Exploring Constraints on a Wetland Methane Emission Ensemble with GOSAT

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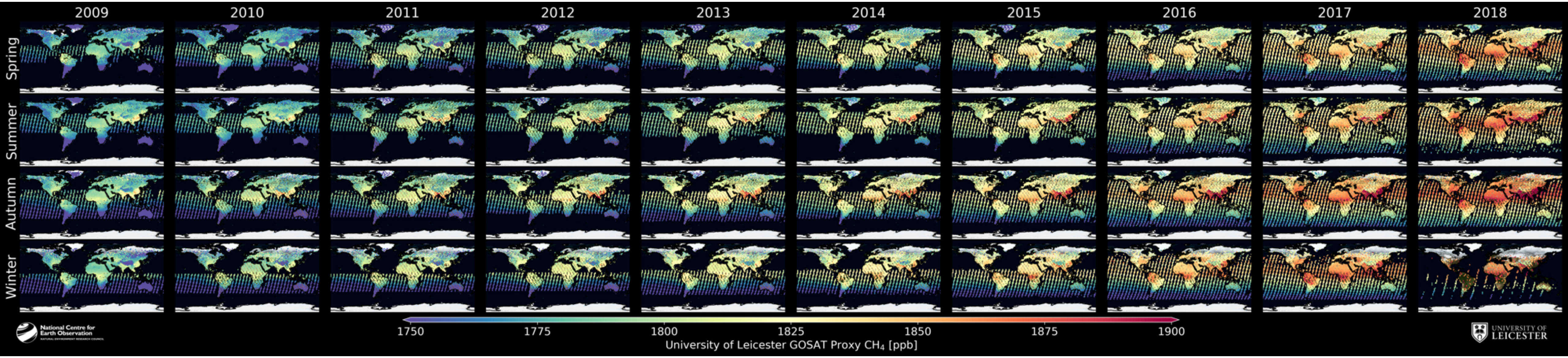
University of Leicester GOSAT Proxy XCH_4

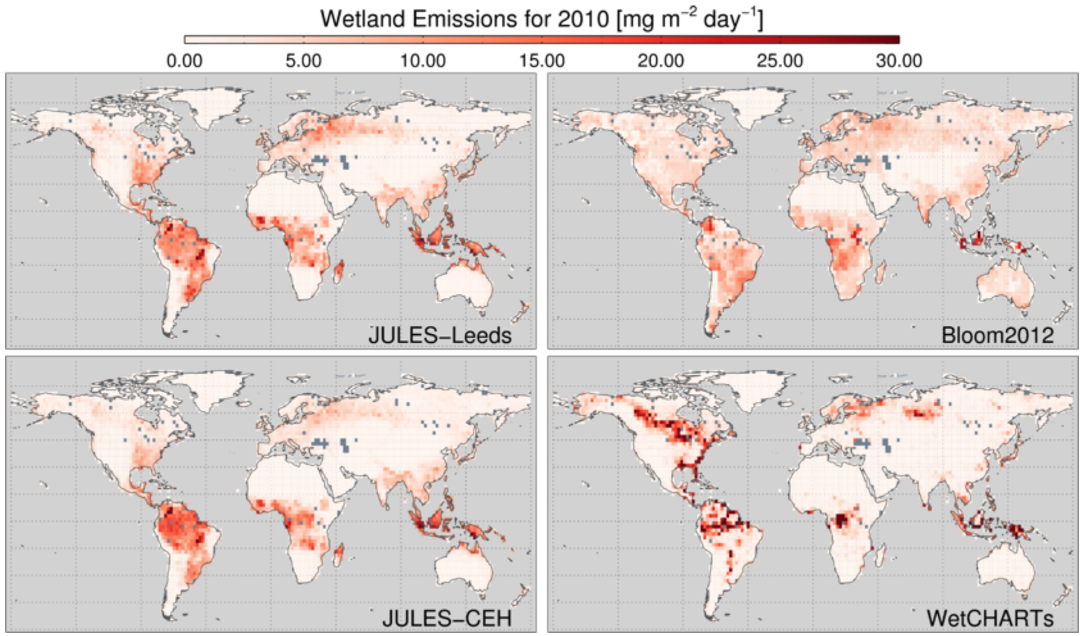


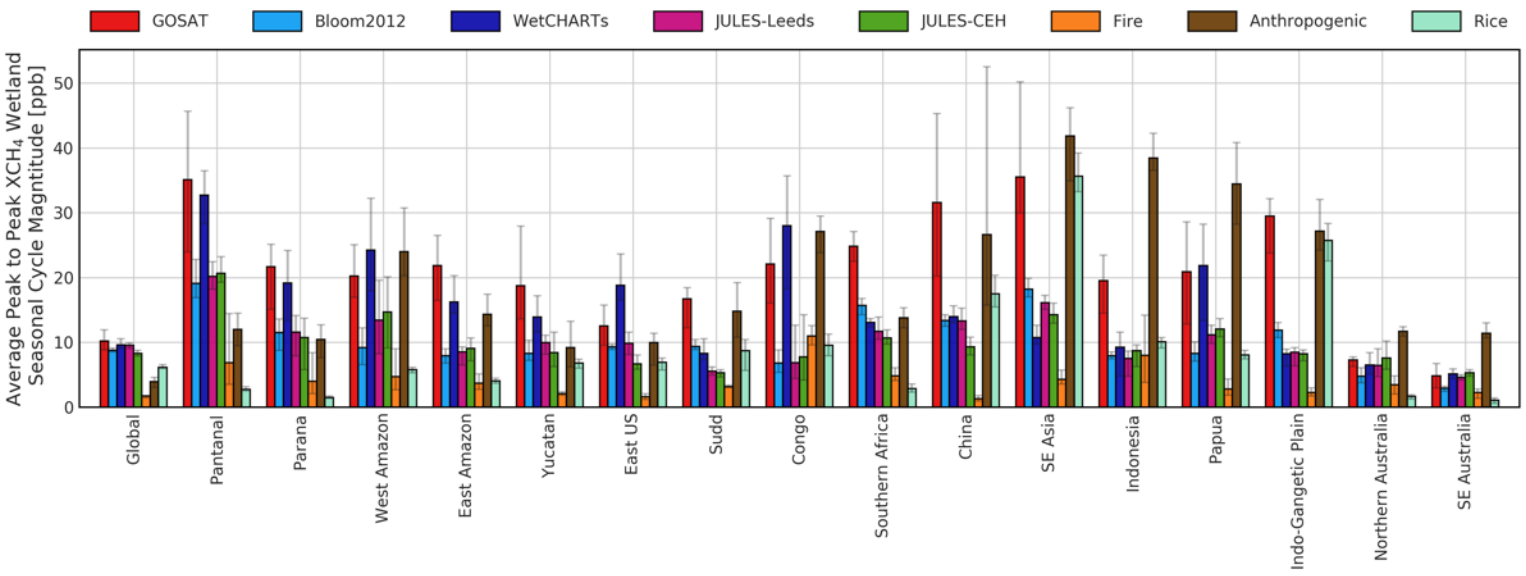
- ❑ This work uses our GOSAT Proxy XCH_4 data
- ❑ Data recently extended to 2018
- ❑ Developed as part of ESA-GHG CCI
- ❑ Updated annually as part of EU Copernicus Climate Change Service
- ❑ Has been used in many publications
- ❑ Feel free to get in touch if interested ☺

