes at the target site.



Reed et al. accepted

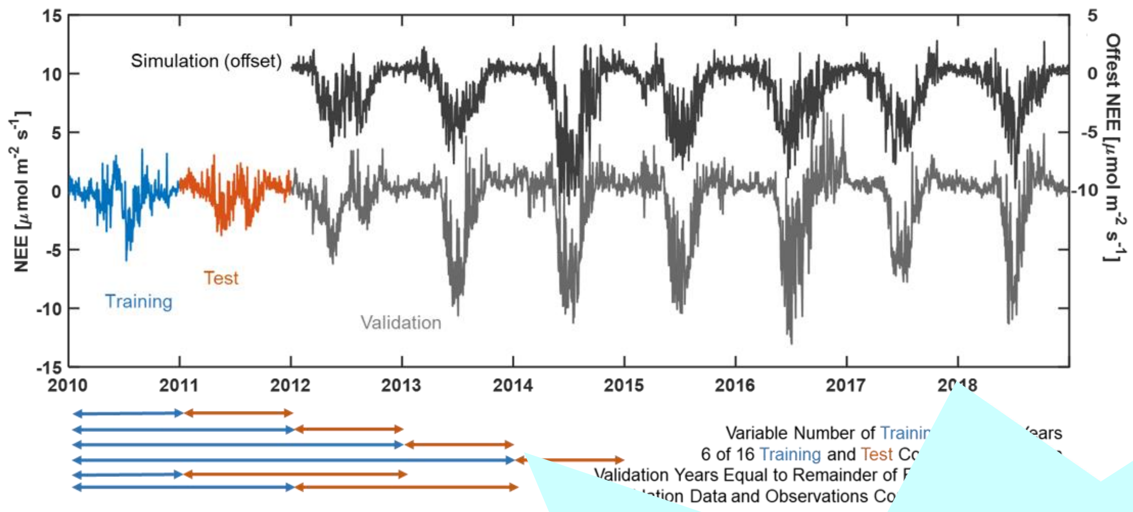
Major Lessons

1. C flux can be estimated with the same amount of uncertainty as the observations themselves, with uncertainties of 20%, 22%, and 8% for annual NEE, Reco, and GPP, respectively.

2. We also show that 32 ANN models can estimate sums of Reco and GPP fluxes without needing the constraint of similar land-cover-type, with annual uncertainties of 12% and 10%.

