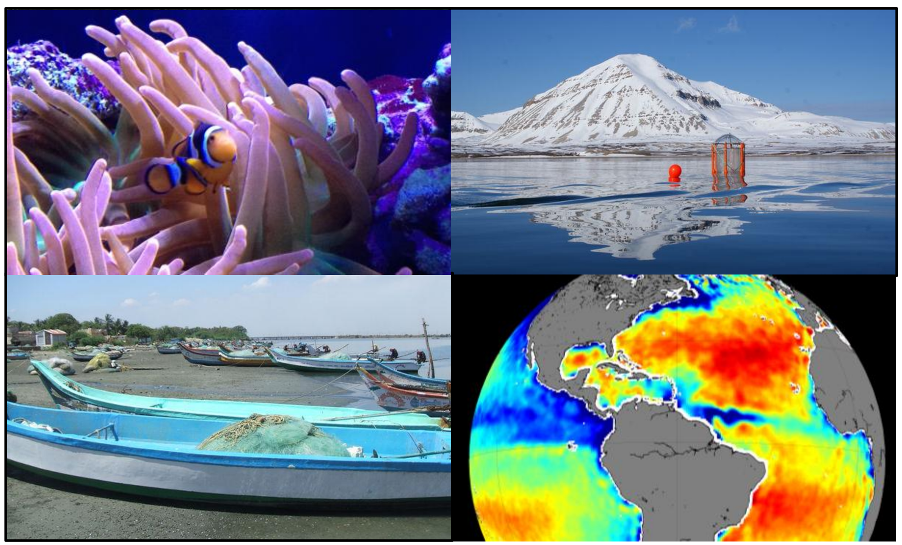
The other CO_2 problem from a different angle: Studying Ocean Acidification using satellite Earth observation

Jamie Shutler, Fanny Girard-Ardhuin, Peter Land, Helen Findlay, Roberto Sabia, Ian Ashton, Bertrand Chapron, Jean-Francois Piolle, Antoine Grouazel, Nicolas Reul, Yves Quilfen, Joe Salisbury, Doug Vandemark, Richard Bellerby, Punyasloke Bhadury, Ian Ashton



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PML Plymouth Marine Laboratory
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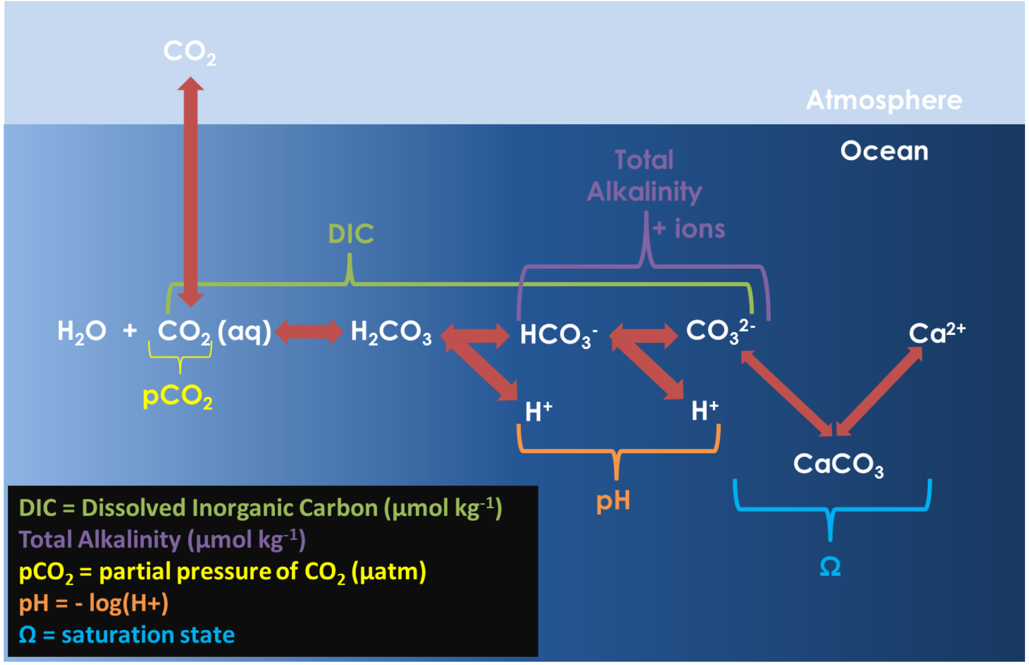
Ocean acidification

