Beyond Carbon and Toward a Holistic Understanding of Terrestrial Ecosystems in Regulating Climate

Jiquan Chen

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

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Measuring photosynthesis: chamber-based at leaf level (snapshots)

LiCor6400 (LI6800)

CO_2 & H_2O concentration

PAR, temperature

Measuring photosynthesis: chamber-based at leaf level (continuous)

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.
- Many orchestrated networks (FLUXNET, ChinaFLux, AmeriFlux, USCCC, ICOS, etc.)
- Beyond CO_2 and H_2O: 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

J-Rover tested at the Kellogg Biological Station (KBS) in 2003

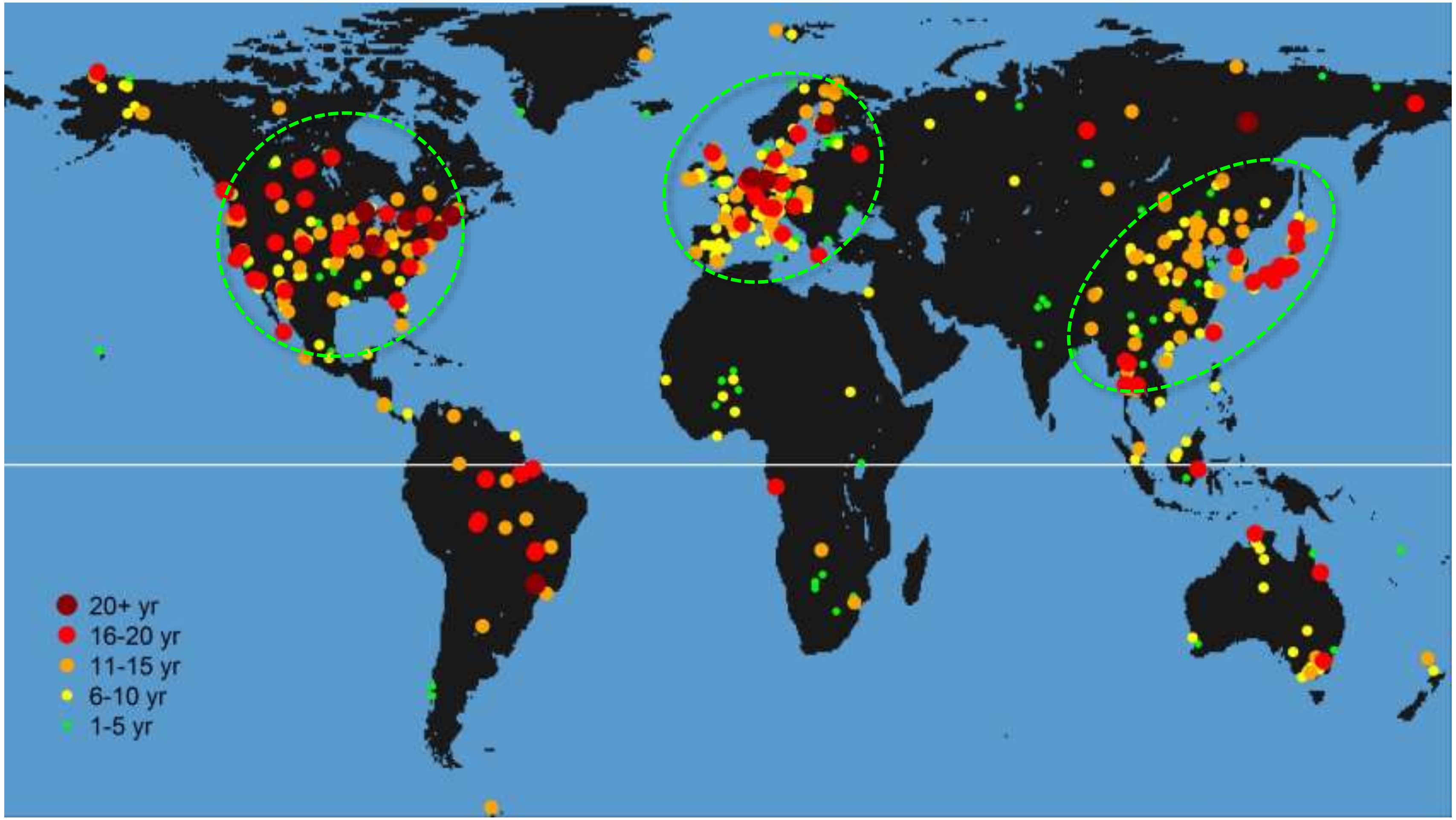
Among the Challenges are

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
5) Life Cycle Assessment (LCA) of carbon flux is urgently needed because *in situ* NEE DOES NOT reflect C sequestration