Motivation

In Parker et al. 2018, *Evaluating year-to-year anomalies in tropical wetland methane emissions using satellite CH_4 observations*, we found:

- ❑ Observations show that models **underestimate** tropical seasonal cycle of methane
- ❑ **Large discrepancies** between model and observations over South American wetlands
- ❑ Changes to wetland extent driven by **ENSO** cause large differences
- ❑ Wetland extent changes caused by overbank inundation, a process **missing** in these models
- ❑ This work builds upon this by considering **larger ensembles** of wetland emission datasets (WetCHARTs, JULES) and **evaluates** them against GOSAT CH_4 satellite observations
- ❑ Focus of this presentation will be an **initial evaluation of WetCHARTs**





WetCHARTs

- WetCHARTs is an **ensemble** of CH_4 emissions produced by A. Bloom (NASA JPL)
- Different constraints on global total, respiration model, temperature dependence and extent parameterisation
- We used the ensemble mean in Parker et al. 2018 but now we want to study the full ensemble and **compare to GOSAT CH_4 observations**
- Interested in which ensemble members perform better in which regions to try and understand what factors are important (e.g. temperature vs extent)

4-digit code describes ensemble member - ABCD

A	1	2	3
Global Scale Factor (Tg CH_4/yr)	124.5	166	207.5

B	1-8	9
Heterotrophic Respiration Model	MsTMIP Models	CARDAMOM

C	1	2	3
Temperature Dependence	q10 = 1	q10 = 2	q10 = 3

D	1	2	3	4
Extent Parameterisation	SWAMPS & GLWD	SWAMPS & GLOBCOVER	PREC & GLWD	PREC & GLOBCOVER

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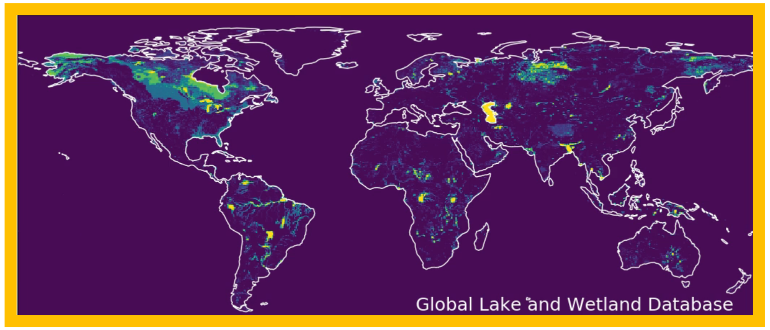
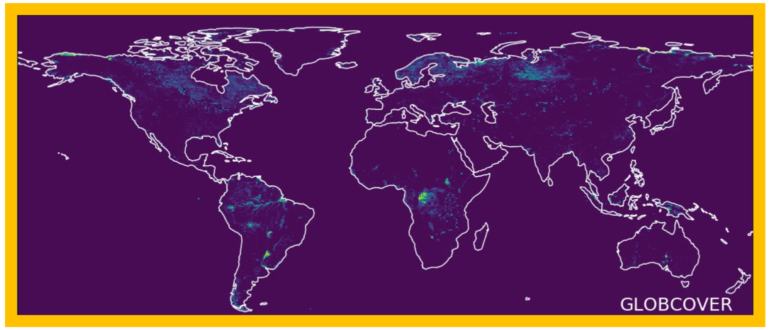
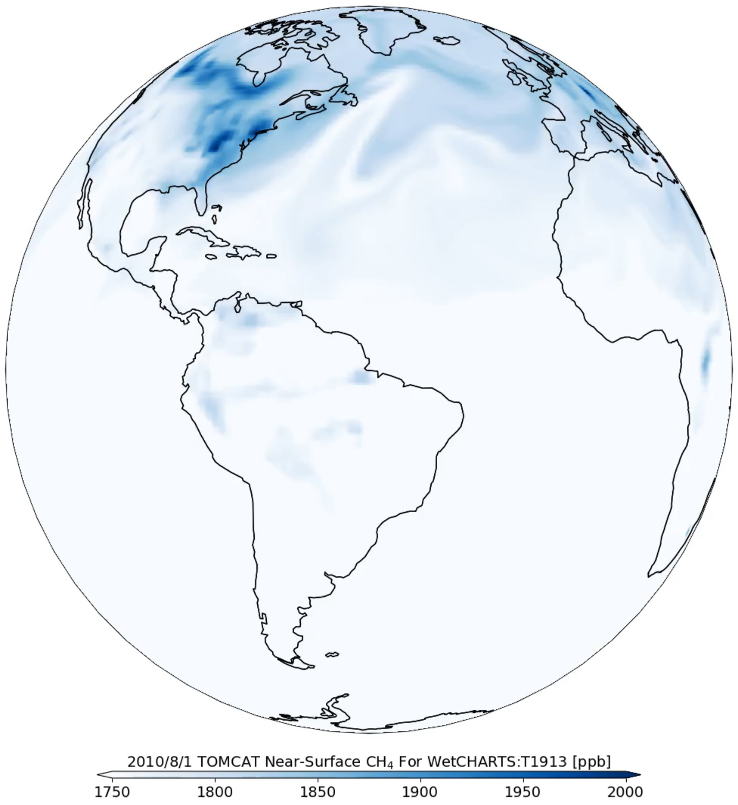
January 2001