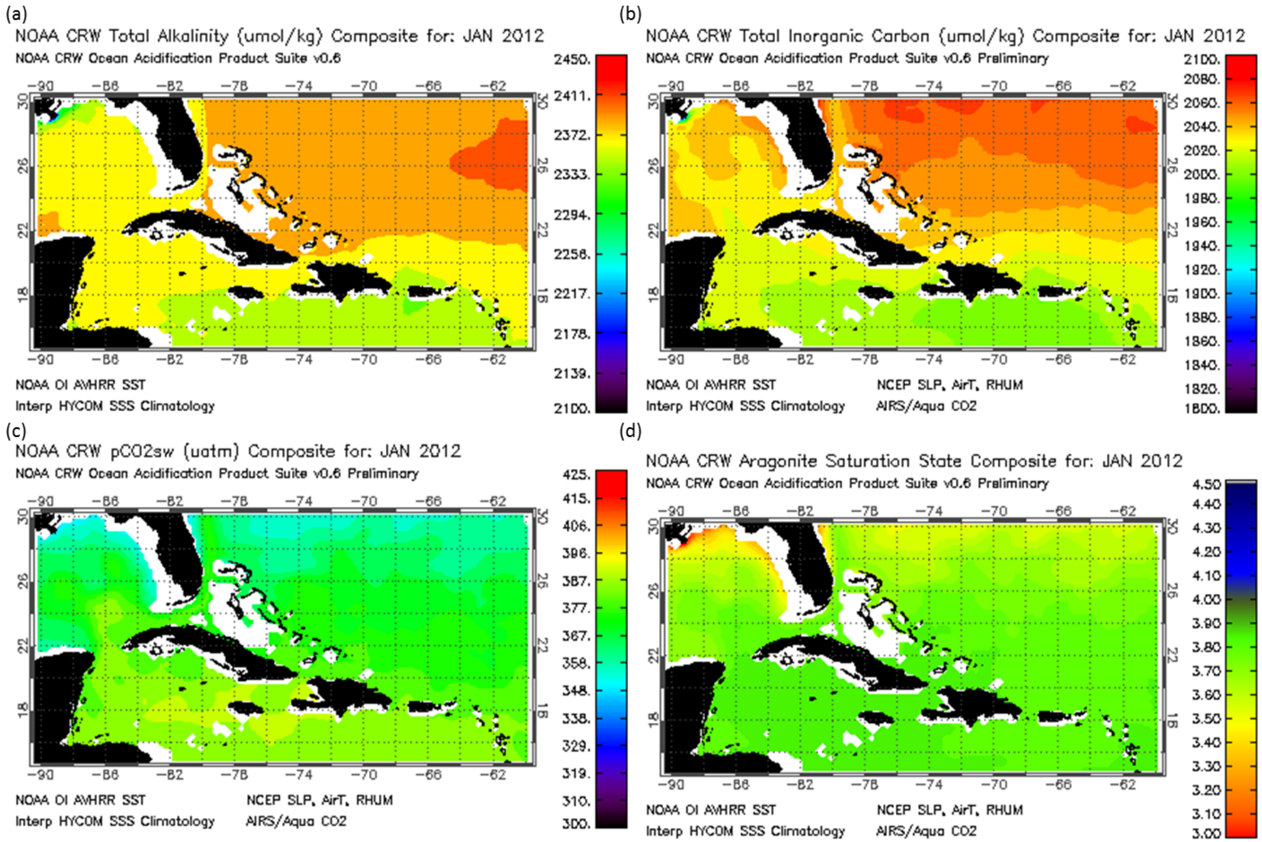


- Oceans annually absorbs ~25% of anthropogenic CO_2 emissions.
- This lowers the pH of sea water and can lead to a decrease in calcium carbonate saturation state, with potential implications for marine animals, especially calcifying organisms.
- Measuring SST and salinity and any two of the four “key” parameters (C_T, A_T, pCO_2 and pH) enables the carbonate system to be monitored.

Ocean acidification

- Understanding of Ocean Acidification has been limited by availability of carbonate system data
- In 2012, OA researchers formed the Global OA Observing Network to bring together datasets, research and resources
- Algorithms using in situ hydrographic, Earth observation and/or model data have been developed
- Increase in data, e.g. from the Ship of Opportunity Programme and data buoys provides opportunity to test algorithms

Ocean acidification



NOAA Ocean Acidification Product Suite (OAPS)

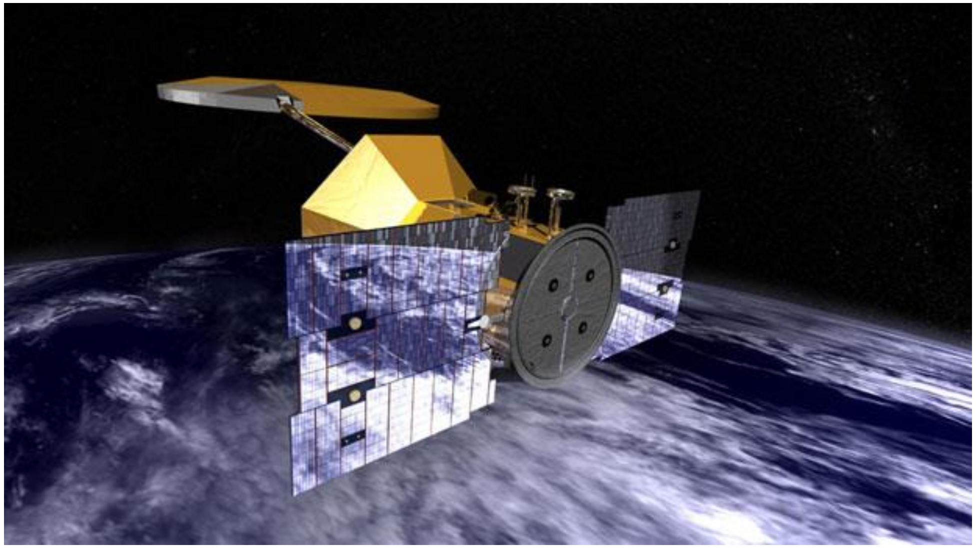
- Many regional OA parameter algorithms exist that use combinations of inputs that could exploit satellite data.