Among the Challenges are

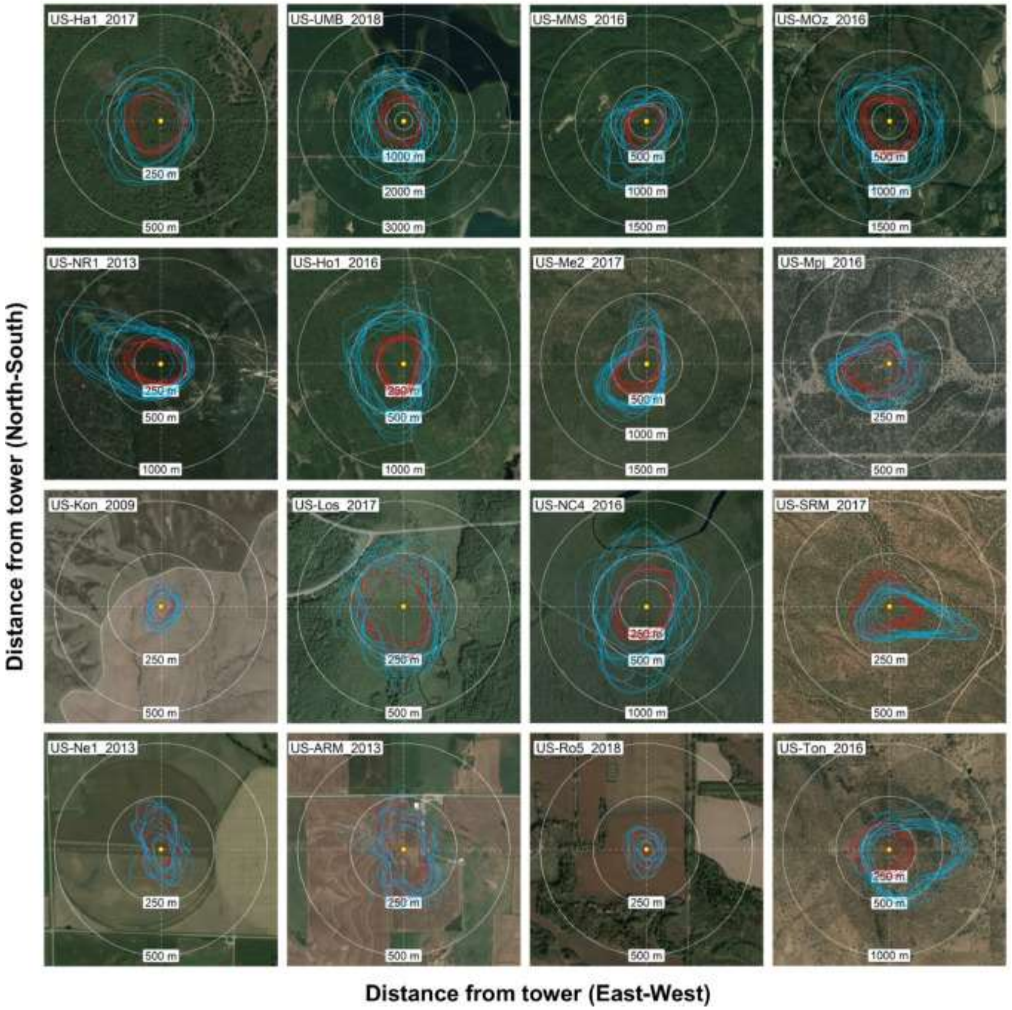
https://fluxnet.org/sites/site-summary/

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



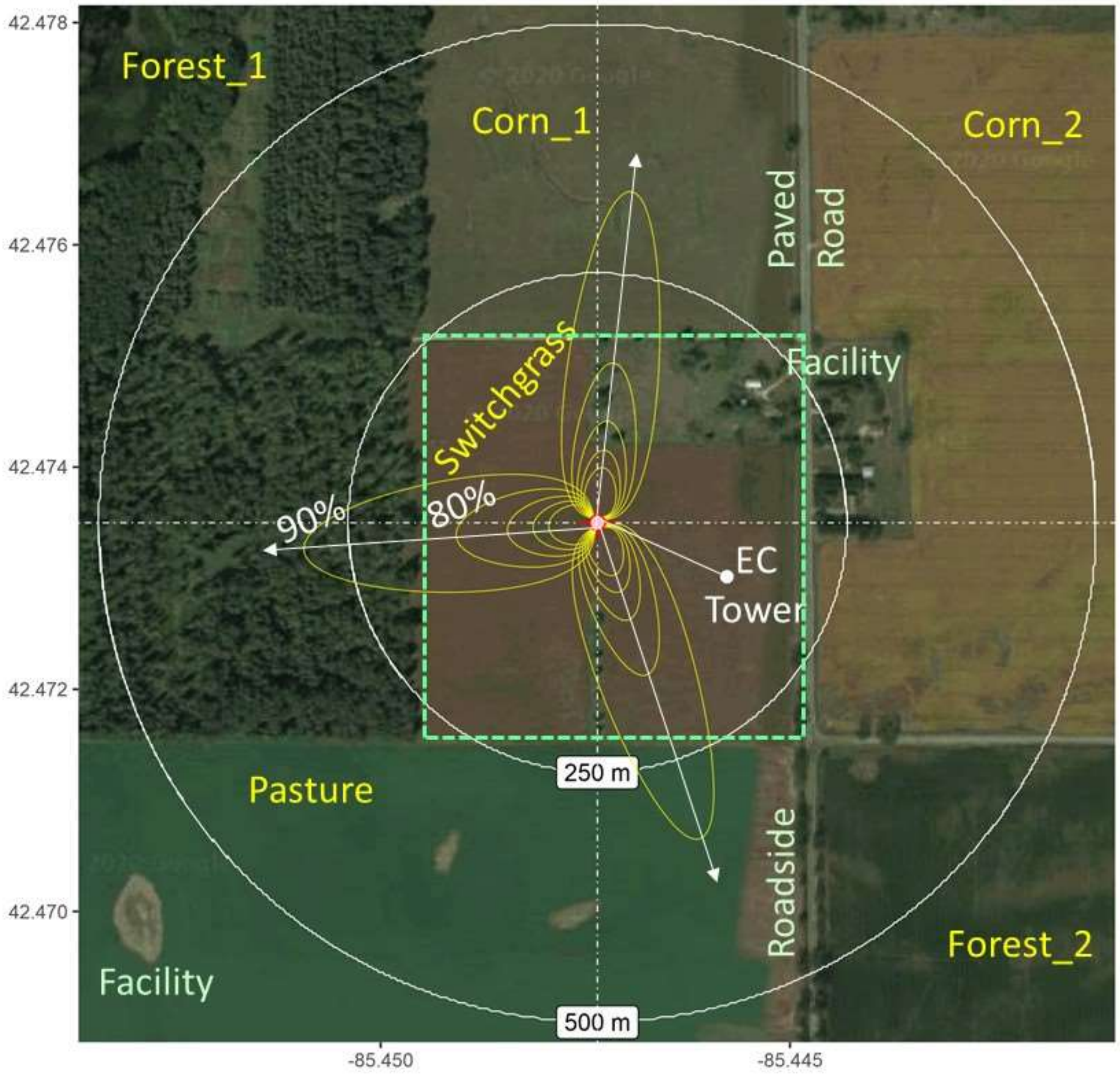
Among the Challenges are

- Most sites are not large enough

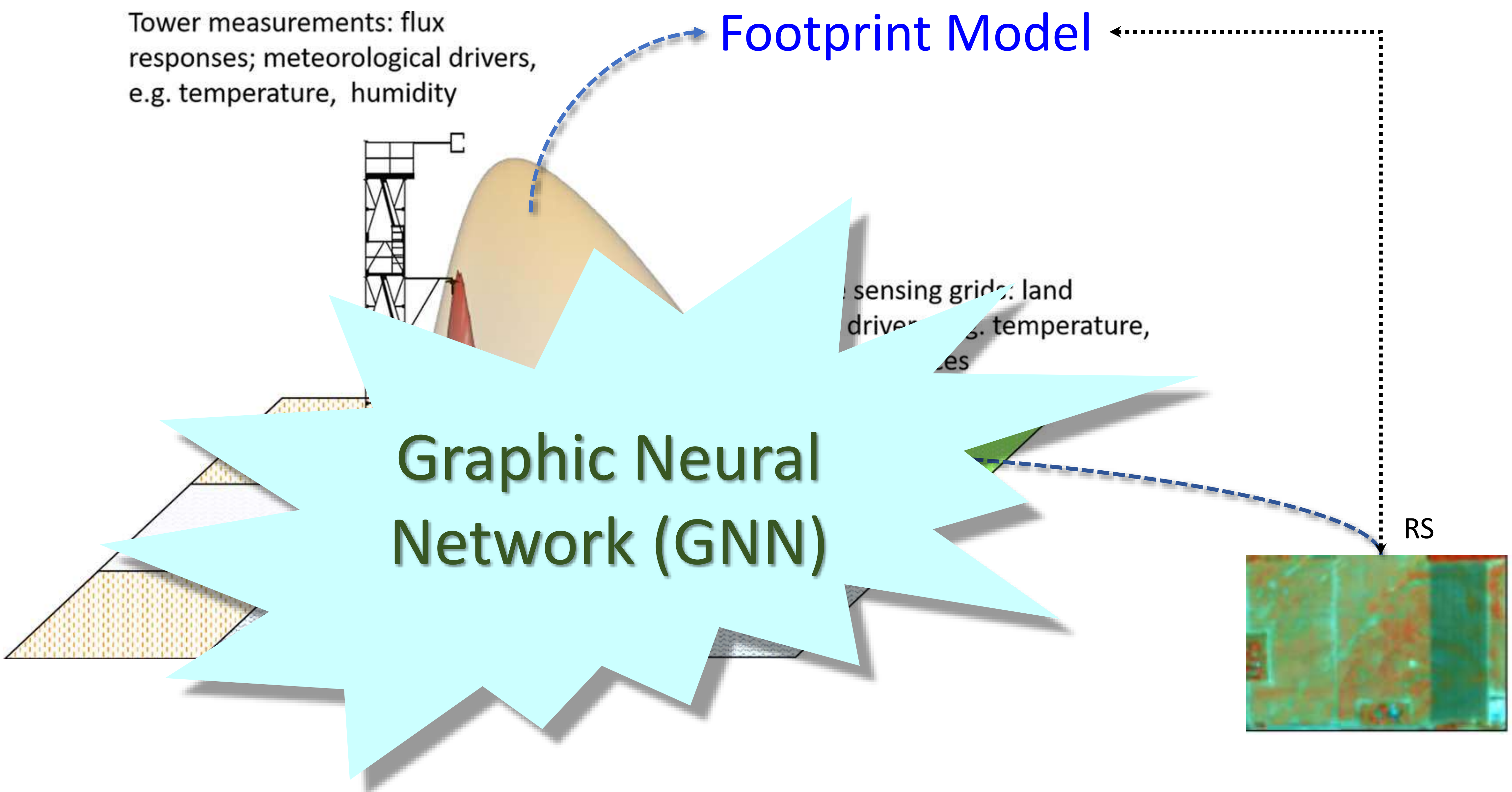


Chu et al. 2021. Ag. For. Met.