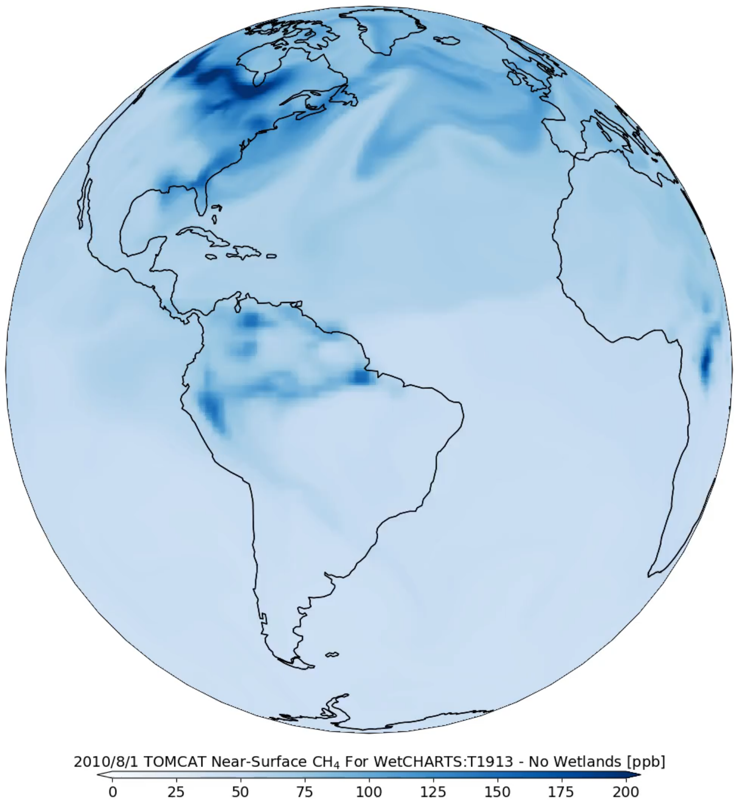
Near-surface Model CH_4 for August/September 2010

Full model (WetCHARTs:1913)



Model Without Wetlands

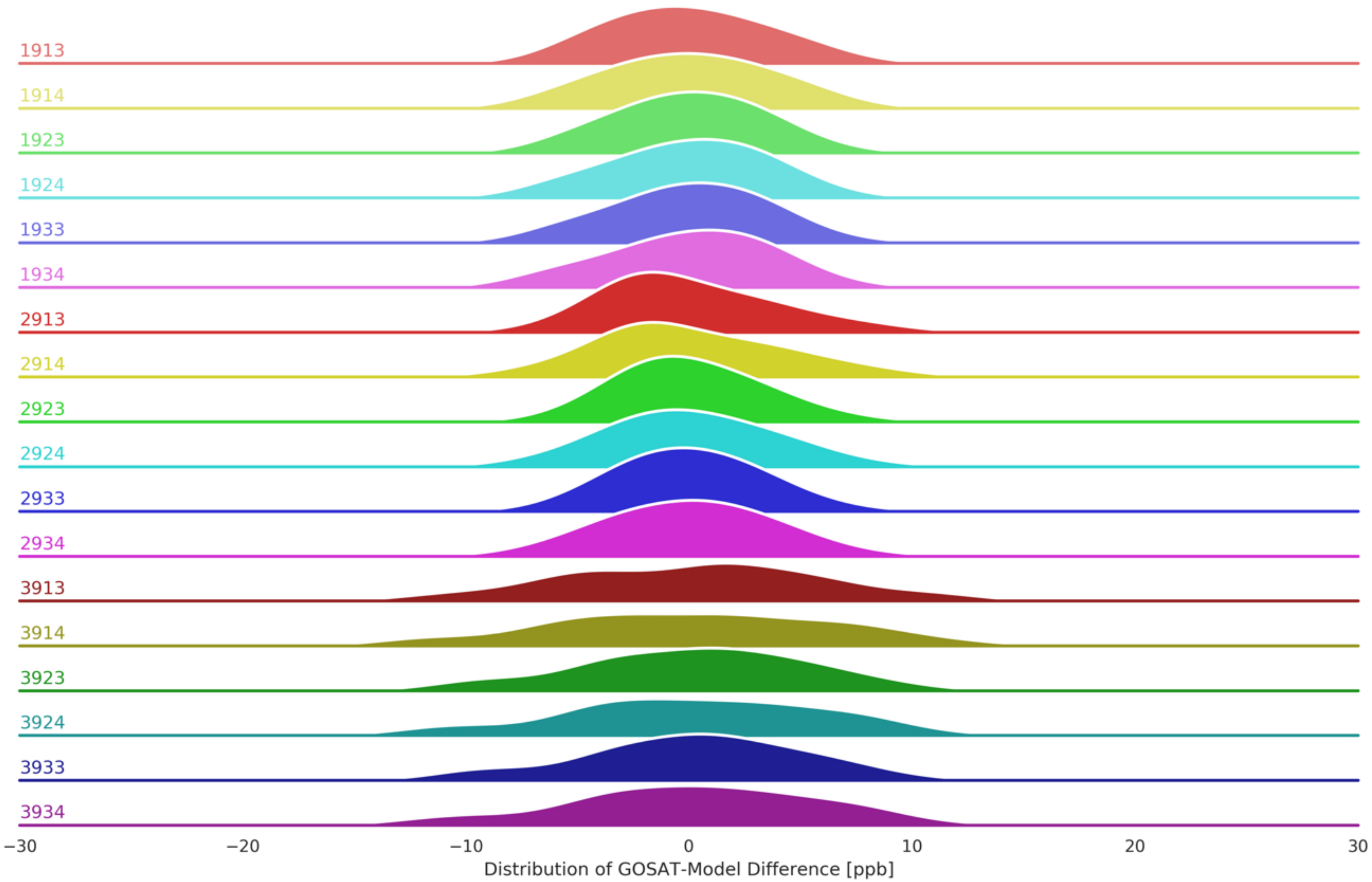
Difference



Global Scale Factor (Tg CH_4/yr): 124.5
Temperature Dependence: q10 = 1
Extent Parameterisation: Precipitation and GLWD