- Are the new satellite salinity data of any use?

Ocean acidification

Measuring sea surface salinity from space

- ESA SMOS and NASA-CONAE Aquarius were launched in 2009 and 2011, both measuring global SSS



Review and forward look paper

Environmental Science & Technology

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Salinity from Space Unlocks Satellite-Based Assessment of Ocean Acidification

Peter E. Land,[*,†] Jamie D. Shutler,[‡] Helen S. Findlay,[†] Fanny Girard-Ardhuin,[§] Roberto Sabia,[∥] Nicolas Reul,[§] Jean-Francois Piolle,[§] Bertrand Chapron,[§] Yves Quilfen,[§] Joseph Salisbury,[⊥] Douglas Vandemark,[⊥] Richard Bellerby,[#] and Punyasloke Bhadury[∇]

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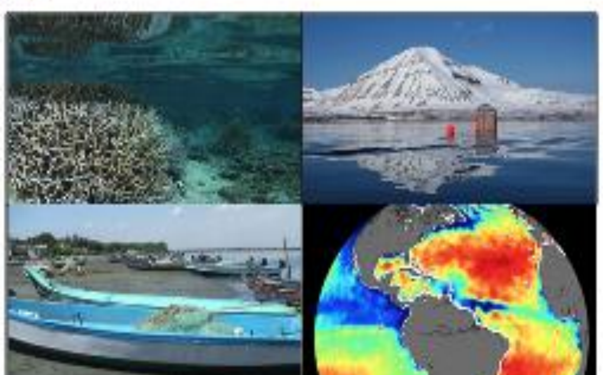

Highlights that salinity from space enables us to monitor and study alkalinity-salinity relationship

Review and forward look paper

Environmental Science & Technology

Feature

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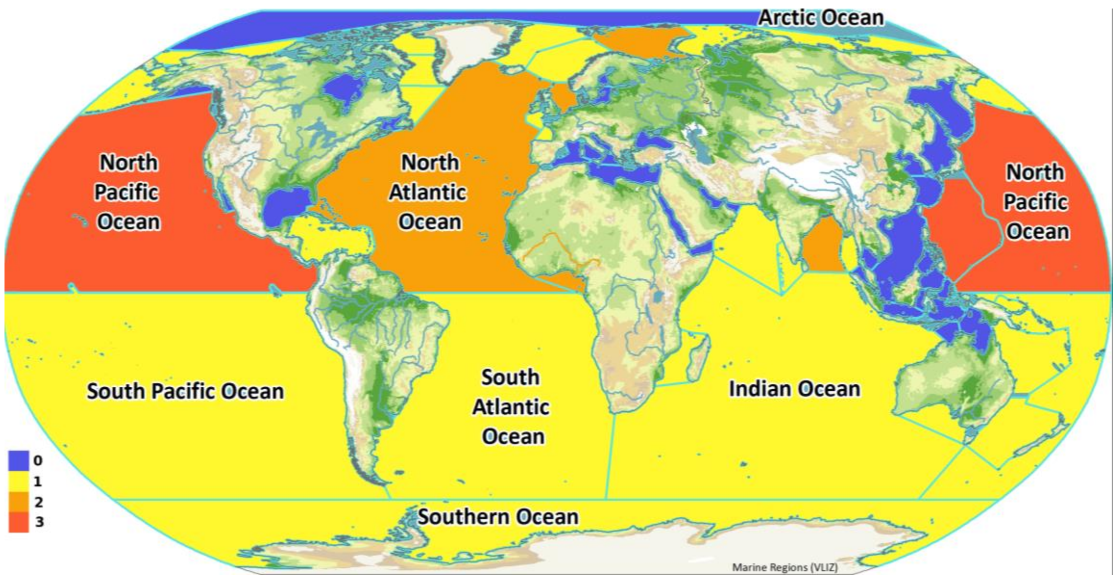
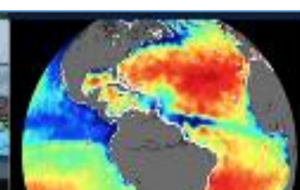
Salinity from Space Unlocks Satellite-Based Assessment of Ocean Acidification