A switchgrass cropland at the Kellogg Biological Station



Spatial information



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

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

4 parameters

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

Chen 2021

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

	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

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

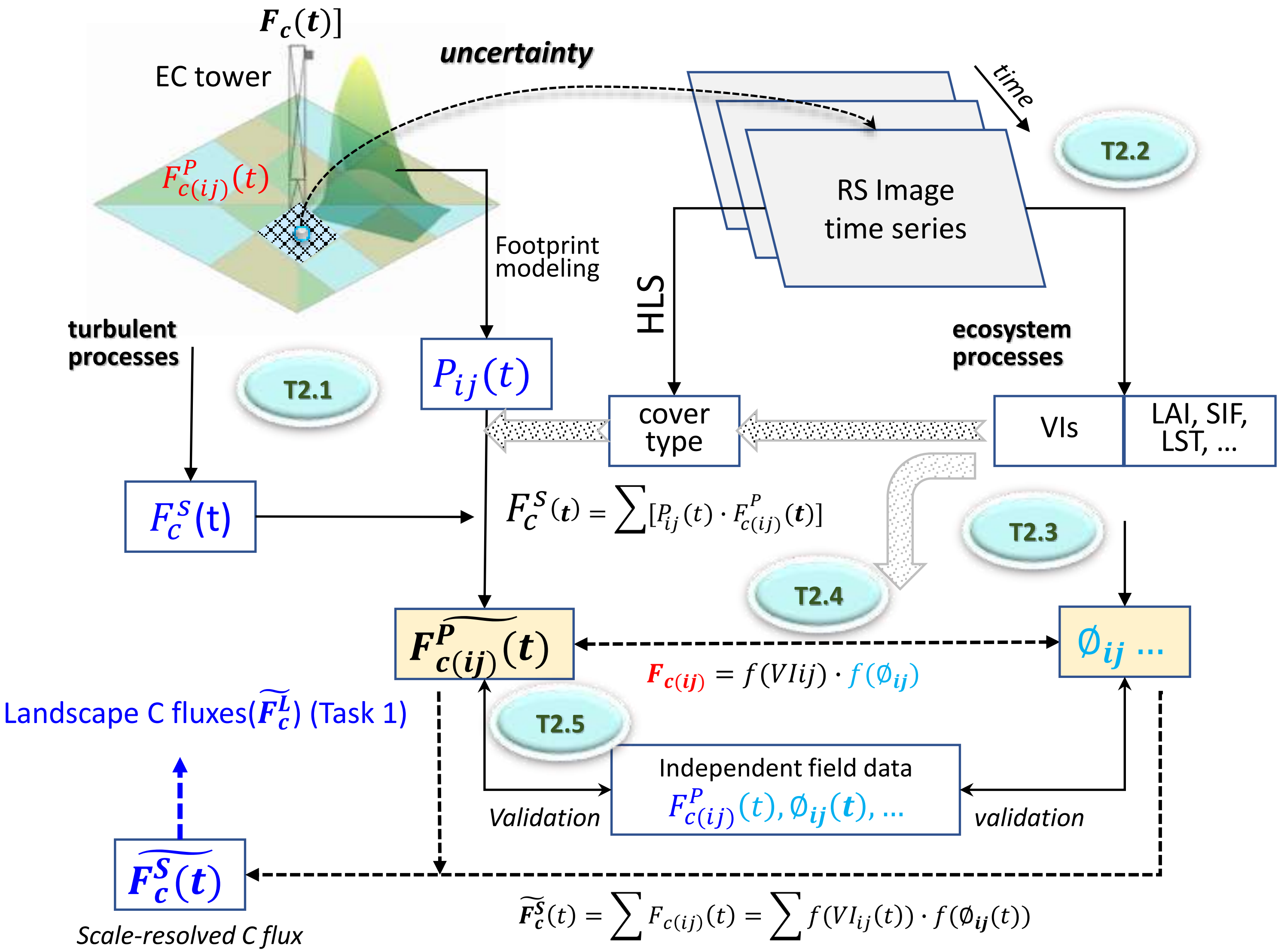
2. Evolving analytical tools

Mechanistic models	Computing Power	Machine Learning

Mechanistic and/or empirical explorations

Accurate predictions of fluxes and underline regulations

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



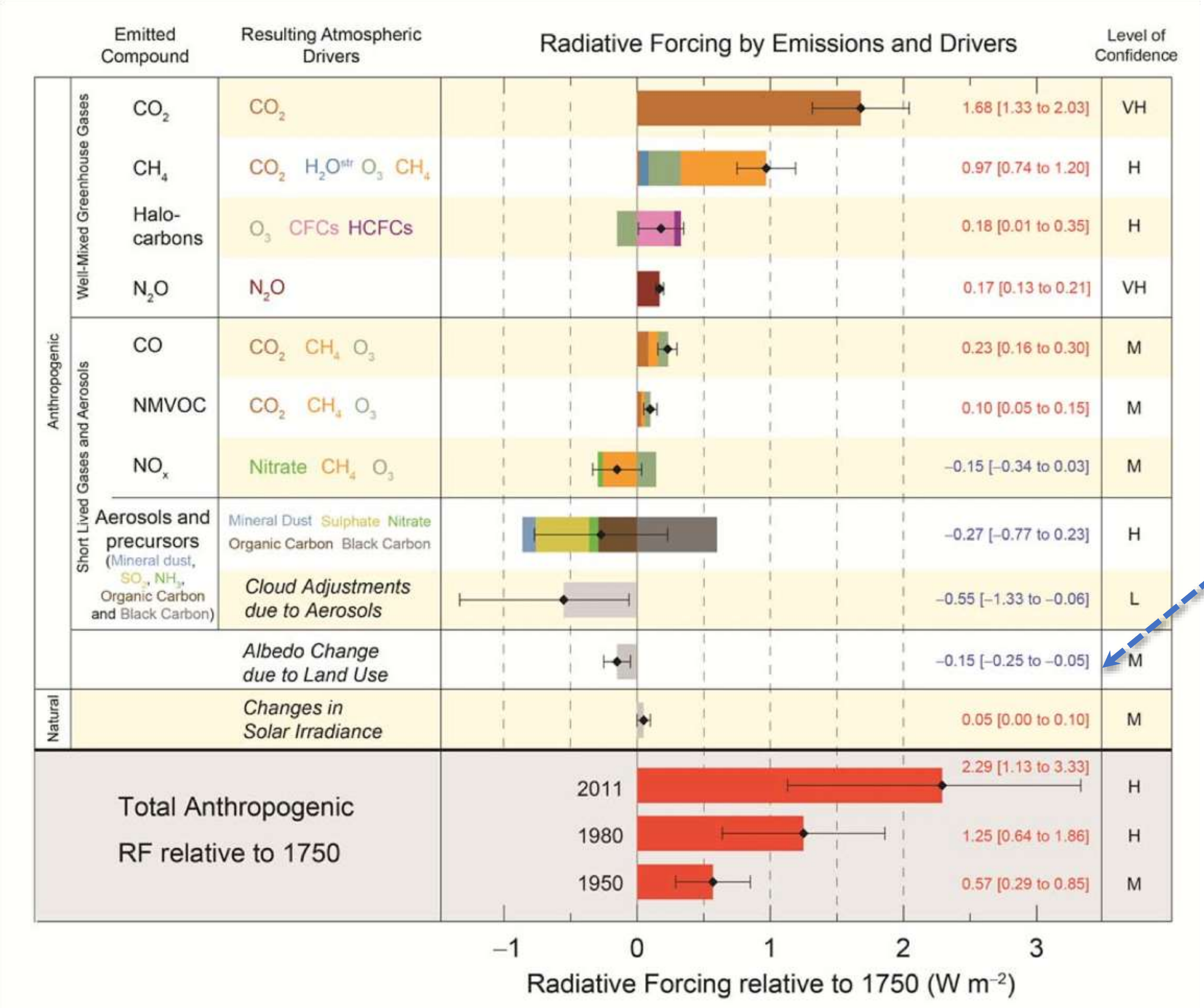
Among the Challenges are

- 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

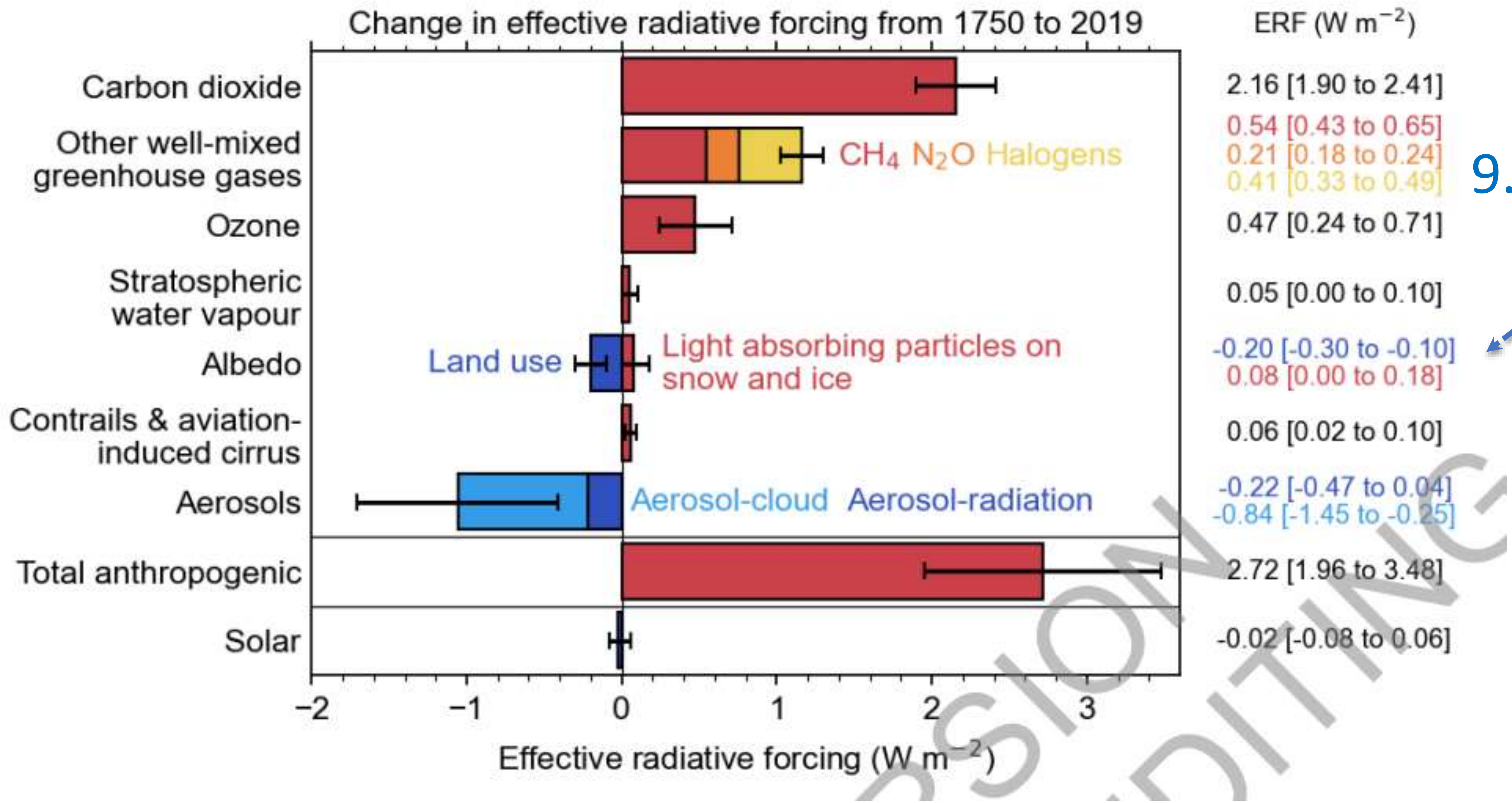
Irvin et al. 2021. https://doi.org/10.1016/j.agrformet.2021.108528

Contributions of major warming/cooling species (IPCC 2013)



8.93% of CO_2

Contributions of major warming/cooling species (IPCC 2021)



9.25% of CO_2

SCIENCE \ ENVIRONMENT

As a last resort, Andrew Yang proposes space mirrors to save the planet

The plan is already raising some eyebrows

By Justine Calma | @justcalma | Aug 26, 2019, 5:26pm EDT

SHARE

That last part is where Yang's plan starts to get a little wonky, but it's totally on brand for the startup entrepreneur. He's the only candidate whose plan to avert the climate crisis banks on geoengineering (aka developing technologies to manipulate the environment). His plan would invest $800 million* in researching geoengineering methods like space mirrors. That's right, he's looking into "giant foldable space mirrors" that would reflect the Sun's light away from the Earth as a "last resort."

