GHG-CCI satellite XCO_2: comparisons with global models

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GHG-CCI Splinter Session: Model-data comparisons

ESRIN, Frascati, Italy

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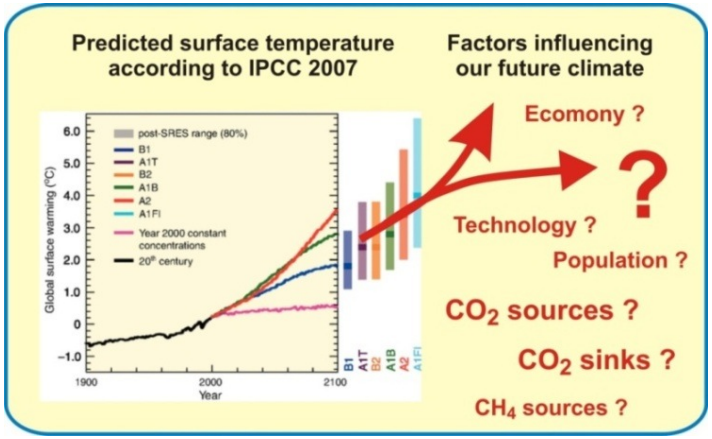
ECV GHG

CO_2 and CH_4 – two most important anthropogenic GHGs.



Reliable climate prediction requires good understanding of natural and anthropogenic (surface) CO_2 and CH_4 sources and sinks:

- Distribution?
- Magnitude?
- Climate change response?

Better understanding requires appropriate global observations and (inverse) modelling.

ECV GHG

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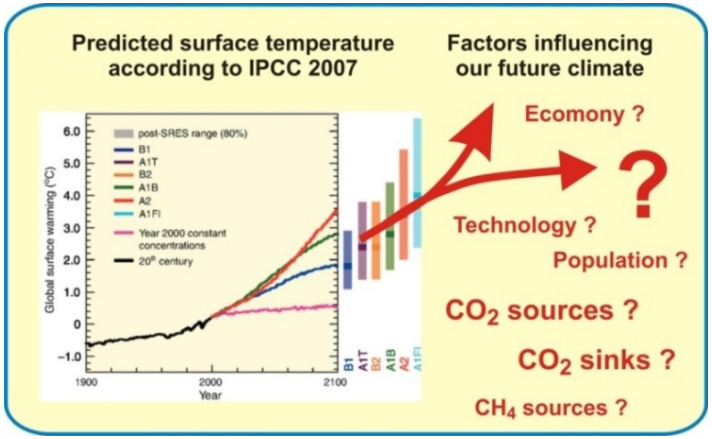