EC towers provide multiple time series data of dozens variables

Reed et al. accepted



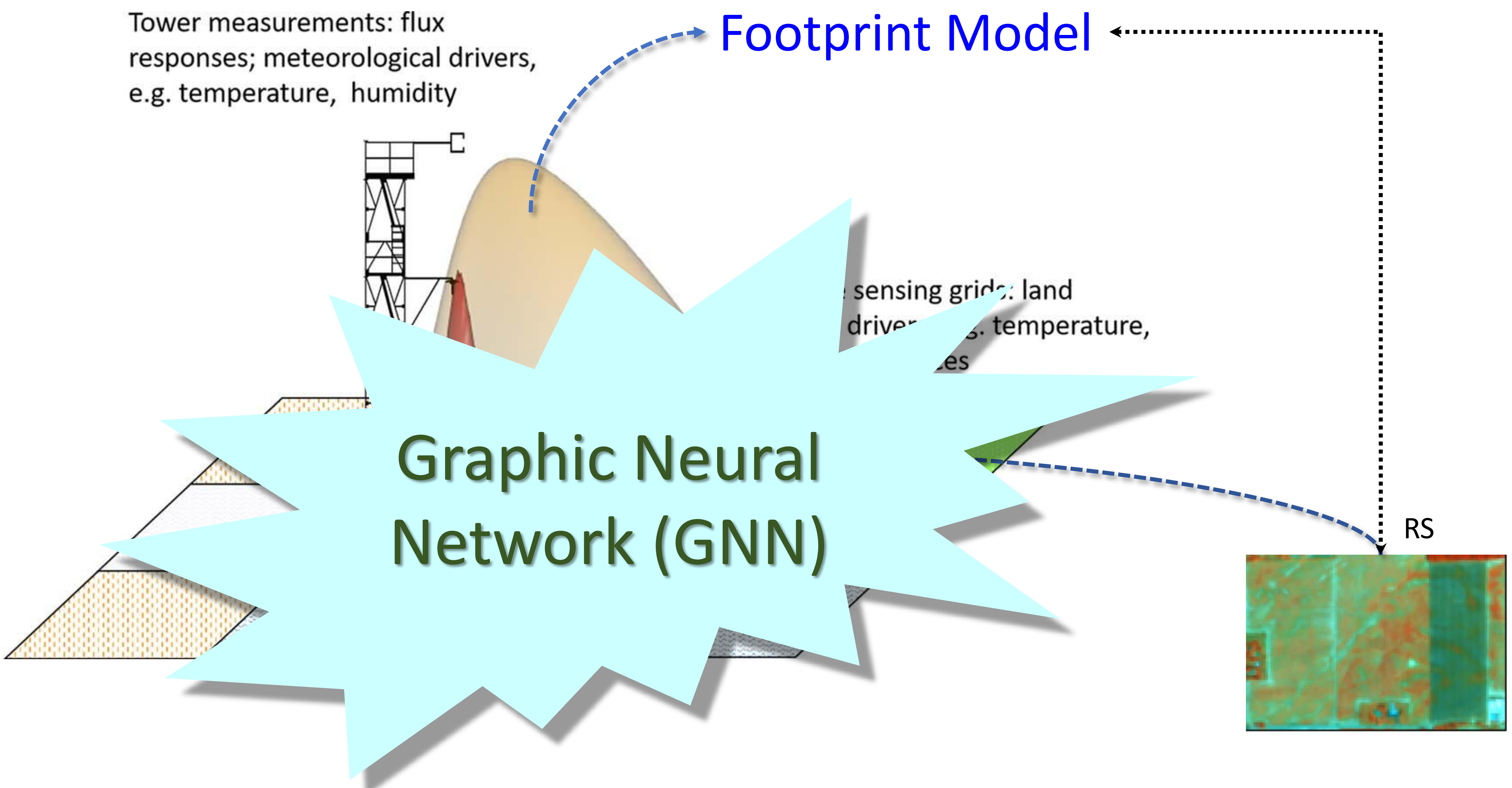
- Does the snow fall fro
  for current
- Would
  for present pr
- Are heatwaves in the ng
  growing season NEP?

Recurrent Neural Network (RNN)