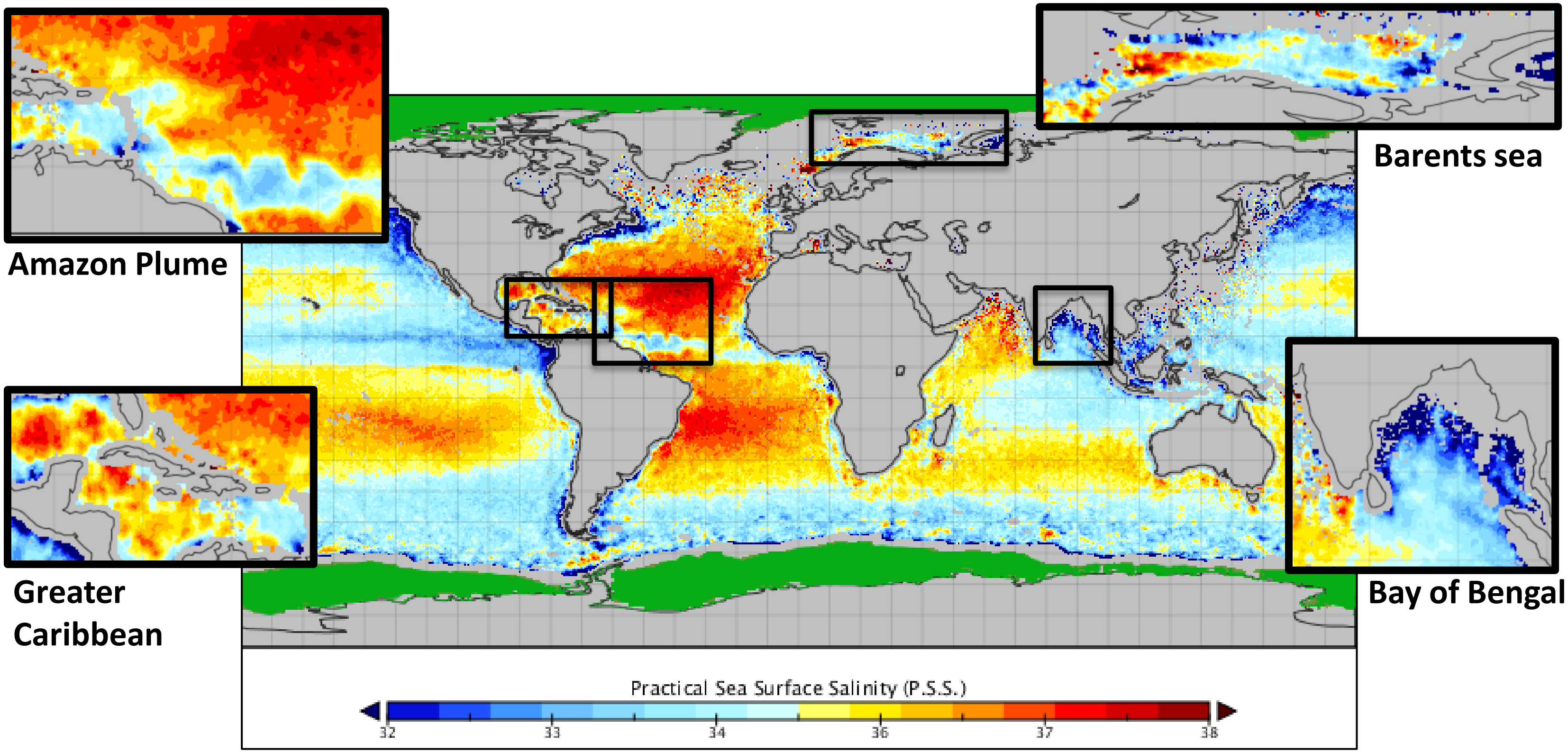




enables us to monitor and study alkalinity-salinity relationship

Case Study Regions

5 regions



Global, SMOS salinity for October 2010 (blue-red)
Sea ice (green)

European Space Agency Pathfinders Ocean Acidification

- Evaluate existing empirical algorithms using satellite, climatological and re-analysed in situ data as inputs.
- Evaluation of algorithms in different regions using all possible inputs and compare to an example Earth System model (HadGEM2-ES).
- Determine if satellite observed inputs outperform, equals or deteriorates performance of empirical algorithms.
- Rank performance to determine optimum algorithm and input (termed model).

European Space Agency Pathfinders Ocean Acidification

- Evaluate existing empirical algorithms using satellite, climatological

Massive data collation and quality control effort

> 100 TB of satellite data from >15 satellite sensors

➢ 14,000,000 *in situ* data

deteriorates performance of empirical algorithms.

- Rank performance to determine optimum algorithm and input (termed model).

Earth observation data

No.	Sensor/name (version)	Spatial resolution (temp. resolution)	Temporal period	Geographic coverage	Parameters	References	Data held
1.	**Cryosat-2 (GlobWave GDR)**	~300 m along track, ~4 km across track (daily, monthly)	2010-present	Global	U10, Ice coverage, Ice thickness	Laxon et al., (2013)	Yes
2.	**SMOS (CATDS v2)**	0.25° × 0.25° (monthly) 0.5° × 0.5° (daily)	2010-present	Global	SSS, U10	Font et al. (2010)	Yes
3.	MERIS (3rd reprocessing)	RR 1km (daily, monthly)	2002-2012	Global	Rrs, chl	Rast et al. (1999)	Yes
4.	MODIS-Aqua (Seadas 7)	1 km, 4 km, 9 km (daily, monthly)	2002-present	Global	Rrs, chl, SST	NASA Ocean colour website oceancolor.gsfc.nasa.gov	Yes
5.	AATSR	1 × 1 km (daily, monthly)	2002-2012	Global	SSTskin	-	Yes
6.	ESA SST CCI (ARC v1.1.1)	0.1° × 0.1° (monthly)	1992-2012	Global	SSTskin, SSTsub	Merchant et al. (2012)	Yes
7.	ESA Ocean Colour CCI (v0.95)	4 × 4 km (daily, monthly)	1997-2012	Global	Rrs, chl	Brewin et al., (2012)	
8.	RA2 (GlobWave GDR)	400 m along track, 80 km across track at equator over 35	2002-2012	Global	U10	www.gobwave.info	Yes