Global GOSAT-Model Difference

- ❑ Comparing the model data to GOSAT after linear detrending
- ❑ Histograms for each of the 18 different WetCHARTs ensemble members
- ❑ Global mean typically in good agreement but different ensemble members show quite different distributions



WetCHARTs Model Ensemble Configuration: 4-digit format **ABCD**: A = Global scale factor; B = Heterotrophic respiration model; C = Temperature dependence; D = Extent parameterisation
A: (1) 124.5 Tg CH_4/yr; (2) 166 Tg CH_4/yr; (3) 207.5 Tg CH_4/yr | **B**: (1-8) MsTMIP models; (9) CARDAMOM | **C**: (1) CH_4:C q10 = 1; (2) CH_4:C q10 = 2; (3) CH_4:C q10 = 3 | **D**: (1) SWAMPS & GLWD; (2) SWAMPS & GLOBCOVER; (3) PREC & GLWD; (4) PREC & GLOBCOVER

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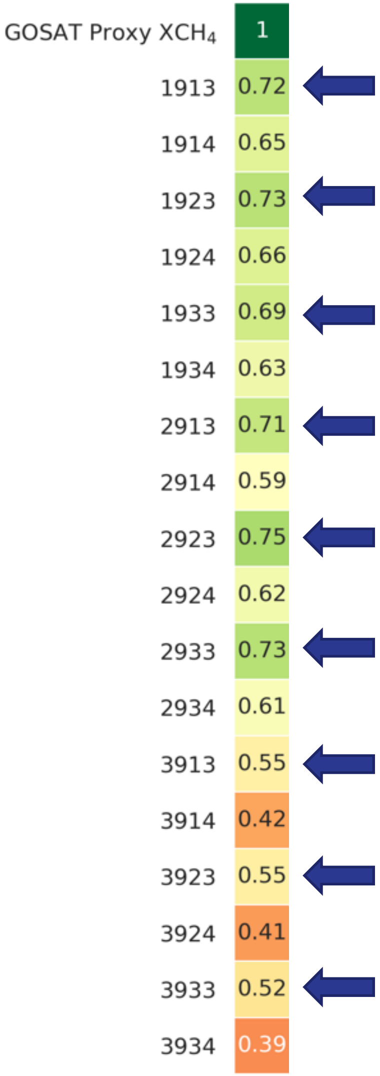
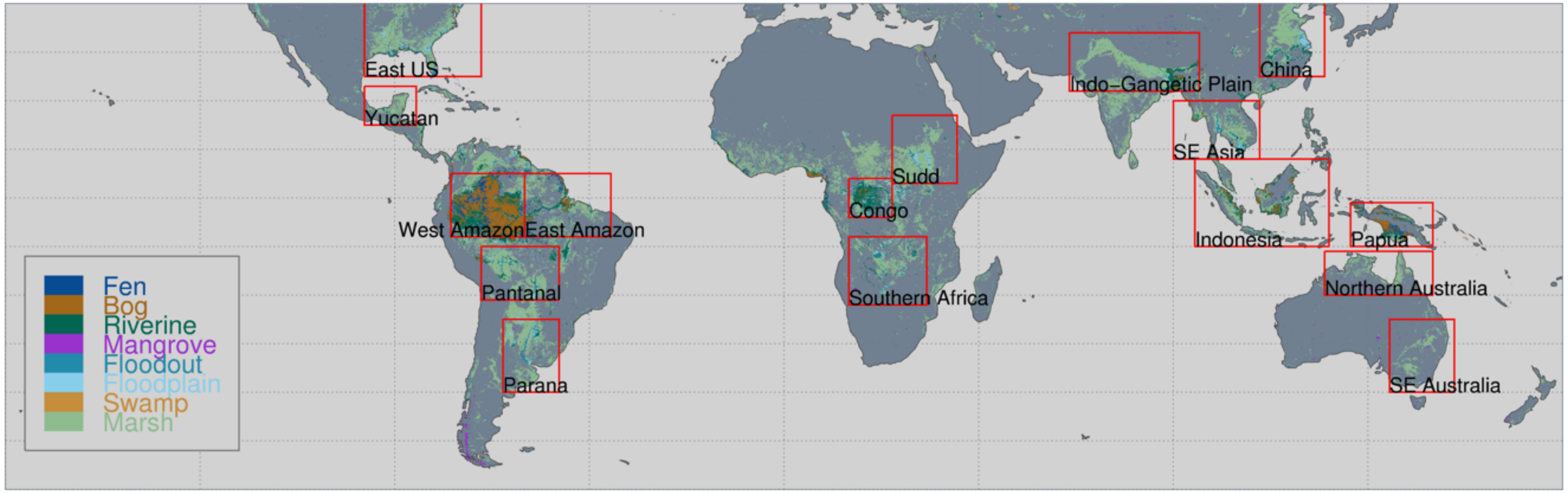
Global Correlation Between GOSAT and Different Ensemble Members