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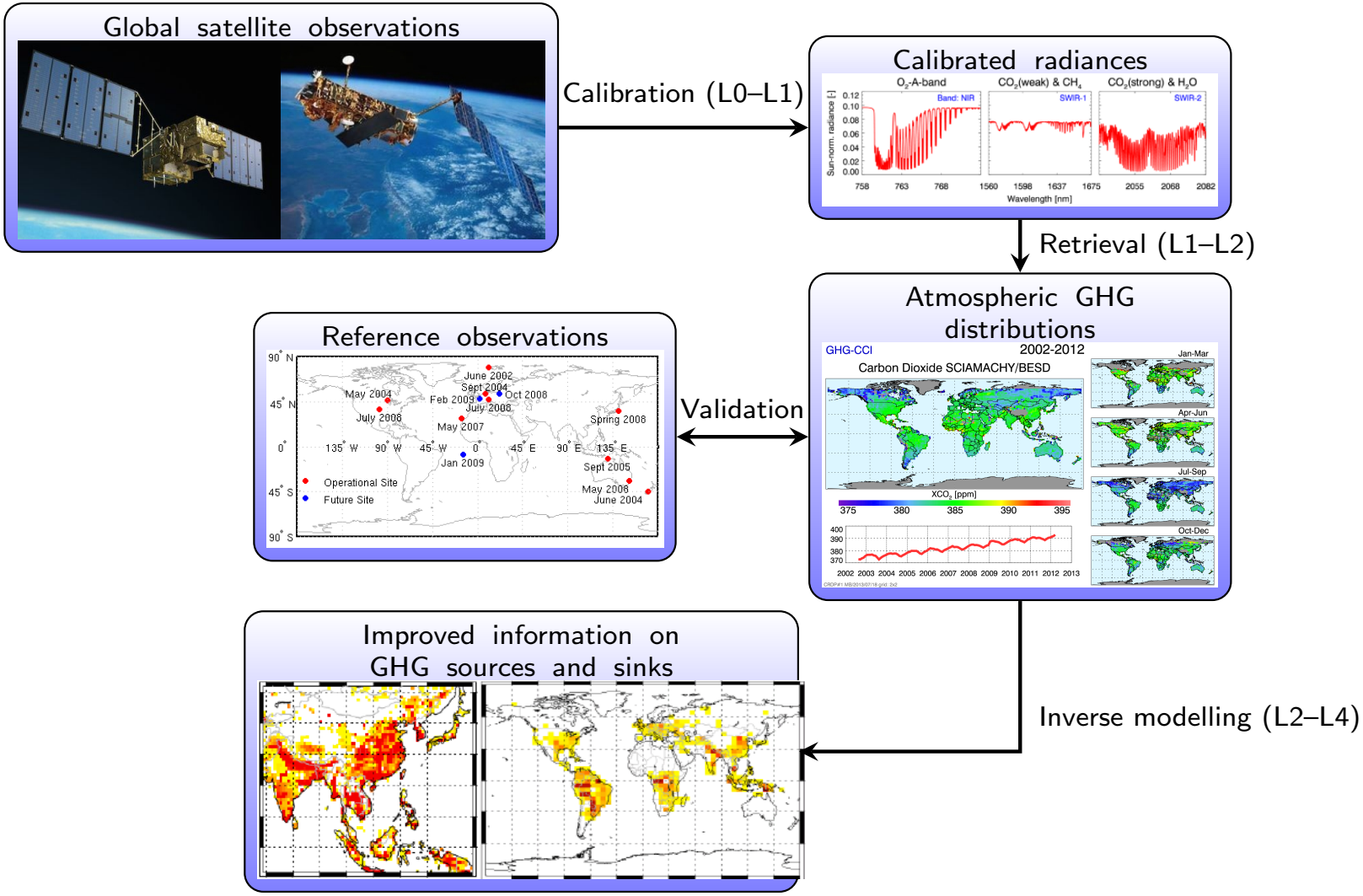
ECV GHG

Global distribution of atmospheric GHGs CO_2 and CH_4, of sufficient quality to estimate regional sources and sinks.

Retrieval procedure



Small XCO_2 column gradients (column averaged CO_2 dry air mole fraction)):

- High precision to resolve small CO_2 source / sink (0.2–0.3%) variations.
- High accuracy essential to avoid regional-scale biases (<0.15%).