Chile's Atacama desert: World's driest place in bloom after surprise rain -- BBC

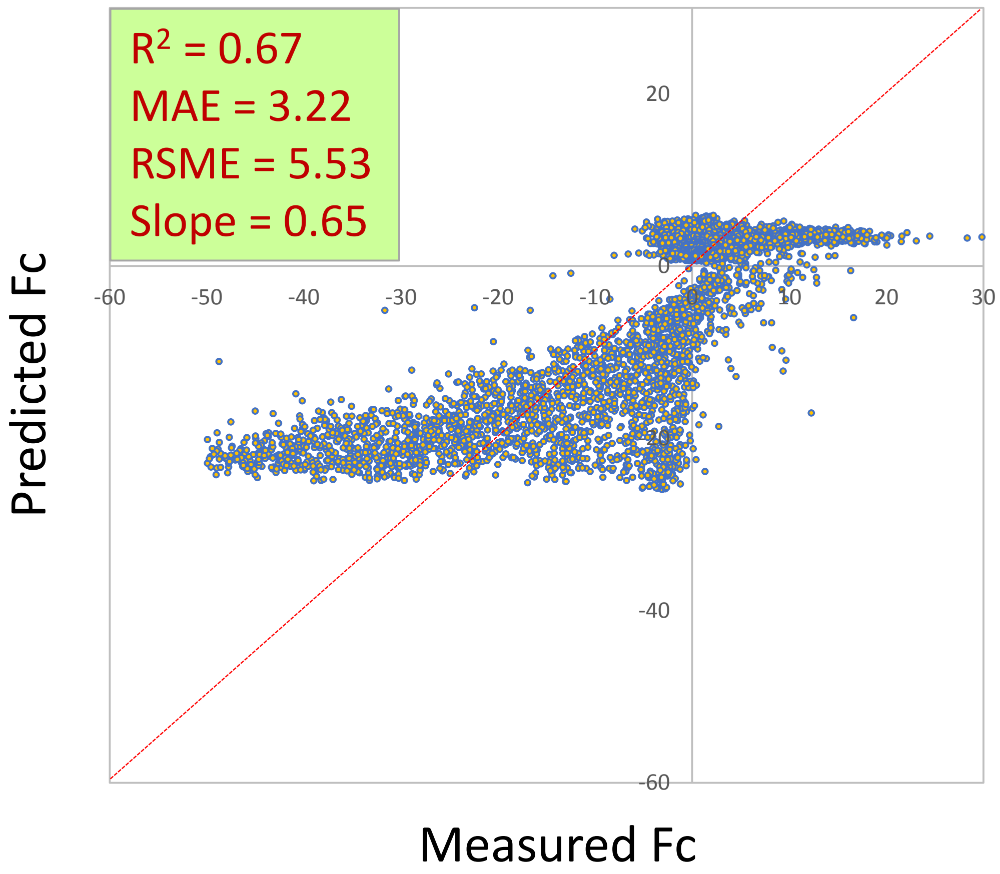
https://www.bbc.com/news/world-latin-america-41021774