LOOKING INTO "GIANT FOLDABLE SPACE MIRRORS" THAT WOULD REFLECT THE SUN'S LIGHT AWAY FROM THE EARTH

nature COMMUNICATIONS

ARTICLE

https://doi.org/10.1038/s41467-022-31558-z OPEN

Albedo changes caused by future urbanization contribute to global warming

Zutao Ouyang[1,2✉], Pietro Sciusco[2], Tong Jiao[3], Sarah Feron[1,4,5], Cheyenne Lei[2], Fei Li[6], Ranjeet John[7], Peilei Fan[8], Xia Li[9], Christopher A. Williams[3], Guangzhao Chen[10,11], Chenghao Wang[1] & Jiquan Chen[2✉]

The replacement of natural lands with urban structures has multiple environmental consequences, yet little is known about the magnitude and extent of albedo-induced warming contributions from urbanization at the global scale in the past and future. Here, we apply an empirical approach to quantify the climate effects of past urbanization and future urbanization projected under different shared socioeconomic pathways (SSPs). We find an albedo-induced warming effect of urbanization for both the past and the projected futures under three illustrative scenarios. The albedo decease from urbanization in 2018 relative to 2001 has yielded a 100-year average annual global warming of 0.00014 [0.00008, 0.00021] °C. Without proper mitigation, future urbanization in 2050 relative to 2018 and that in 2100 relative to 2018 under the intermediate emission scenario (SSP2-4.5) would yield a 100-year average warming effect of 0.00107 [0.00057,0.00179] °C and 0.00152 [0.00078,0.00259] °C, respectively, through altering the Earth's albedo.