GHG-CCI ECV products

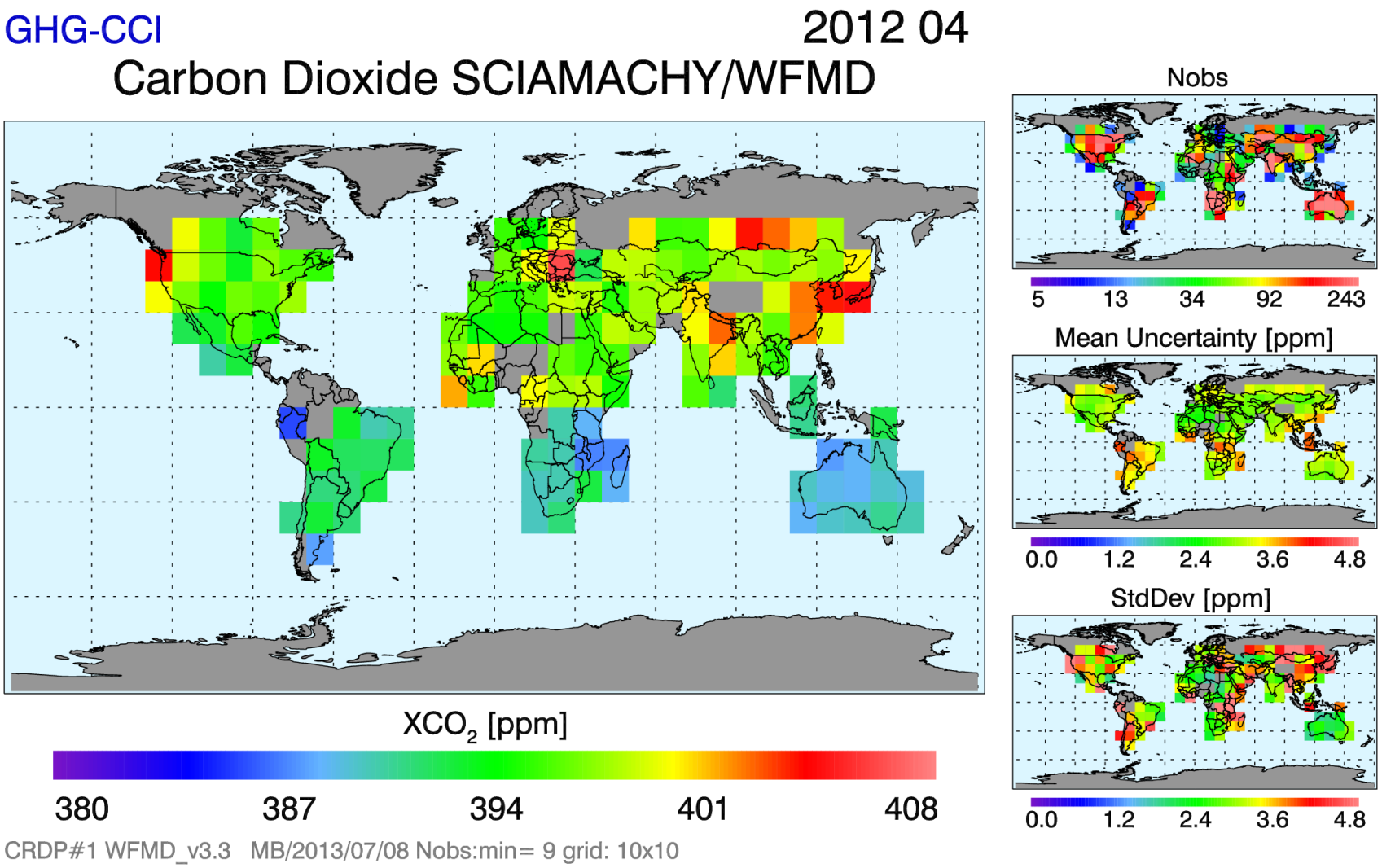
Algorithm ID	Type	Data product	Institution / algorithm
CO2_SCI_BESD	ECA	XCO_2 from SCIAMACHY	IUP, Univ. Bremen, FP algorithm BESD
CO2_SCI_WFMD	ECA	XCO_2 from SCIAMACHY	IUP, Univ. Bremen, PR algorithm WFM-DOAS
CO2_GOS_OCFP	ECA	XCO_2 from GOSAT	Univ.Leicester (ULE), FP algorithm (OCO algo.)
CO2_GOS_SRFP	ECA	XCO_2 from GOSAT	SRON, FP algorithm of SRON
CH4_SCI_WFMD	ECA	XCH_4 from SCIAMACHY	IUP, Univ. Bremen, PR algorithm WFM-DOAS
CH4_SCI_IMAP	ECA	XCH_4 from SCIAMACHY	SRON, PR algorithm IMAP
CH4_GOS_OCFP	ECA	XCH_4 from GOSAT	Univ.Leicester (ULE), FP algorithm (adjusted OCO algo.)
CH4_GOS_SRPR	ECA	XCH_4 from GOSAT	SRON, PR algorithm for GOSAT XCH_4
CH4_GOS_SRFP	ECA	XCH_4 from GOSAT	SRON, FP algorithm for GOSAT XCH_4

Table S-1: Overview GHG-CCI ECV Core Algorithms (ECAs).