Spatial information

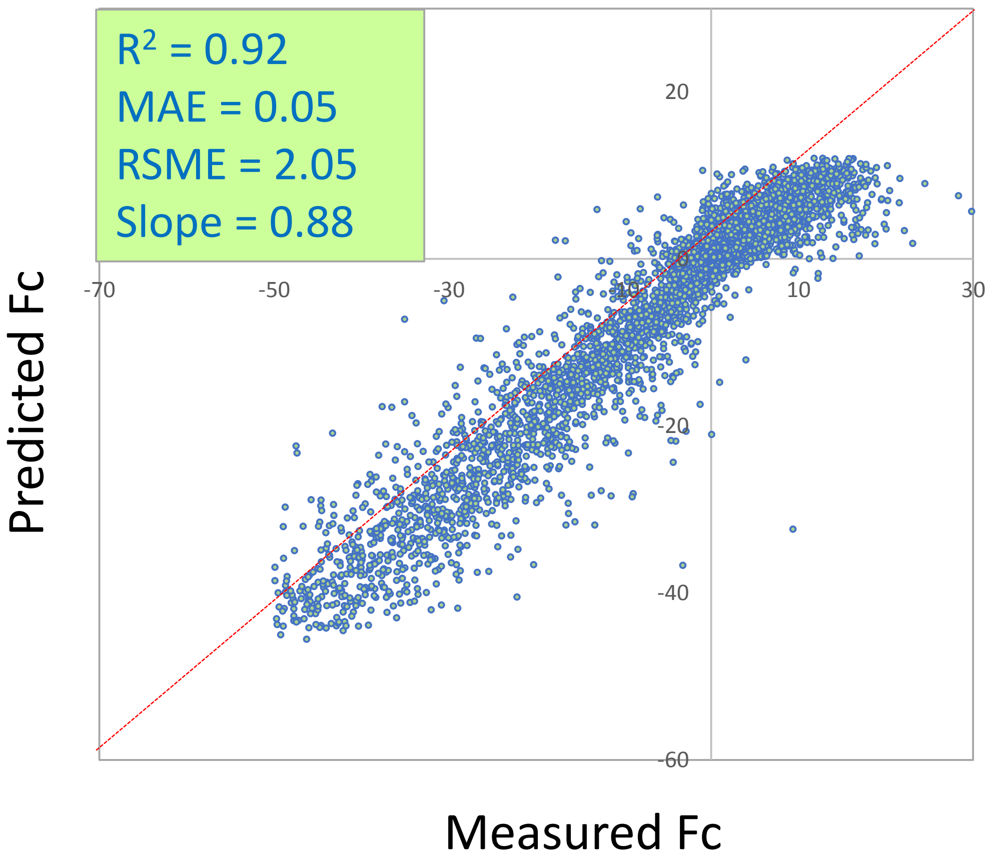


Predictions based on conventional "biophysical models" and recurrent neural network (RNN) at an agricultural land in KBS