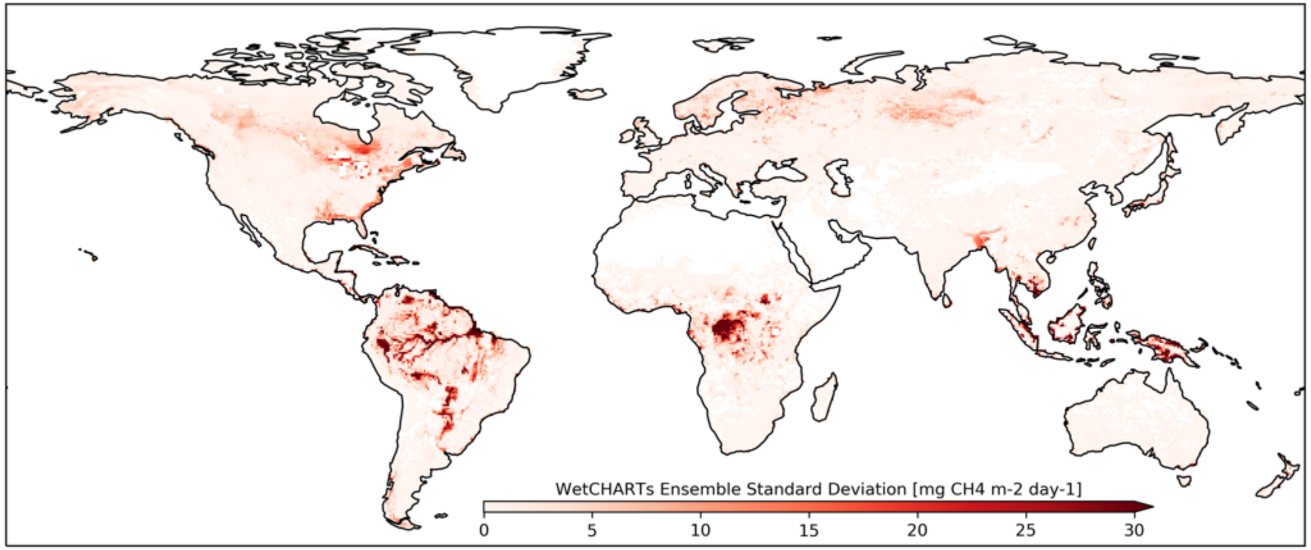
- Correlation shows GOSAT vs each ensemble member
- Globally the GLWD-constrained ensemble members (i.e. xxx3) seem to correlate best to observations
- Correlation of ensemble members against each other is useful for determining sensitivity to different constraints
- Scaling of total global emissions is most obvious driver of differences between ensemble members, with the medium value of 166 Tg/year performing best



Global Wetland Locations

- We choose geographic areas to concentrate on based on a static wetland database (SWAMP)
- The standard deviation of the 18-member WetCHARTs ensemble shows (as expected) that many of these regions have a large spread across the ensemble
- The **objective** is to begin investigating these regions and to **diagnose what is driving this variability** within the ensemble and to **evaluate which members perform best against observations**





Model-GOSAT Correlation for Different Regions

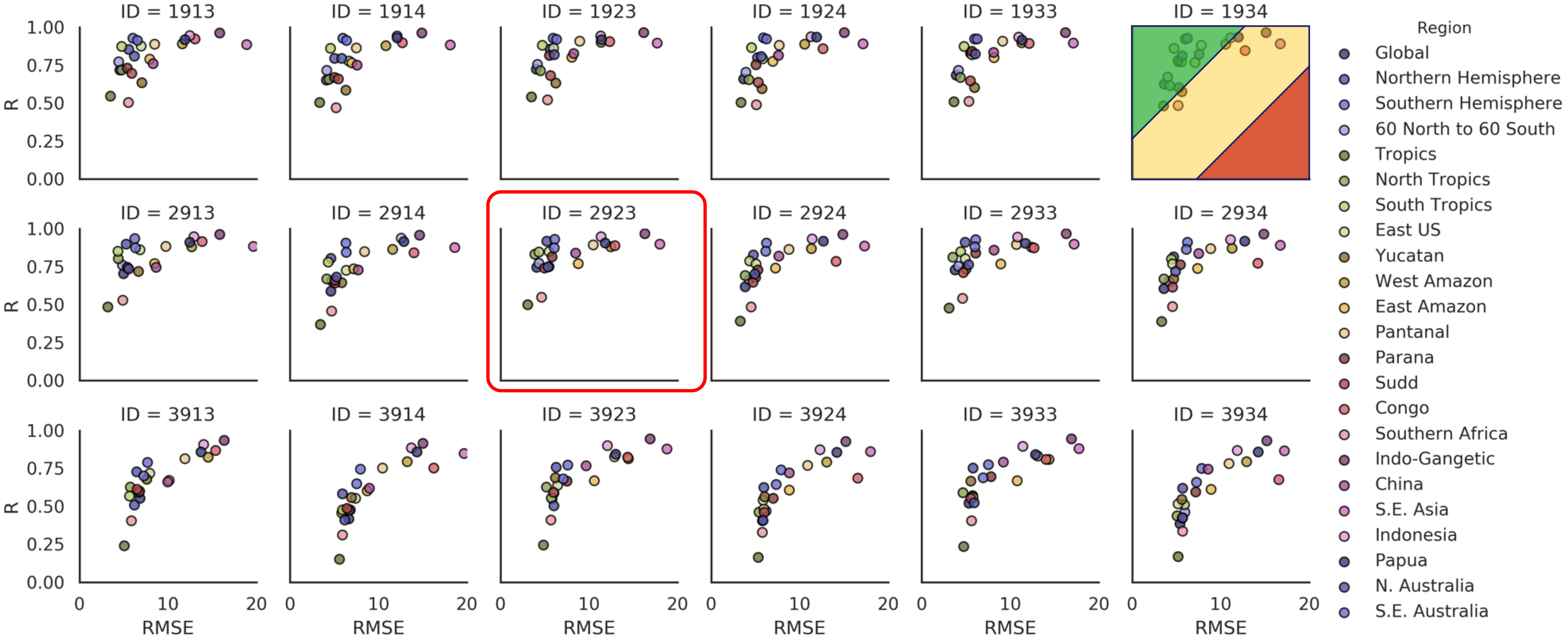
- Correlations between Model ensemble members and GOSAT for different regions
- Some interesting patterns starts to emerge:
  - As we saw on previous slide, the **GLWD-constrained** members not only do better globally but do better for majority of regions (very evident over Sudd, Parana, East US, Yucatan, etc)
  - Ensemble members scaled to a high global total (3xxx) do **particularly poorly** but more so in the Southern Hemisphere
  - The **medium scaling** (2xxx) seems to do the best for most regions