Publically available *In situ* data

No.	Dataset name	Temporal period	Geographic location	Parameters	N	References	Access secured
1.	SOCAT v2.0	2005-2011	Global (incl. CS regions *)	fCO_{2W}, SSS, SST	6,000,000+	Bakker et al. (2013)	Yes
2.	LDEO v2012	1980-present	Global (incl. CS regions *)	pCO_{2W}, SSS, SST	6,000,000+	Takahashi et al. (2013)	Yes
3.	GLODAP	1970-2000	Global	A_T, DIC, SSS, SST, Nitrate	10,000+	Key et al. (2004)	Yes
4.	CARINA AMS v1.2, CARINA ATL v1.0, CARINA SO v1.1	1980-2006	Arctic, Atlantic, Southern Ocean	A_T, DIC, SSS, SST	1500+	CARINA group (2009a) CARINA group (2009b) CARINA group (2010)	Yes
5.	AMT	1995-present	Atlantic	pCO_{2W}, SSS, SST, Chl, pH	1000+	Robinson et al., 2009	Yes
6.	NIVA Ferrybox	2008-present	Arctic	pCO_{2W}, A_T, DIC, SSS, SST	1000+	Yakushev and Sørensen (2013)	Yes
7.	OWS Mike	1948-2009	Arctic	A_T, DIC, SSS, SST, Chl	1000+	Skjelvan et al. (2008)	Yes
8.	RAMA Moored buoy array	2007-present	Bay of Bengal	SSS, SST	1000+	McPhaden et al. (2009)	Yes
9.	ARGO floats	2003-present	Global	SSS, SST	1,000,000+		Yes

New *in situ* data from collaborators

No.	Collection method	Temporal period	Geographic location	Parameters	N	Contact/owner	Access promised
1.	Research cruise	Nov-Dec 2013	Bay of Bengal	SSS, SST, A_T, pCO_{2W}, DIC, pH	30+	Dr Joe Salisbury (see letter of support)	Yes
2.	RAMA Moored buoy array	2007-present	Bay of Bengal	SSS, SST	100+	Dr Joe Salisbury (see letter of support)	Yes
2.	Research cruises	Dec 2013-onwards	Bay of Bengal	A_T, DIC, SSS, SST, pCO_{2W}	100+	Dr Punyasloke Bhadury (See letter of support)	Yes
3.	Research expedition	Aug 2013, 2014	Arctic	A_T, DIC, SSS, SST	50+	Dr Helen Findlay	Yes
4.	Research expedition	Mar-Sep 2014	Arctic	A_T, DIC, SSS, SST	50+	Dr Helen Findlay	Yes

Overview of methods

1. Convert all data (*in situ*, climatology, model, satellite) binned to daily and monthly $1^o \times 1^o$.

1. Identify locations and times where we have *in situ* carbonate parameters to compare with estimates generated from empirical algorithms.

2. Generate performance statistics for C_T, T_A, pH and pCO_2:
   a. Calculate all statistics for all possible comparisons for each model (optimal characterisation of each model e.g. accuracy assessment).

   b. Calculate all statistics for only common data points for each model to produce an aggregated model performance (rank model performance based on choice of input data).

Overview of methods

1. Convert all data (*in situ*, climatology, model, satellite) binned to daily and monthly 1º x 1º.

Very few pH data coincident or usable.

Performance of pCO_2 models was very poor.

So here we are presenting C_T and T_A results

(optimal characterisation of each model e.g. accuracy assessment).

b. Calculate all statistics for only common data points for each model (rank model performance based on choice of input data).

Algorithms tested

5 region (Global, Amazon plume, Caribbean, Bay of Bengal, Arctic Barents)

Possible inputs to choose from:

5 sets of SST data

7 sets of salinity data

3 sets of nitrate data

Total alkalinity (T_A) – the ability for water to neutralise an acid:

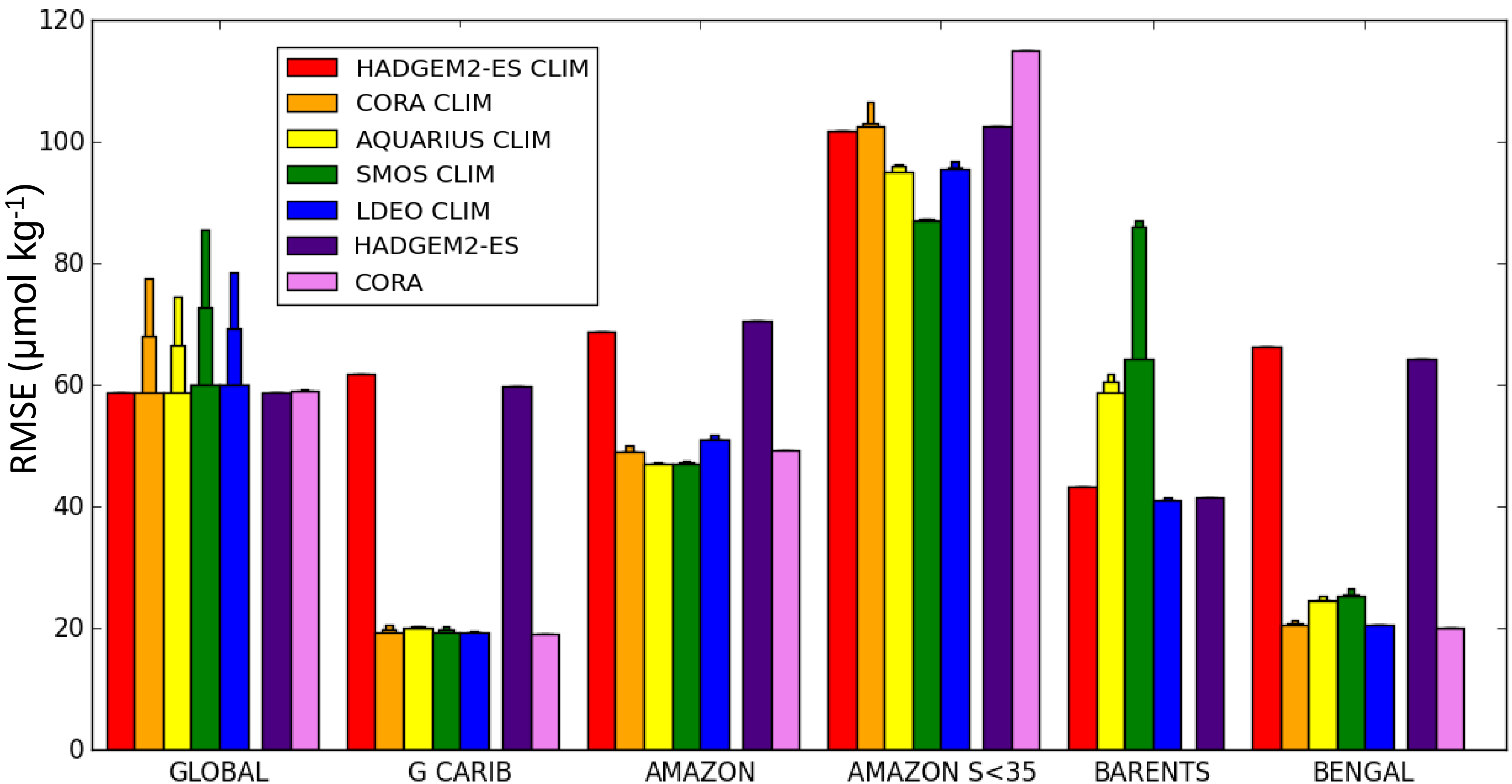
- 5 algorithms (HadGEM2-ES,Lee2006,Cai2010,Lefevre2010,Takahashi2013)

Total carbon (C_T) – also called Dissolved Inorganic Carbon

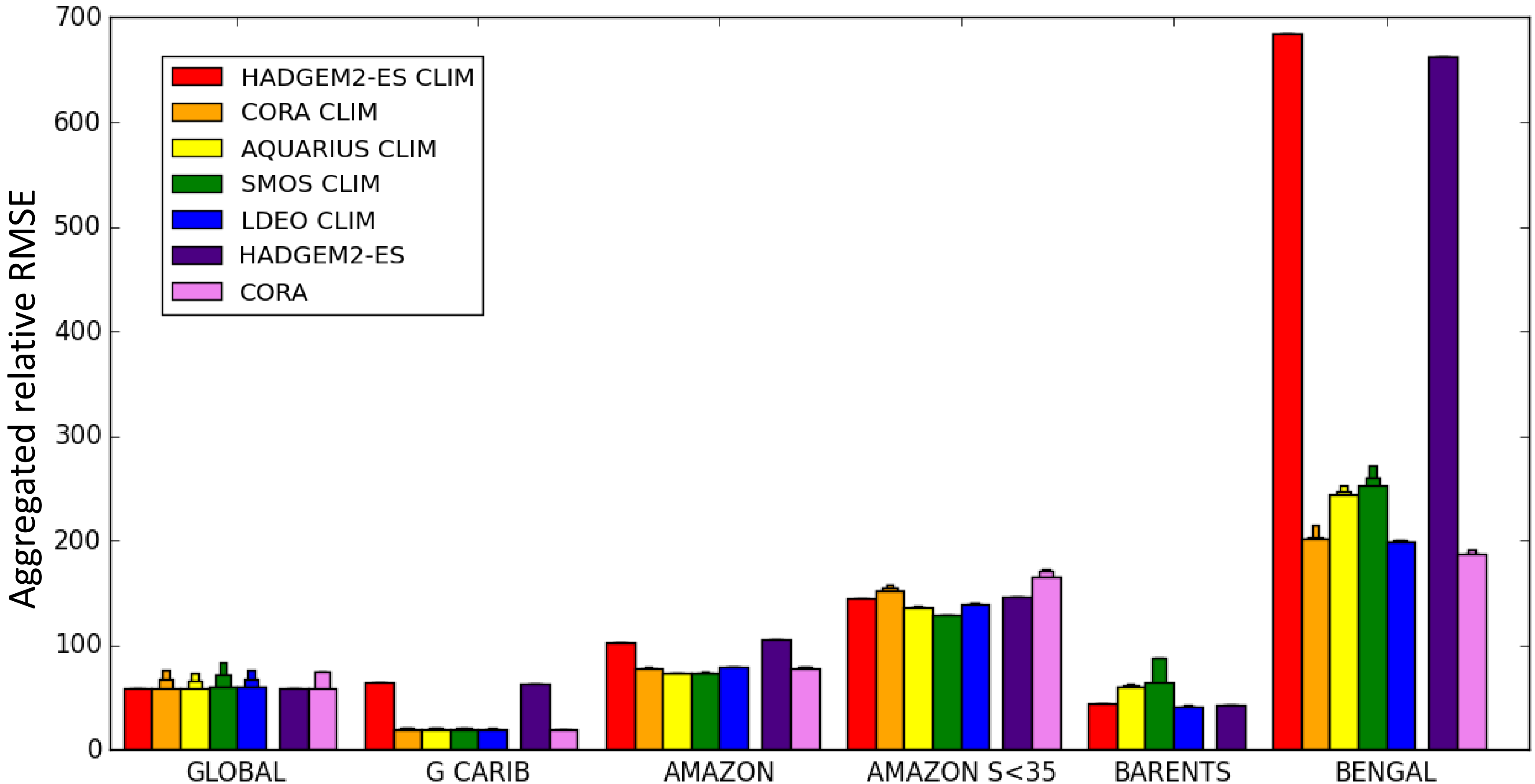
- 4 algorithms (HadGEM2-ES,Lefevre2010,Bonou2016,Lee2000)