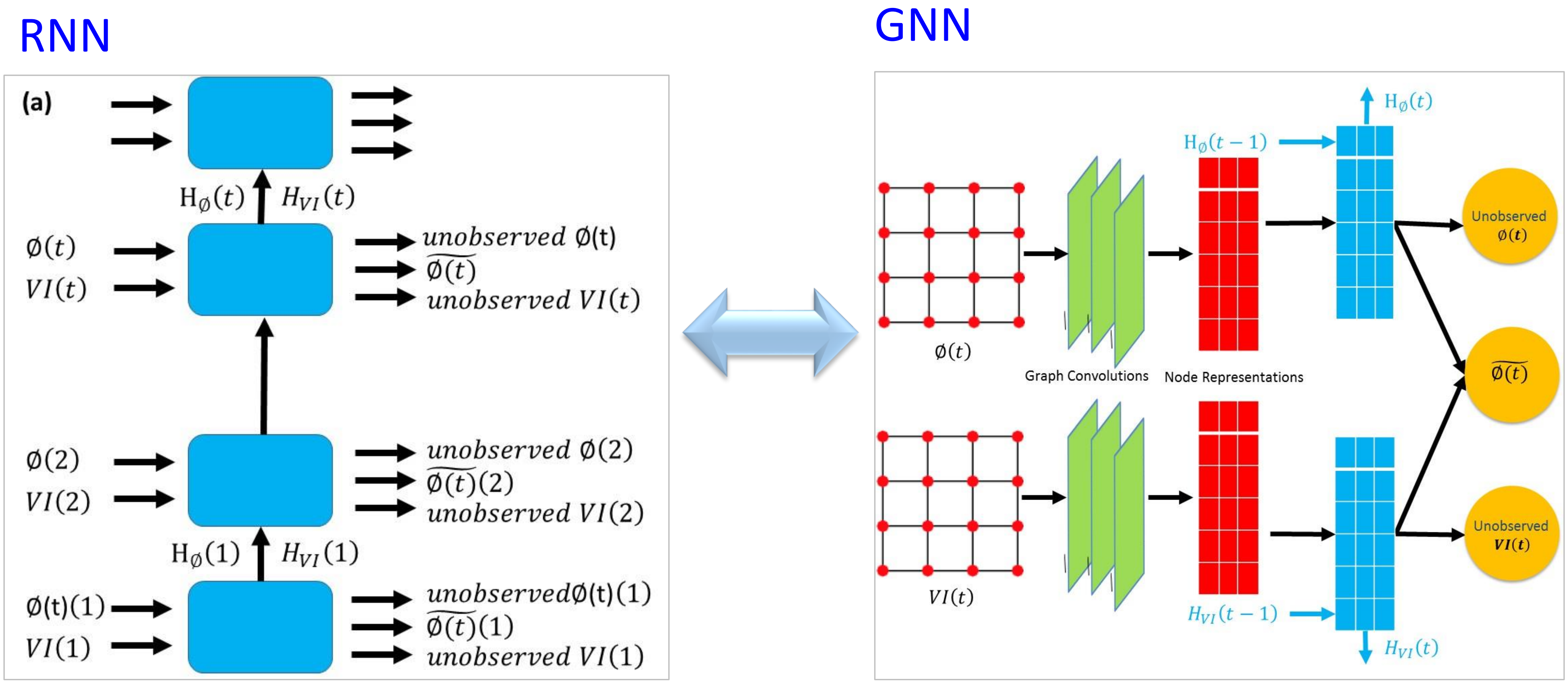
[MM + Q10] model



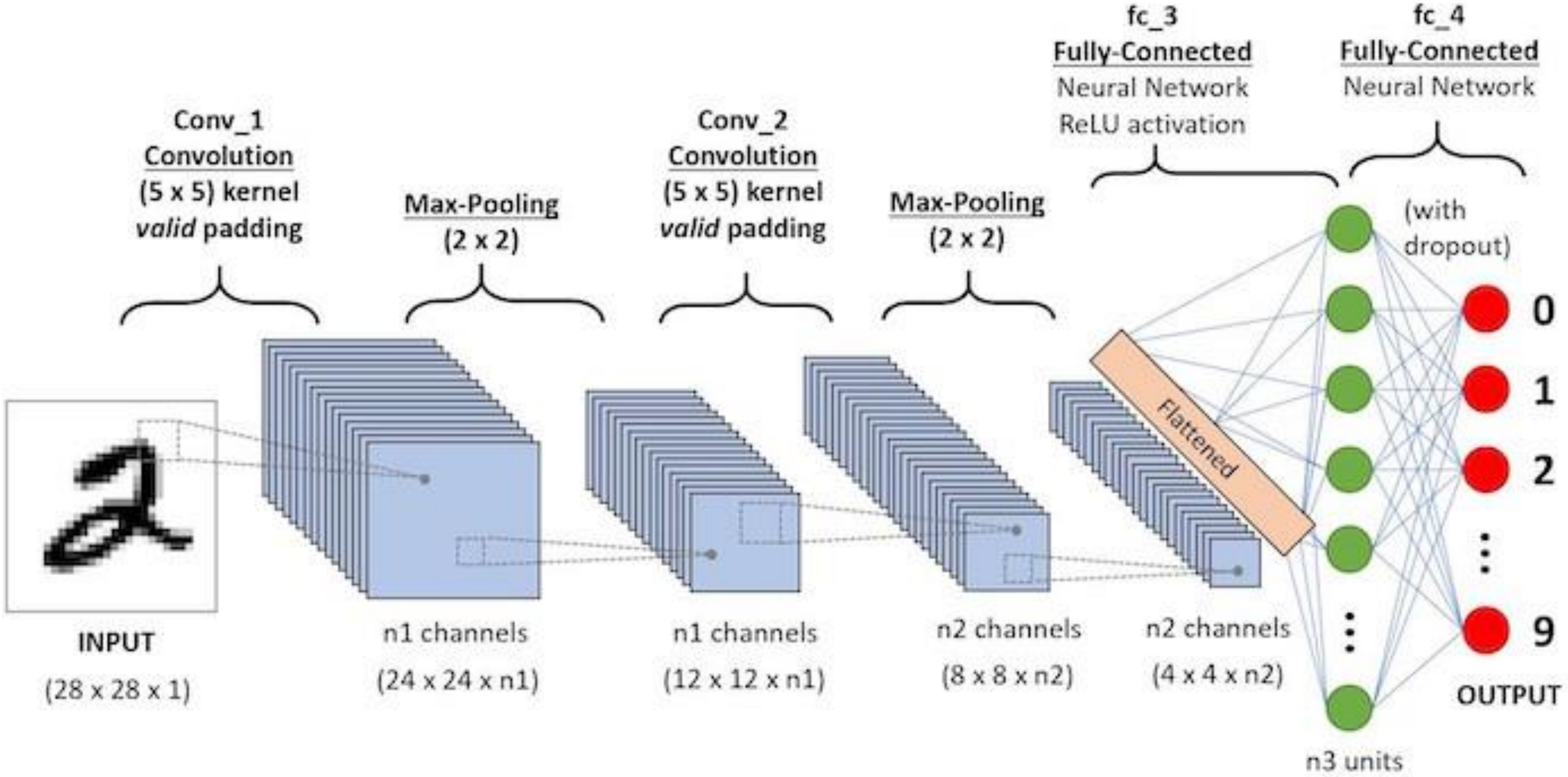
RNN model



Proposed architecture of GNN & RNN for estimating model parameters with partially known, or unknown mechanisms by assuming missing values of $\emptyset_{ij}(t)$ and VI(t) at any giving time (t) and space (i,j) (*i.e.*, nodes)