GHG-CCI ECV products

Current estimates of achieved data quality: XCO_2 (in ppm)					
Sensor	**Algorithm**	**Precision** **Single observation**	**Precision** **Regional / monthly**	**Relative accuracy**	**Method / comments**
SCIAMACHY	BESD v01.00.01	2.5 2.3	NA 1.5	0.8 0.9	DP (IUP, Section 7.1) EMMA (Section 12.5)
SCIAMACHY	WFMD v2.2	3.8 4.4	1.6 2.0	0.8 1.3	DP (IUP, Section 7.2) EMMA (Section 12.5)
GOSAT	OCFP v3.0	2.7 2.3	0.2 1.6	0.8 0.8	DP (ULE, Section 7.3) EMMA (Section 12.5)
GOSAT	SRFP v1.1	2.6 2.5	NA 1.0	1.0 0.9	DP (SRON, Section 7.4) EMMA (Section 12.5)
SCIAMACHY and GOSAT	EMMA v1.3a	3.1	0.8	0.8	EMMA (Section 12.5)
	Required:	< 8.0	< 1.3	< 0.5	**/URD GHG-CCI v1/**

GHG-CCI ECV products



Model – satellite comparisons

Considerations for direct comparison of satellite and model data:

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Apply averaging kernel A to model output (x_{model}) to simulate instrument sensitivity to atmosphere x_a:

$$X = X_a + A(x_{model} - x_a) \tag{1}$$

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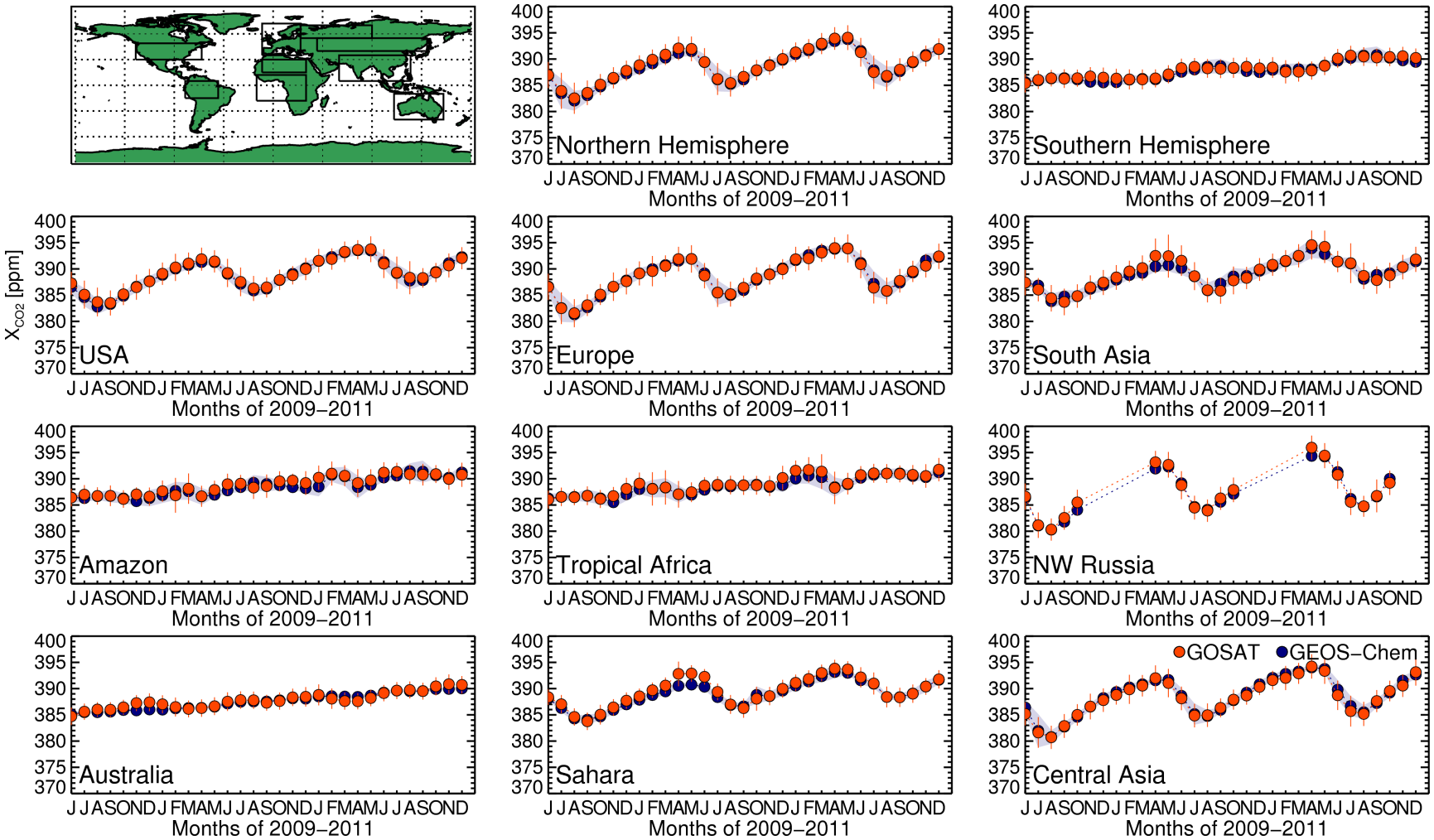
Spatio-temporal interpolation beteen grids.
Vertical interpolation especially careful, model and retrieval on different grids:

- Interpolation of VMR will not maintain total column.
- Layer vs level.

Satellite assessment

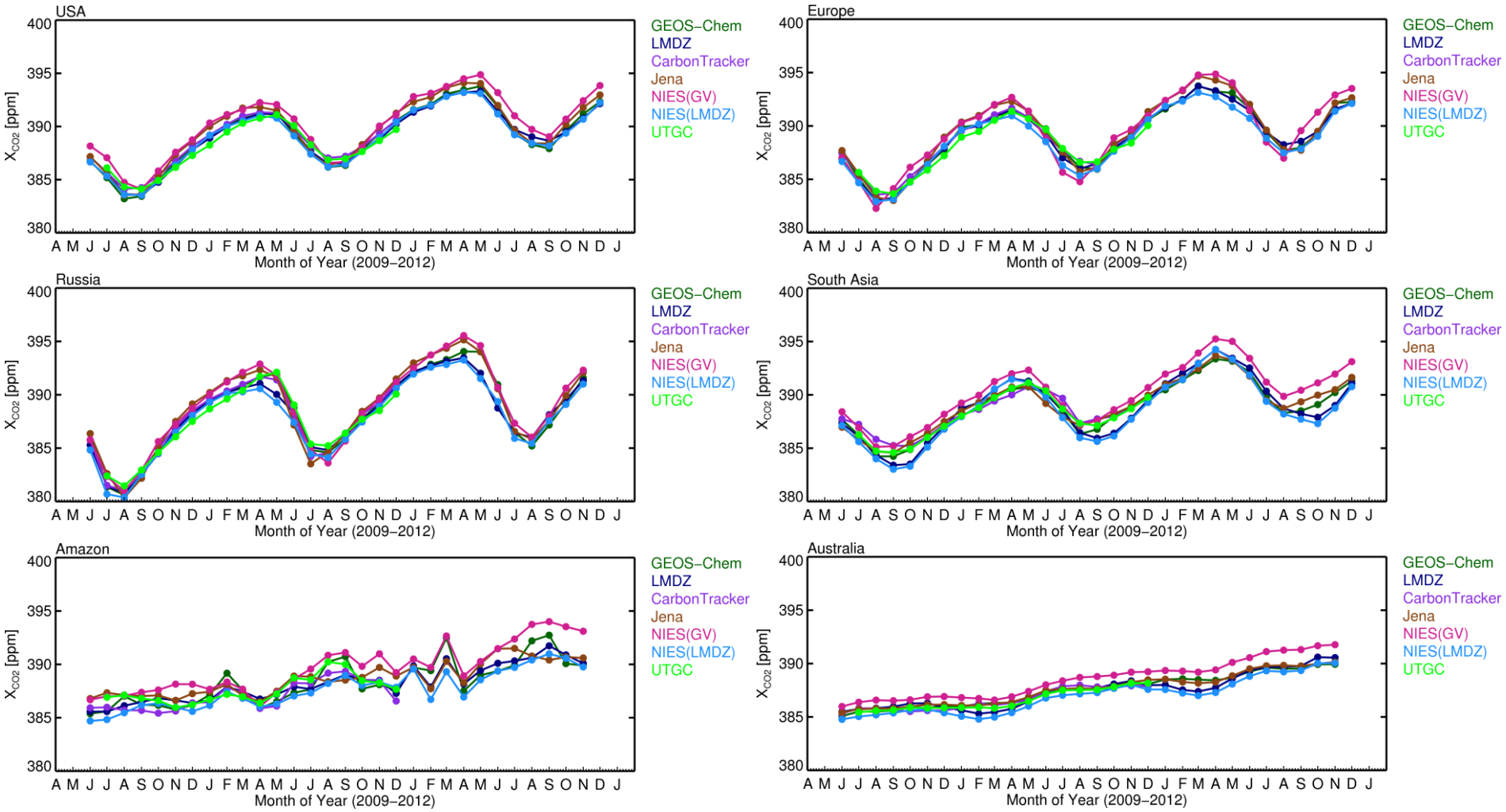
UoL GOSAT FP (obs.) vs. Edinburgh GEOS-Chem (model)



Max. model–data Δ in regions where both models and satellite data are uncertain (no validation; high cirrus + aerosols loads).