	Global	Northern Hemisphere	Southern Hemisphere	60 North to 60 South	Tropics	North Tropics	South Tropics	East US	Yucatan	West Amazon	East Amazon	Pantanal	Parana	Sudd	Congo	Southern Africa	Indo-Gangetic	China	S.E. Asia	Indonesia	Papua	N. Australia	S.E. Australia
1913	0.72	0.86	0.93	0.77	0.55	0.72	0.87	0.88	0.64	0.89	0.79	0.89	0.73	0.7	0.92	0.51	0.96	0.76	0.89	0.95	0.92	0.81	0.91
1914	0.65	0.8	0.93	0.72	0.51	0.66	0.86	0.78	0.59	0.88	0.77	0.87	0.67	0.66	0.9	0.47	0.96	0.75	0.88	0.94	0.93	0.8	0.91
1923	0.73	0.86	0.93	0.76	0.54	0.71	0.88	0.86	0.63	0.9	0.8	0.91	0.82	0.68	0.91	0.52	0.97	0.83	0.9	0.94	0.92	0.82	0.92
1924	0.66	0.8	0.93	0.7	0.51	0.65	0.87	0.79	0.6	0.89	0.78	0.88	0.75	0.64	0.86	0.49	0.97	0.82	0.89	0.94	0.94	0.81	0.92
1933	0.69	0.83	0.92	0.72	0.51	0.67	0.88	0.82	0.6	0.9	0.8	0.91	0.84	0.65	0.89	0.51	0.97	0.84	0.9	0.94	0.92	0.83	0.92
1934	0.63	0.77	0.92	0.67	0.48	0.62	0.86	0.77	0.58	0.89	0.77	0.88	0.78	0.6	0.85	0.48	0.96	0.82	0.89	0.93	0.93	0.81	0.93
2913	0.71	0.9	0.94	0.76	0.49	0.8	0.85	0.86	0.72	0.88	0.77	0.89	0.75	0.75	0.92	0.53	0.96	0.75	0.88	0.95	0.91	0.74	0.88
2914	0.59	0.81	0.91	0.66	0.37	0.67	0.78	0.73	0.65	0.86	0.74	0.85	0.64	0.66	0.84	0.46	0.96	0.73	0.88	0.94	0.92	0.68	0.85
2923	0.75	0.92	0.93	0.77	0.5	0.83	0.85	0.85	0.75	0.88	0.77	0.9	0.82	0.74	0.89	0.55	0.97	0.84	0.9	0.95	0.91	0.75	0.88
2924	0.62	0.83	0.91	0.67	0.39	0.69	0.79	0.77	0.68	0.87	0.74	0.87	0.73	0.65	0.79	0.49	0.96	0.82	0.89	0.93	0.92	0.7	0.85
2933	0.73	0.91	0.93	0.75	0.48	0.81	0.85	0.8	0.73	0.88	0.77	0.9	0.84	0.71	0.88	0.54	0.97	0.86	0.9	0.95	0.9	0.76	0.88
2934	0.61	0.82	0.91	0.65	0.39	0.67	0.8	0.77	0.67	0.87	0.74	0.87	0.76	0.62	0.77	0.49	0.97	0.84	0.89	0.93	0.92	0.72	0.87
3913	0.55	0.73	0.79	0.59	0.24	0.63	0.57	0.72	0.68	0.82	0.67	0.81	0.6	0.61	0.87	0.41	0.93	0.66	0.86	0.91	0.86	0.51	0.7
3914	0.42	0.58	0.74	0.48	0.15	0.46	0.48	0.55	0.56	0.79	0.6	0.75	0.47	0.49	0.75	0.31	0.92	0.62	0.85	0.89	0.86	0.41	0.65
3923	0.55	0.76	0.77	0.59	0.24	0.63	0.56	0.64	0.69	0.81	0.67	0.83	0.67	0.59	0.82	0.41	0.94	0.77	0.88	0.9	0.84	0.51	0.68
3924	0.41	0.63	0.74	0.47	0.17	0.46	0.49	0.54	0.56	0.79	0.61	0.77	0.55	0.46	0.69	0.33	0.93	0.72	0.86	0.87	0.85	0.41	0.64
3933	0.52	0.75	0.78	0.57	0.24	0.59	0.57	0.56	0.67	0.81	0.67	0.83	0.7	0.55	0.81	0.41	0.95	0.79	0.88	0.89	0.84	0.52	0.69
3934	0.39	0.62	0.75	0.46	0.17	0.44	0.51	0.52	0.55	0.79	0.61	0.78	0.59	0.42	0.68	0.34	0.93	0.75	0.86	0.87	0.86	0.43	0.66

Correlation To Detrended GOSAT Proxy XCH_4 (colour scale: 0.64, 0.72, 0.80, 0.88, 0.96)