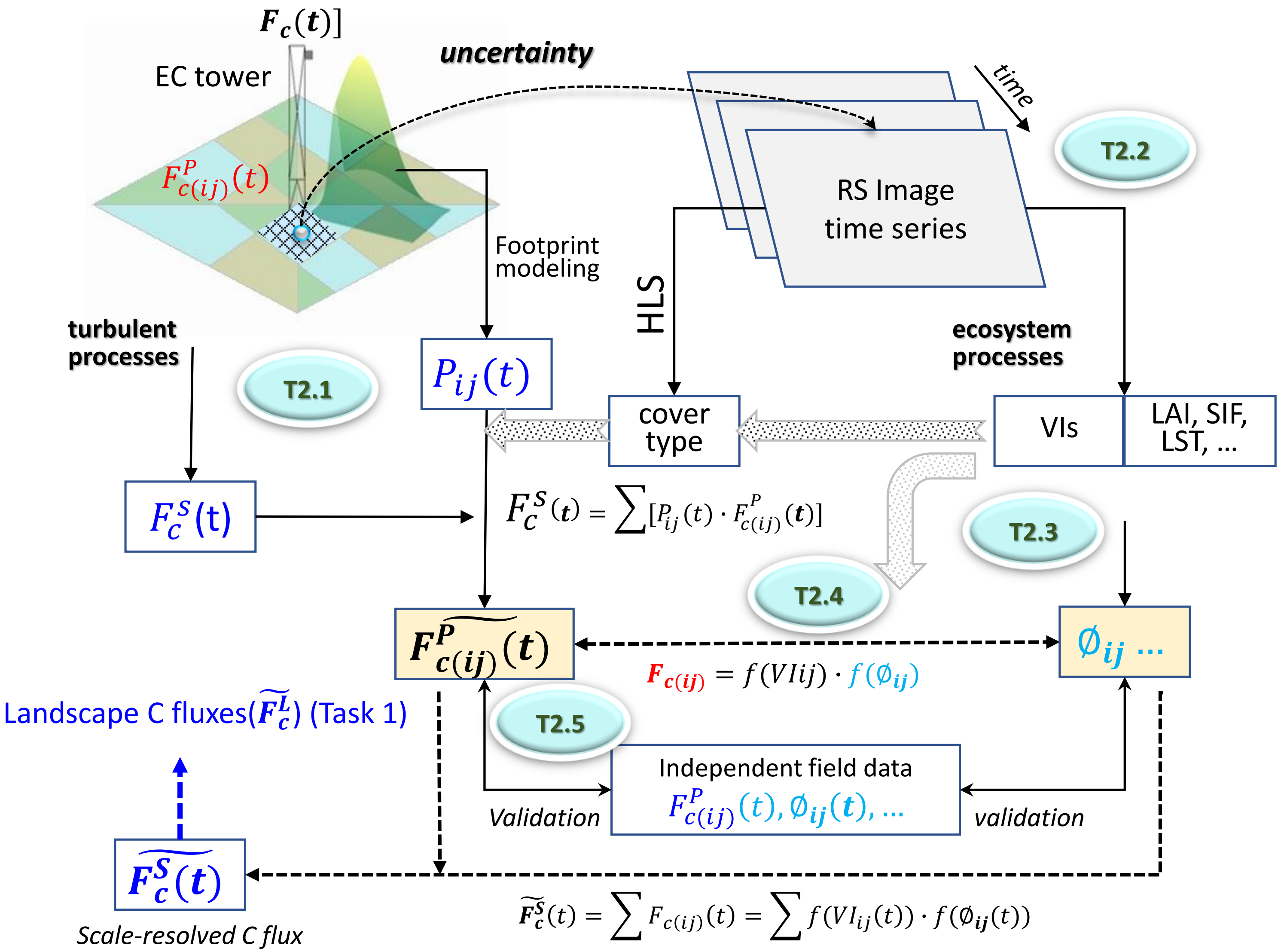


Fully Connected Layer (FC Layer)