ENVIRONMENTAL RESEARCH
LETTERS

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Albedo-induced global warming impact of Conservation Reserve Program grasslands converted to annual and perennial bioenergy crops

Michael Abraha[7,1,2], Jiquan Chen[1,2,3], Stephen K Hamilton[2,4,5], Pietro Sciusco[1,3], Cheyenne Lei[1,2,3], Gabriela Shirkey[1,3], Jing Yuan[1] and G Philip Robertson[2,4,6]

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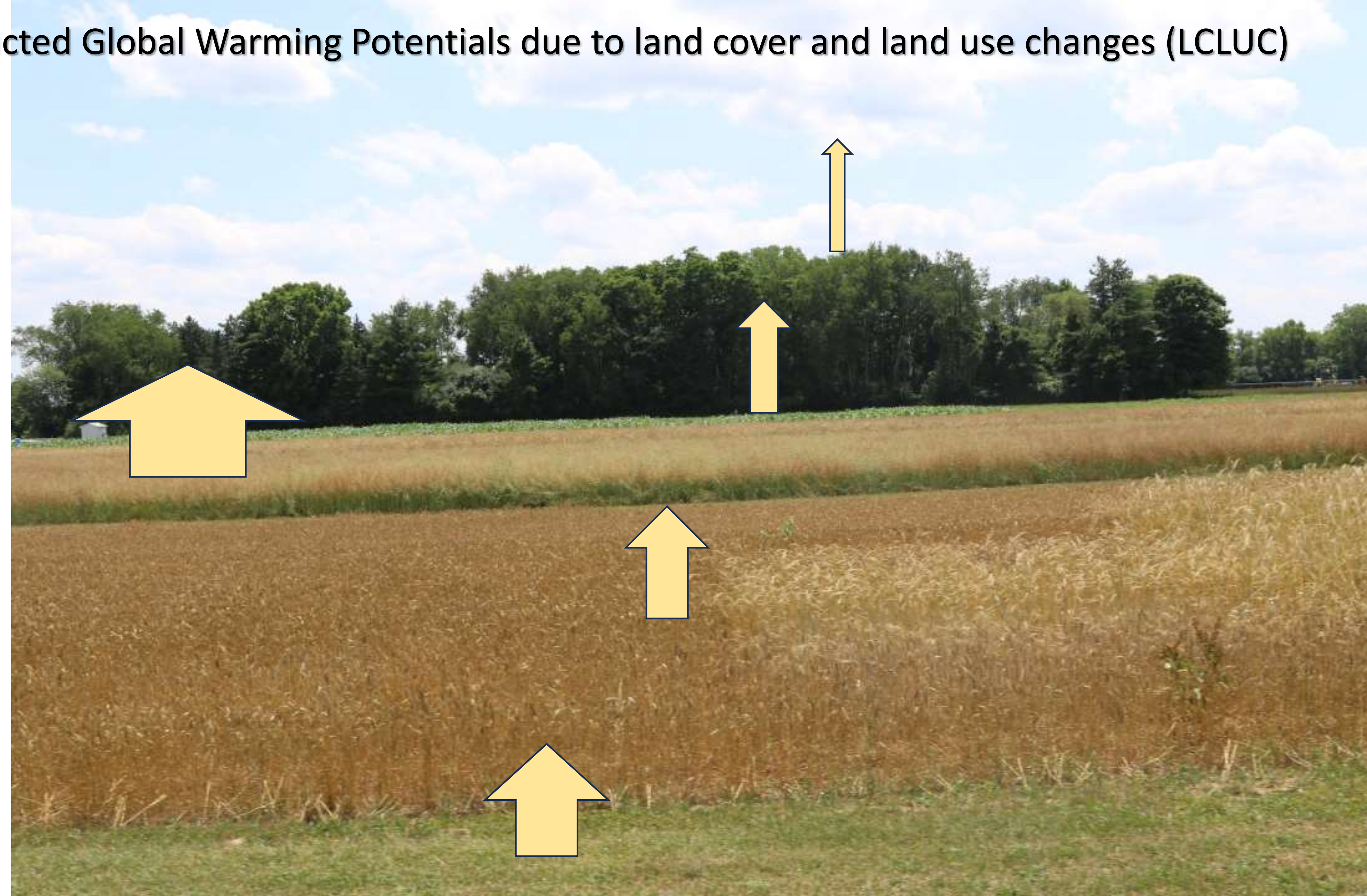
Environmental Research Letters, Volume 16, Number 8

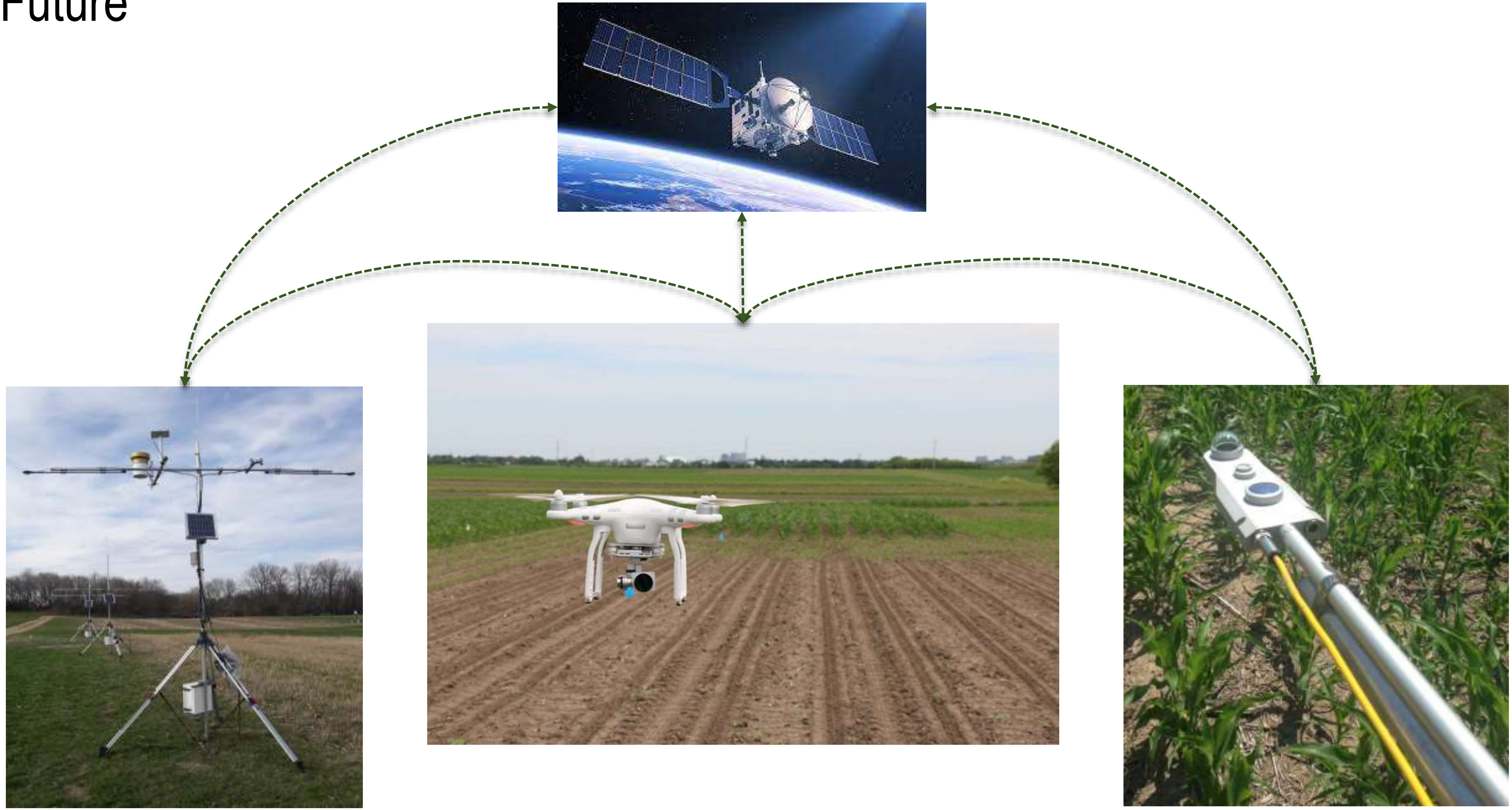
Citation Michael Abraha *et al* 2021 *Environ. Res. Lett.* **16** 084059