Model assessment – ensemble

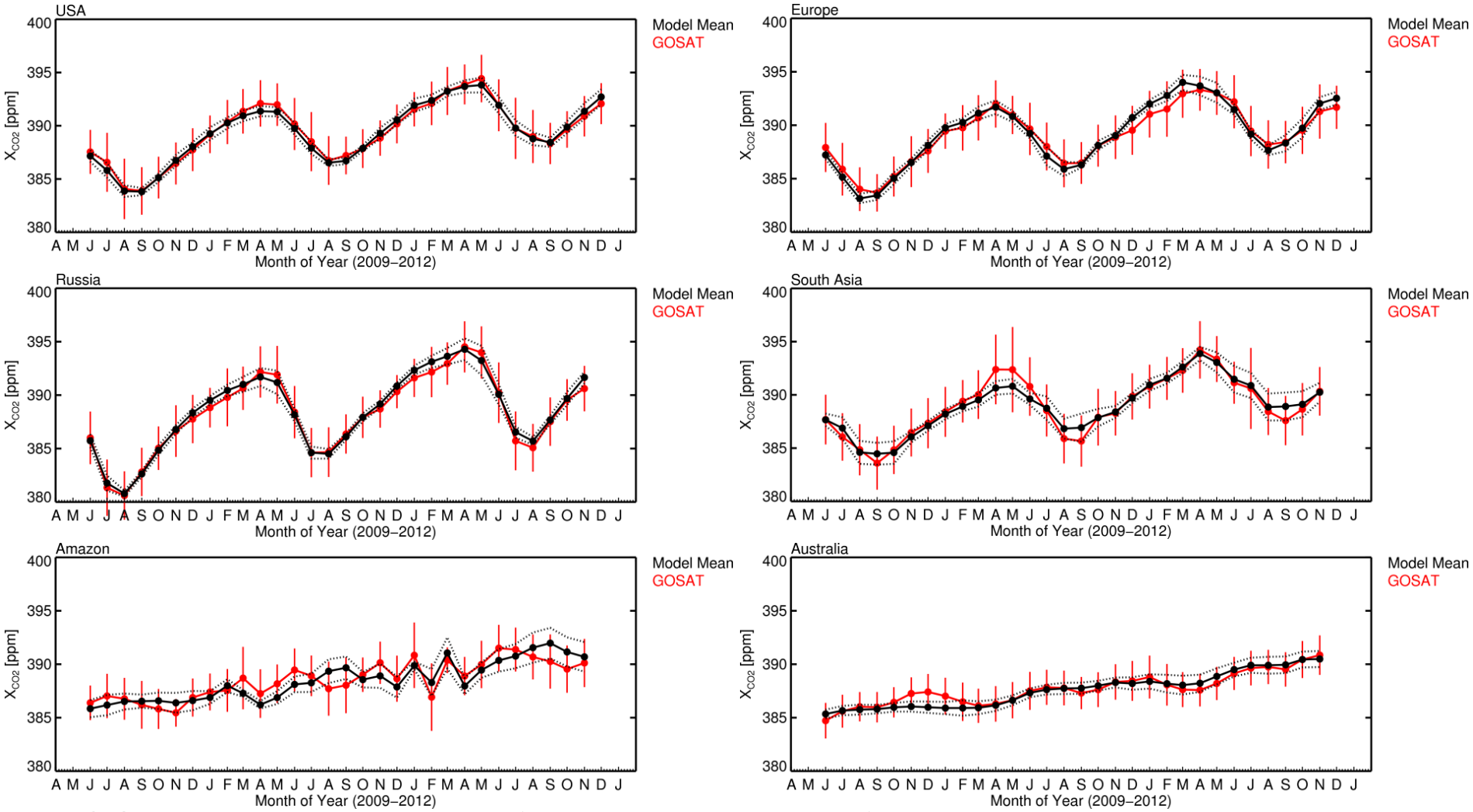
Sampled for satellite location, AKs applied.