Credit: Dr. Jiliang Tang

A conceptual framework to understand EC fluxes with footprint models and spatial databases (RS) using Deep Learnings (RNN and GNN)



In sum,

Integrating time series of multiple variables (RNN) and spatial data (GNN) of various resolutions is a promising direction in flux studies (gap filling, predictions, regional applications).

More details at

1) LEES Webpage:

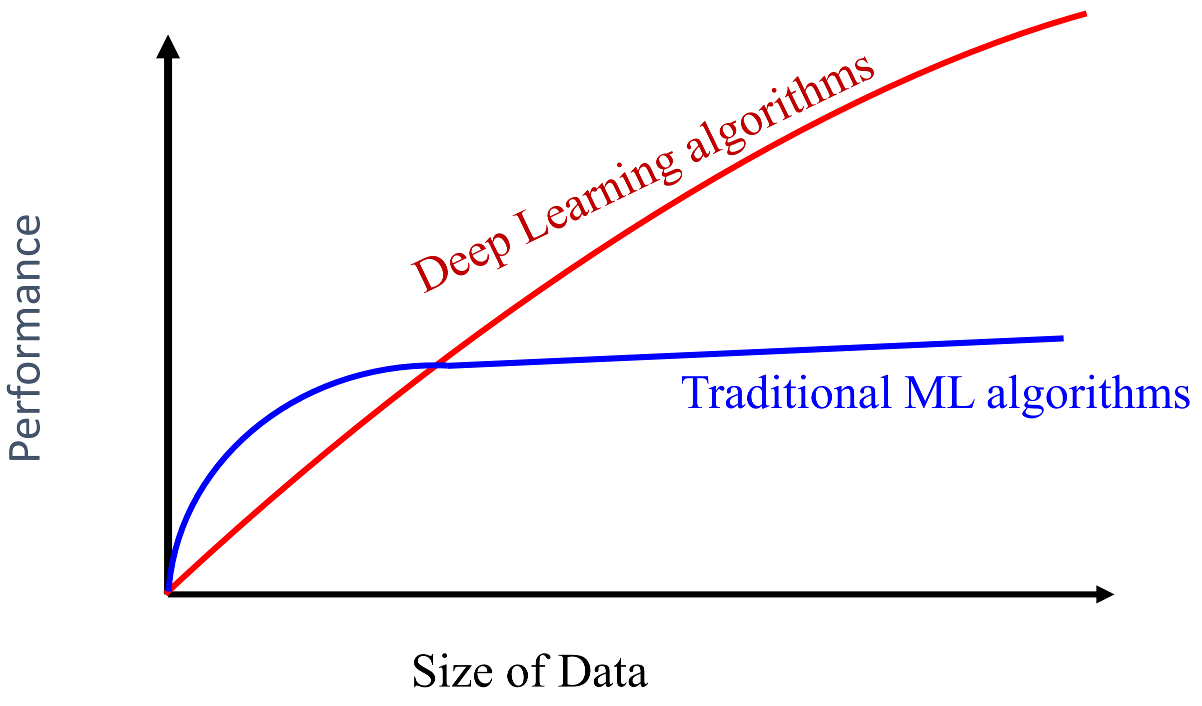
http://lees.geo.msu.edu/

1) Recent publication:

https://scholar.google.com/citations?user=fv8umPcAAAAJ&hl=en&oi=ao

Questions?

Deep Learning vs Traditional Machine Learning



Data is the key

Credit: Dr. Jiliang Tang