- We converted three 22 year old CRP smooth brome grass fields into no-till corn, switchgrass, or restored prairie bioenergy crops
- The corn and perennial fields had higher annual albedo than the grassland they replaced—causing cooling of the local climate
- The cooling of the corn field occurred solely during the non-growing season—especially when surfaces were snow-covered, whereas the cooling of the perennial fields was more prominent during the growing season
- The annual albedo-induced climate benefits add ~35% and ~78% to the annual biogeochemical benefits provided from the switchgrass and restored prairie fields, respectively, and offset ~3.3% of the annual greenhouse gas (GHG) emissions from the corn field

Albedo-inducted Global Warming Potentials due to land cover and land use changes (LCLUC)

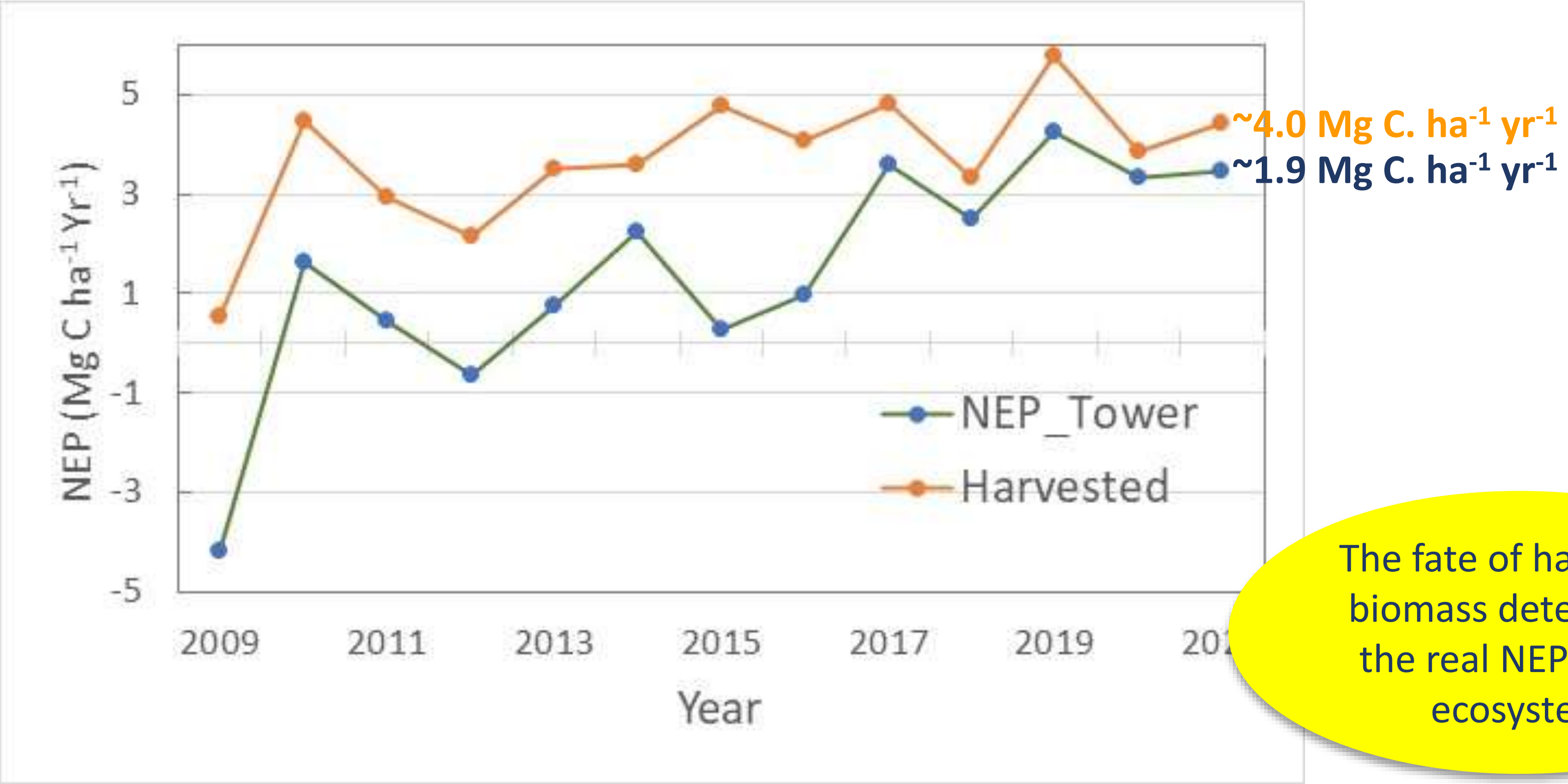


Future



Net Ecosystem Production (NEP) of a corn field in SW Michigan

NEP of a corn field from the flux tower and harvesting



The fate of harvested biomass determines the real NEP of the ecosystem

Careful spatial and temporal "**life cycle assessment (LCA)**" is needed for realistic estimates of GWP (i.e., it is about the differences!)

Abraha et al. in prep.

Questions

1) Did IPCC Underestimate This Contrition?
2) Was this due to intensified land use and land cover changes that elevated albedo (i.e., more cooling effects)? or
3) Is it within the uncertainty of estimate of IPCC?

Further questions

1) What are the albedo-induced RF values of different terrestrial ecosystems?

2) What are the direct implications for land management, such as credit claims?

Machine Learning in flux studies?