Note large spread between models

Model assessment – satellite

UoL GOSAT FP vs. model ensemble mean



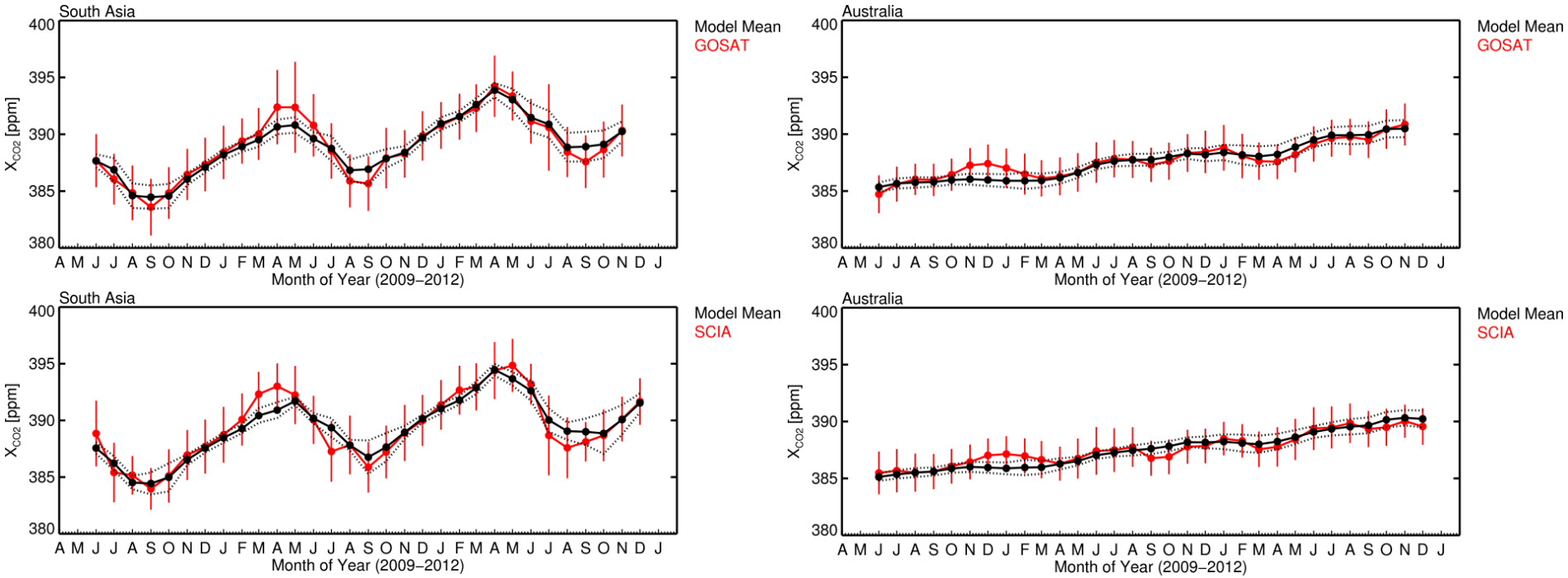
GOSAT – model mean Δ comparable to Δ between individual models and model mean

Model assessment – satellite

UoL GOSAT FP and IUP Bremen SCIAMACHY FP vs. model ensemble mean

S. Asia: Stronger annual cycle or bias in Satellite data?

Australia: Influence of Indonesian fires?



Satellite datasets agree on locations and time of uncertainty... capturing events missed by models?

EMMA – retrieval ensemble

Ensemble median algorithm (EMMA) combines individual soundings of 7 ECAs into one new data set.

Takes advantage of ECAs' independent developments, less influenced by regional and temporal biases of individual algorithms.