Correlation vs RMSE

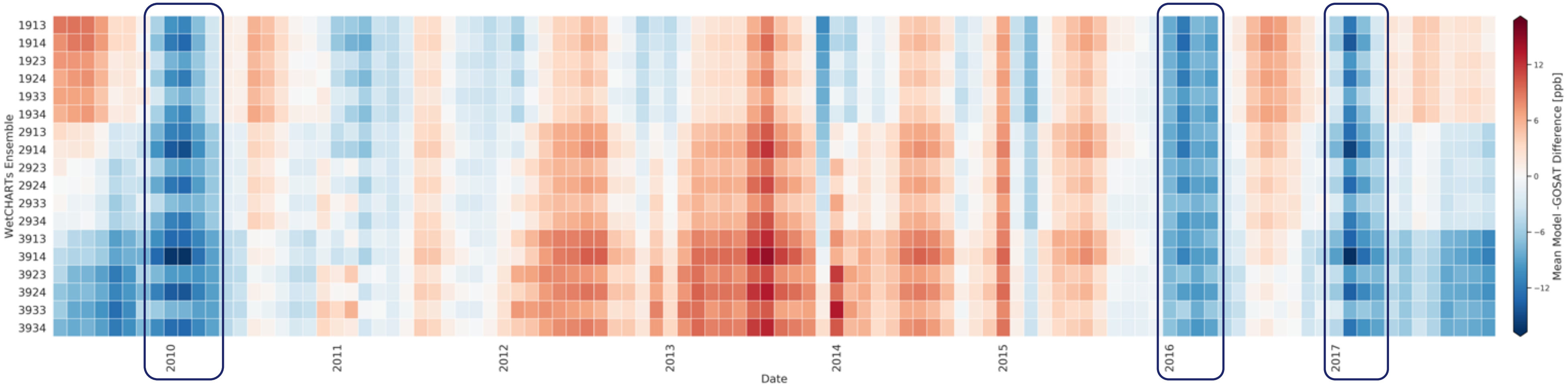
High Correlation and Low RMSE = Good

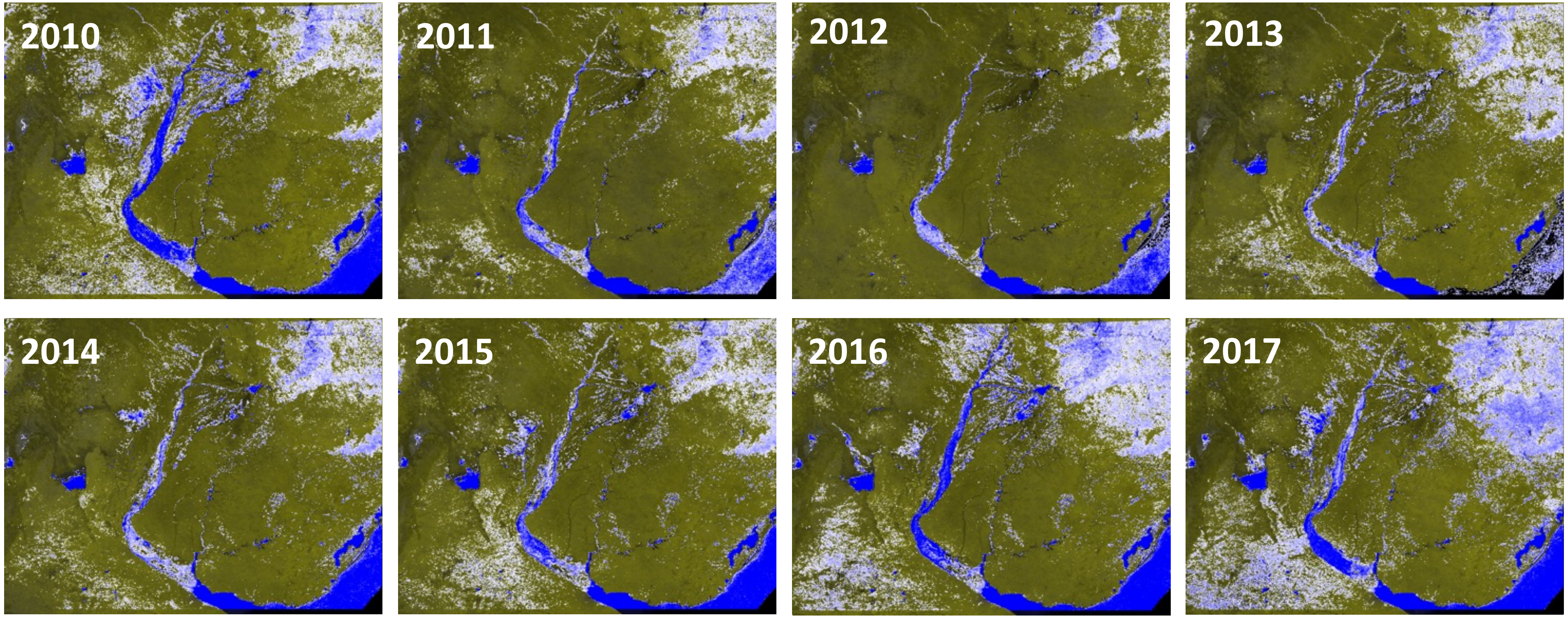


- Correlation coefficient **on it's own** is not a good metric though….
- Also use **root mean square error** (RMSE) of Model-GOSAT differences and examine the two **together**

Parana River

- Previous study (Parker et al., 2018) saw **big discrepancy in early 2010** but data stopped in 2015
- Attributed to **overbank inundation** driven by ENSO
- Can we explain 2016/2017?
- MODIS imagery shows **very significant** flooding in 2016
- Behaviour in 2017 is slightly different in the visible but **significantly increased wetland extent** clearly apparent in NDWI