Speech Recognition

Human **expertise** does not exist

Personalized Medicine

Models must be **customized**

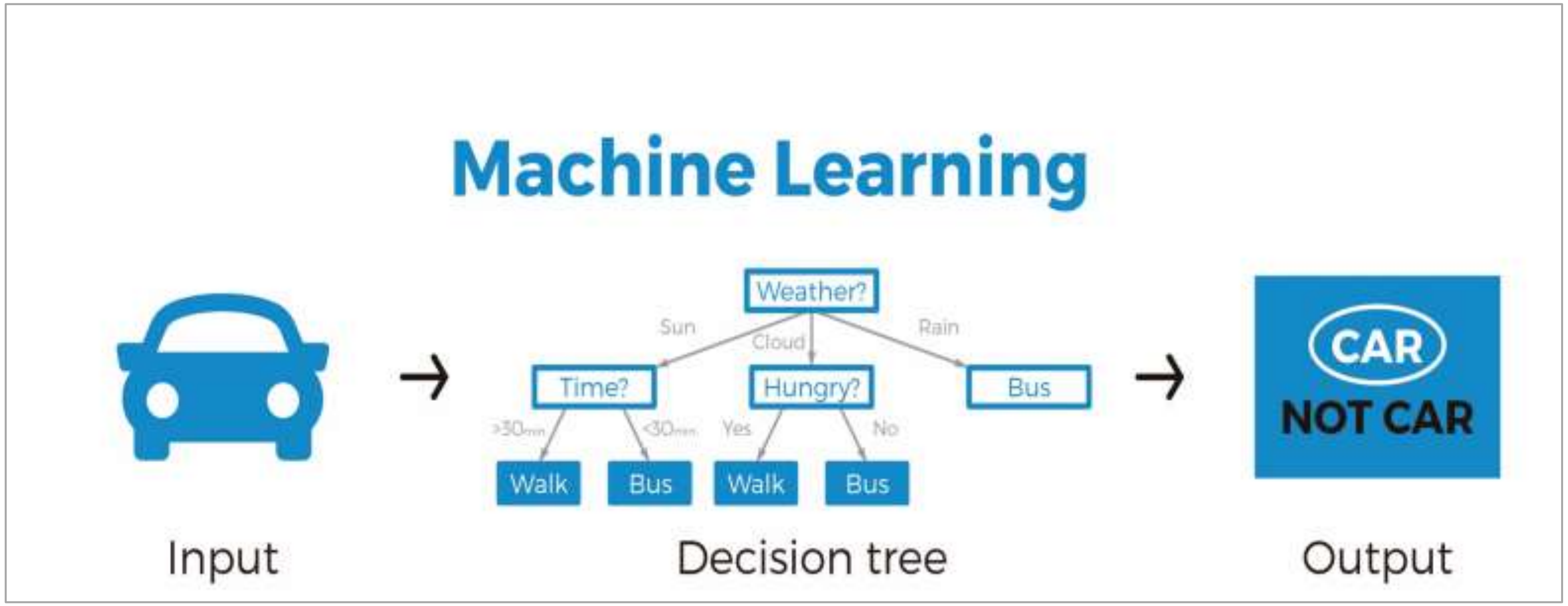
Genomics

Huge amounts of data

Credit: Dr. Jiliang Tang


ChatGPT
Crash Course
ME
How do I... as a beginne
Capabilities
Remembers what user said earlier in the conversation
Allows user to provide follow-up
"Got any creative ideas for a 10

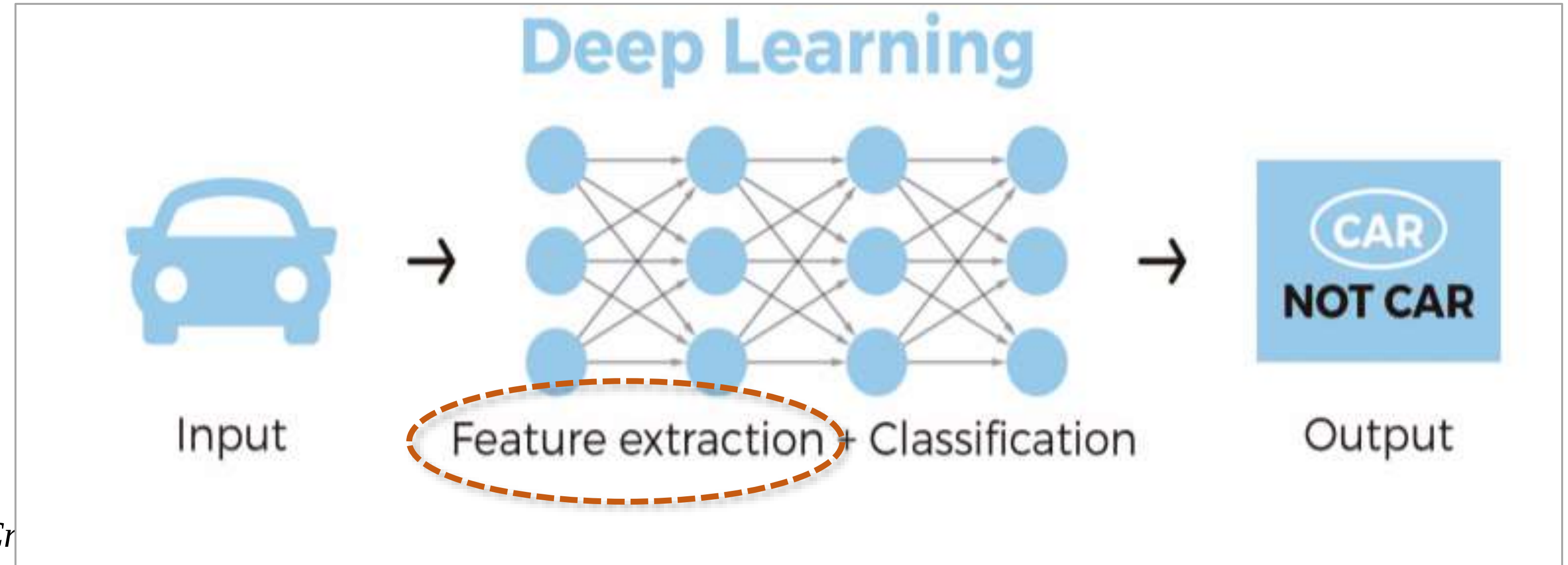
Deep Learning vs Traditional Machine Learning