Reuter et al., ACP 13-4, 2013:
http://dx.doi.org/10.5194/acp-13-1771-2013

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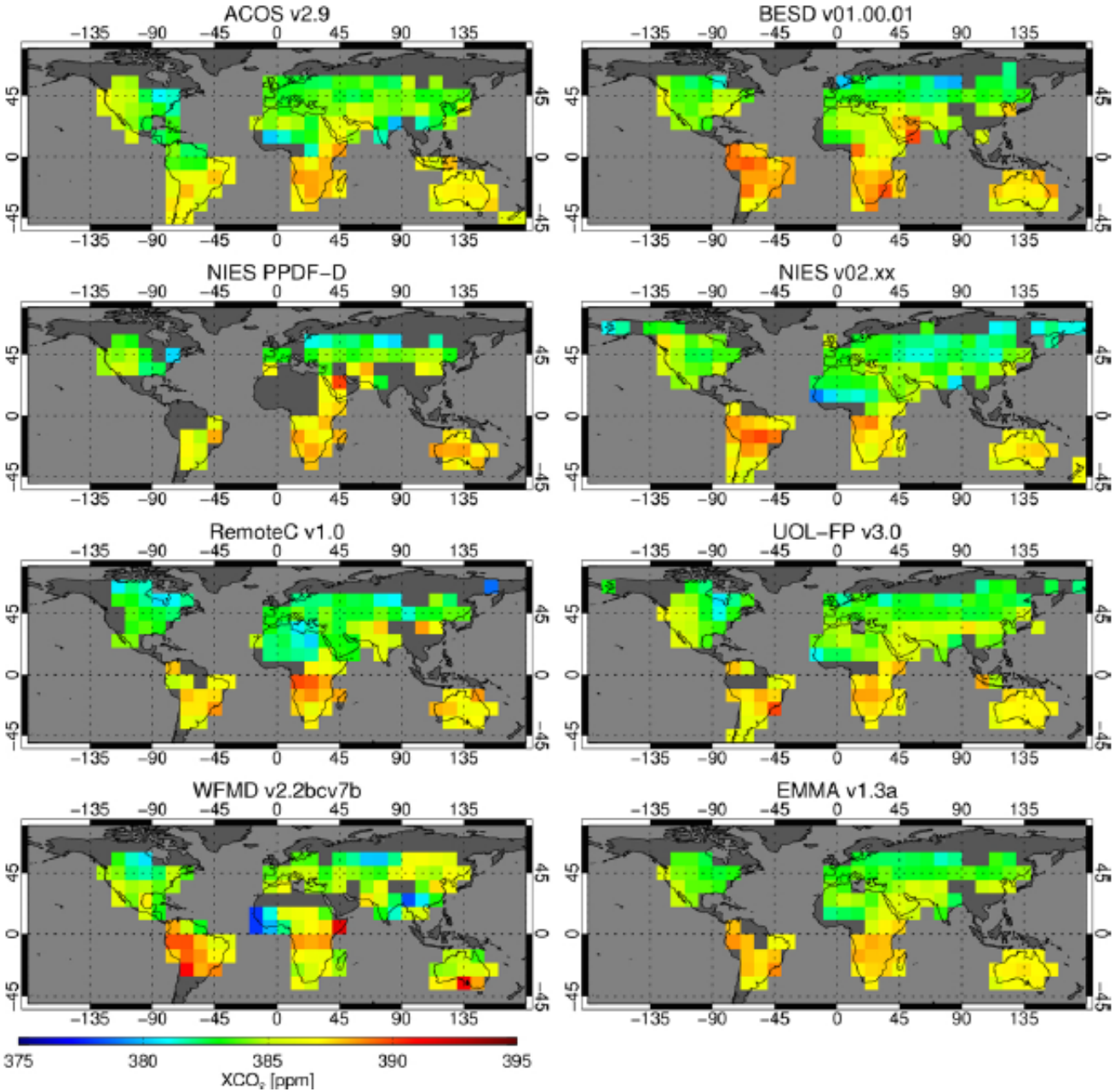

EMMA – retrieval ensemble

Regional bias - ensemble spreads (std. dev. of algorithms) <1 ppm, rising to 2 ppm in Tropics and East Asia.

EMMA tends to better agree with validation data (TCCON).

Summary

Many geographical regions where models are poorly constrained by surface measurements:

- Models might not well reproduce regional carbon cycle and year-to-year variations, or miss specific events.

Satellite XCO_2 data should help to assess and improve models if they have sufficient accuracy and can be properly validated for these regions.

CO_2 models show good consistency (with notable regional differences).
Model data represents a reasonable dataset for testing satellite column data.