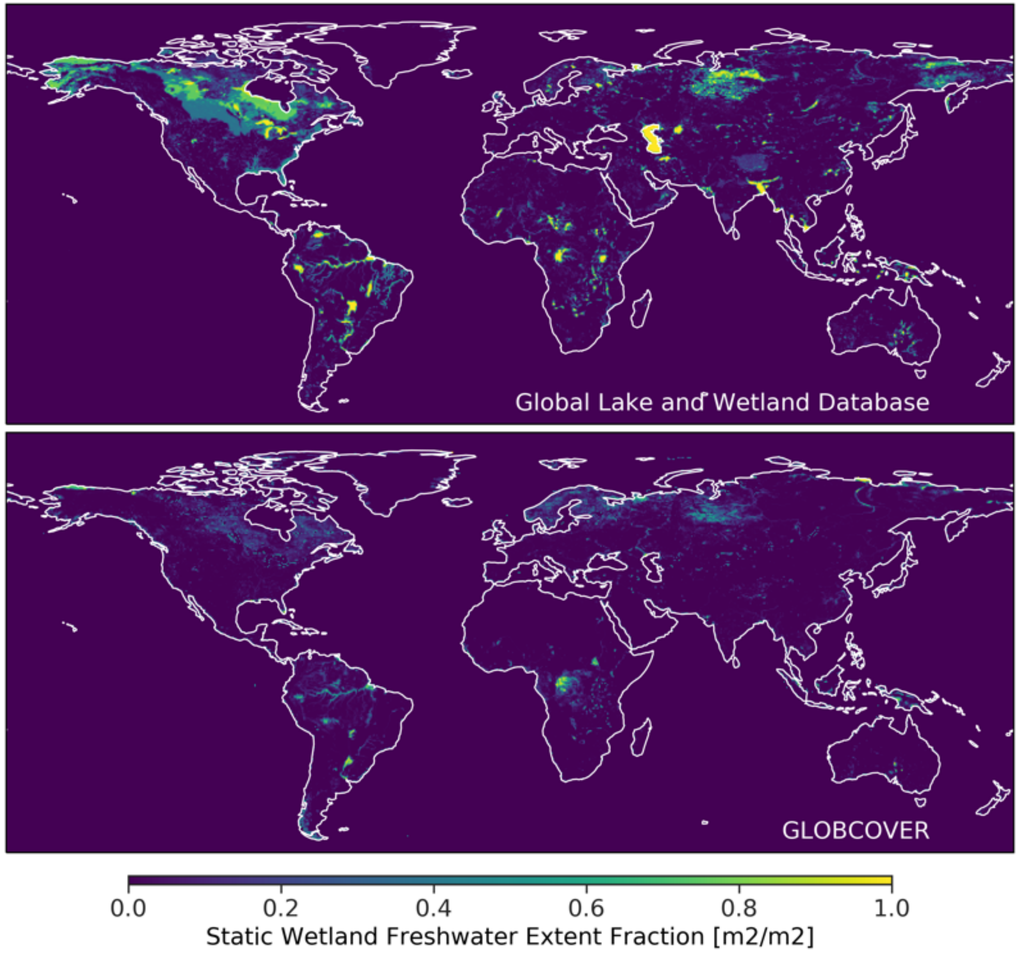




Parana – Wetland Extent

	GOSAT Proxy XCH_4	1913	1914	1923	1924	1933	1934	2913	2914	2923	2924	2933	2934	3913	3914	3923	3924	3933	3934
GOSAT Proxy XCH_4	1	0.73	0.67	0.82	0.75	0.84	0.78	0.75	0.64	0.82	0.73	0.84	0.76	0.6	0.47	0.67	0.55	0.7	0.59
1913	0.73	1	0.99	0.98	0.99	0.96	0.98	0.85	0.8	0.79	0.77	0.77	0.77	0.55	0.47	0.5	0.45	0.49	0.46
1914	0.67	0.99	1	0.95	0.99	0.93	0.97	0.85	0.82	0.76	0.78	0.73	0.76	0.56	0.5	0.48	0.46	0.46	0.46
1923	0.82	0.98	0.95	1	0.99	1	0.99	0.87	0.8	0.85	0.81	0.85	0.82	0.6	0.49	0.59	0.51	0.59	0.53
1924	0.75	0.99	0.99	0.99	1	0.97	1	0.87	0.83	0.83	0.82	0.81	0.82	0.6	0.52	0.56	0.51	0.55	0.53
1933	0.84	0.96	0.93	1	0.97	1	0.98	0.86	0.78	0.86	0.81	0.86	0.83	0.6	0.48	0.6	0.51	0.62	0.54
1934	0.78	0.98	0.97	0.99	1	0.98	1	0.87	0.82	0.84	0.82	0.83	0.83	0.59	0.51	0.57	0.52	0.57	0.54
2913	0.75	0.85	0.85	0.87	0.87	0.86	0.87	1	0.98	0.97	0.98	0.94	0.97	0.91	0.85	0.87	0.84	0.85	0.84
2914	0.64	0.8	0.82	0.8	0.83	0.78	0.82	0.98	1	0.93	0.98	0.89	0.95	0.92	0.9	0.85	0.87	0.82	0.85
2923	0.82	0.79	0.76	0.85	0.83	0.86	0.84	0.97	0.93	1	0.98	1	0.98	0.91	0.83	0.92	0.87	0.92	0.88
2924	0.73	0.77	0.78	0.81	0.82	0.81	0.82	0.98	0.98	0.98	1	0.96	1	0.94	0.9	0.92	0.91	0.9	0.92
2933	0.84	0.77	0.73	0.85	0.81	0.86	0.83	0.94	0.89	1	0.96	1	0.97	0.89	0.8	0.92	0.86	0.93	0.88
2934	0.76	0.77	0.76	0.82	0.82	0.83	0.83	0.97	0.95	0.98	1	0.97	1	0.92	0.87	0.92	0.9	0.91	0.92
3913	0.6	0.55	0.56	0.6	0.6	0.6	0.59	0.91	0.92	0.91	0.94	0.89	0.92	1	0.98	0.97	0.98	0.95	0.97
3914	0.47	0.47	0.5	0.49	0.52	0.48	0.51	0.85	0.9	0.83	0.9	0.8	0.87	0.98	1	0.93	0.98	0.89	0.96
3923	0.67	0.5	0.48	0.59	0.56	0.6	0.57	0.87	0.85	0.92	0.92	0.92	0.92	0.97	0.93	1	0.98	1	0.98
3924	0.55	0.45	0.46	0.51	0.51	0.51	0.52	0.84	0.87	0.87	0.91	0.86	0.9	0.98	0.98	0.98	1	0.96	1
3933	0.7	0.49	0.46	0.59	0.55	0.62	0.57	0.85	0.82	0.92	0.9	0.93	0.91	0.95	0.89	1	0.96	1	0.97
3934	0.59	0.46	0.46	0.53	0.53	0.54	0.54	0.84	0.85	0.88	0.92	0.88	0.92	0.97	0.96	0.98	1	0.97	1

Correlation (0.5 – 1.0)



- Using GLWD as wetland extent constraint (i.e. xxx3) along with higher q10 value (i.e. xx2x and xx3x) gives **best correlation and smallest RMSE** against observations
- Shows importance of constraint on **wetland extent** – only GLWD can put emissions along length of river
- But still not representing the **process** of flooding, but does at least capture the local precipitation effect

Summary

- We now have a really interesting dataset of Global Chemistry Transport model simulations driven by a large ensemble of WetCHARTs data
- Starting to exploit this dataset by comparing to GOSAT observations to evaluate which factors are most important in matching the observed CH_4 distributions
- Analysis is ongoing and lots of interesting features and patterns to digest!
- In general WetCHARTs **performs very well**, capturing the **correct phase and magnitude** of wetland CH4 emissions over many regions
- Ensemble member **2923** seems to perform the best against observations
- The Parana river region which we focused on heavily in Parker et al., 2018 continues to be of interest as 2016/2017 show **strong anomalies consistent with increased wetland extent**
- The wetland mask (GLWD vs GLOBCOVER) makes a big difference to how well the emissions can match observations with **GLWD performing much better**
- However, WetCHARTs relies on precipitation to drive wetland extent and has **no knowledge of hydrology** (i.e. input from upstream) and hence even with a good wetland mask it will **struggle to reproduce anomalous events** (such as those observed in 2010, 2016, 2017) over the Parana

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Heterotrophic Respiration Model	MsTMIP Models		CARDAMOM	
C	**1**	**2**	**3**	
Temperature Dependence	q10 = 1	**q10 = 2**	q10 = 3	
D	**1**	**2**	**3**	**4**
Extent Parameterisation	SWAMPS & GLWD	SWAMPS & GLOBCOVER	**PREC & GLWD**	PREC & GLOBCOVER