Common Knowledge
In flux studies

Ta, VPD, Ms, PAR, Rn, DOY, G, Ts, …

Fc



Partial knowns & unknowns
In flux studies

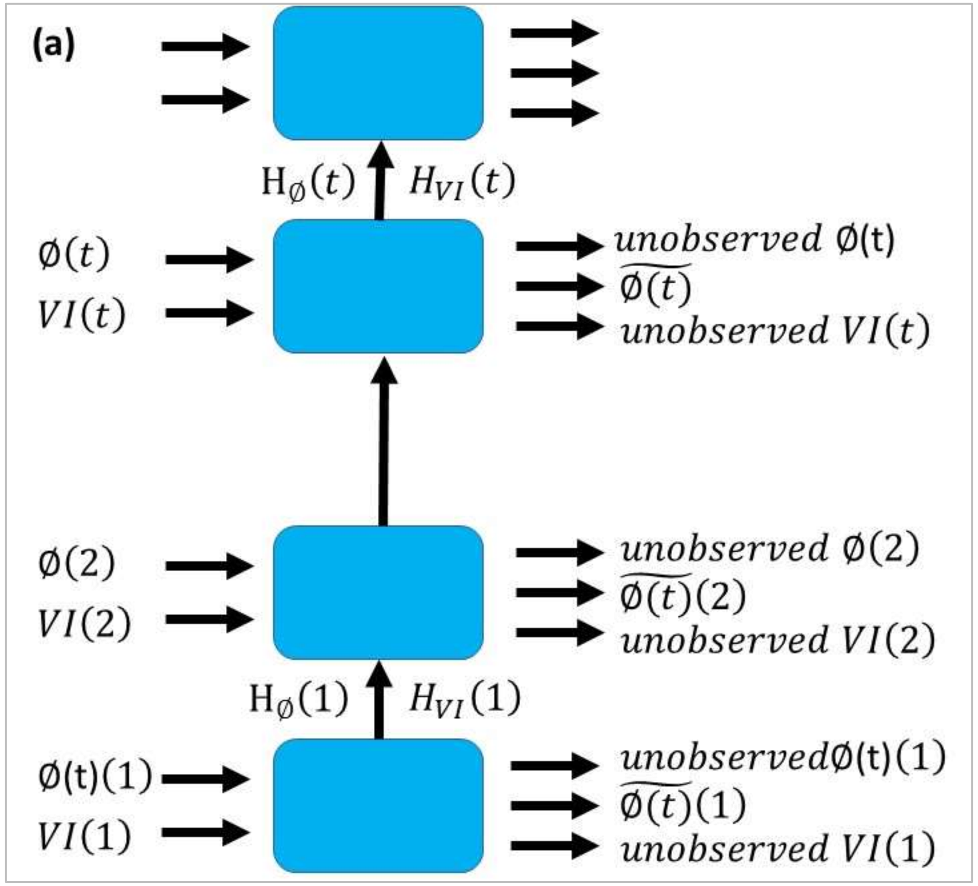
WD, WS, U*, CO_2, RH, …

Fc

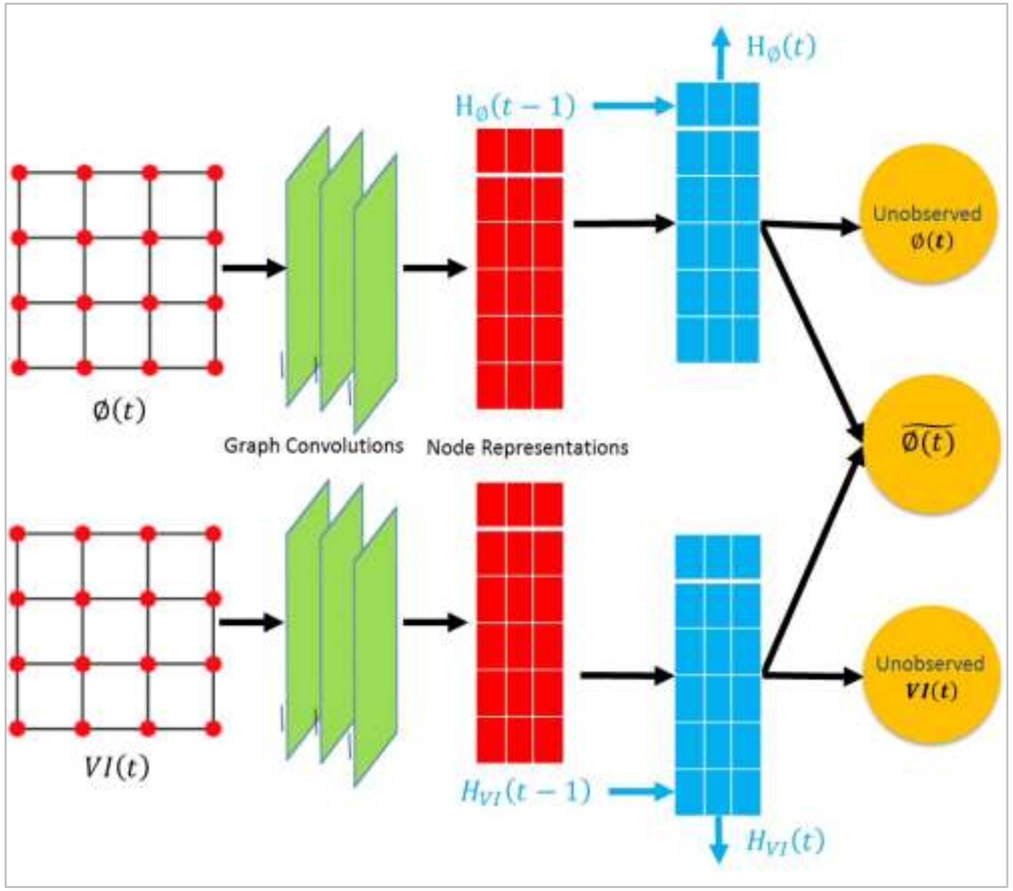
Cr

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)

RNN

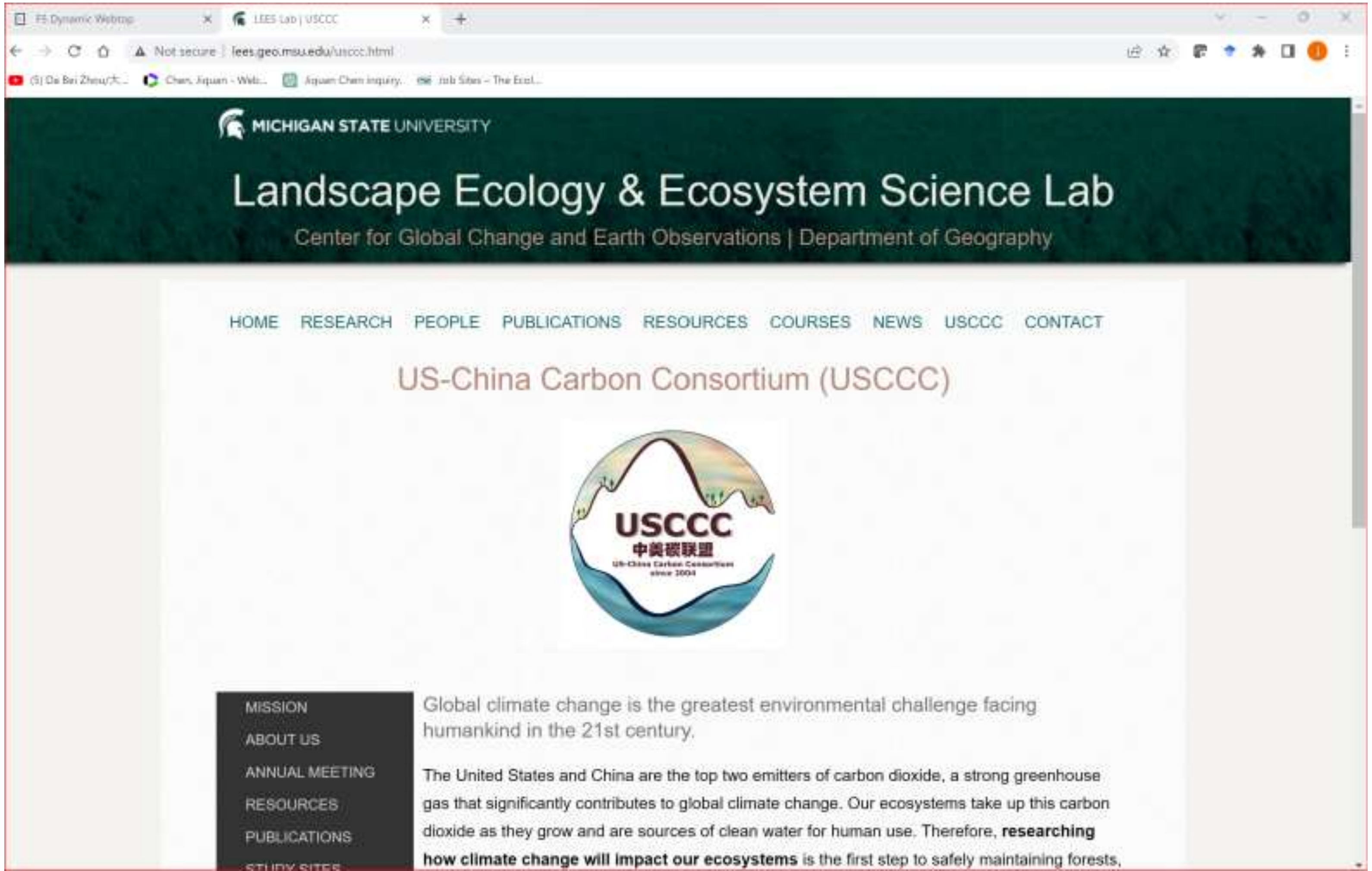


GNN



In sum,

- Holistic approach by including all warming species (CO_2, N_2O), CH_4, albedo, etc.)
- Best use of all spatial and temporal data
- Effective applications of AI technology



Higher Education Press (HEP)

- Book series with a strong focus on ecology/environment/climate change
- Dr. Yan Guan has a desk