Results in >?? possible combinations and permutations.

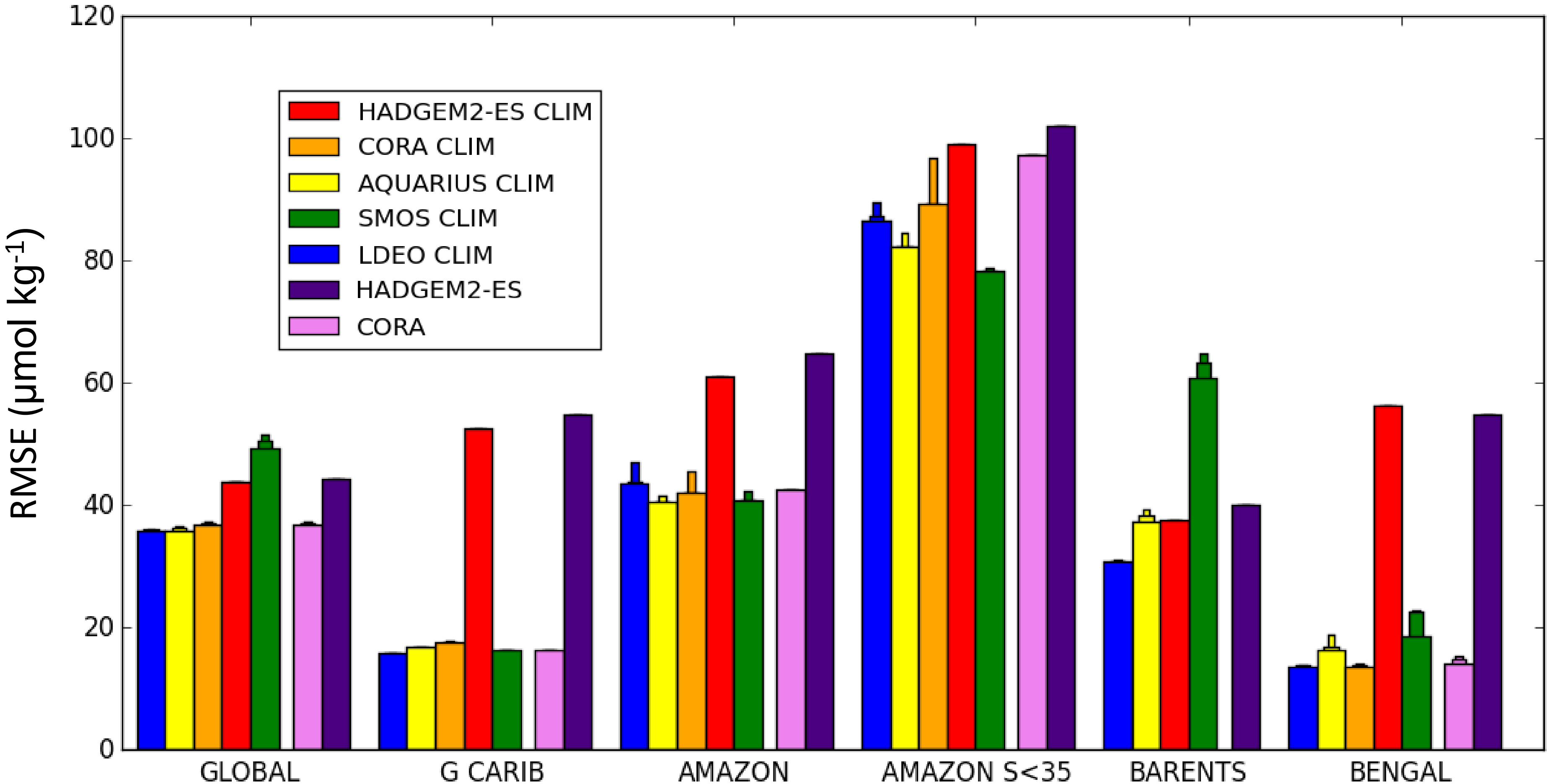
T_A - model accuracy



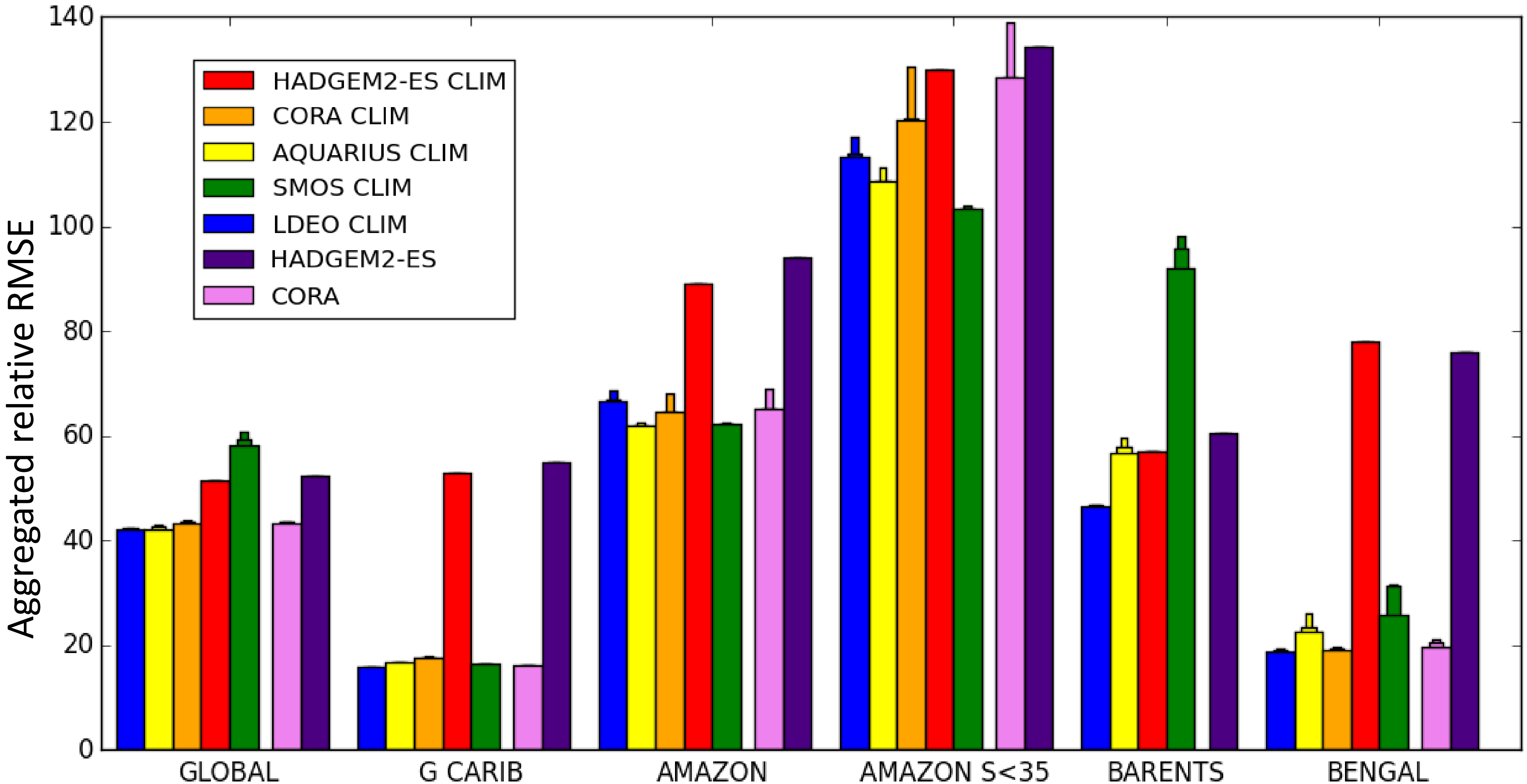
T_A- best salinity ranking



C_T – model accuracy



C_T - best salinity ranking



Conclusions

1. Possible to explore the salinity-alkalinity relationship using satellite data.
2. Globally, all models and inputs give the similar accuracy (mean T_A RMSE ~ 59 μmol kg^{-1}, mean C_T RMSE ~ 35-50 μmol kg^{-1}).
3. Caribbean, all models (except HadGEM2-ES) and inputs give the same accuracy (mean T_A RMSE ~ 20 μmol kg^{-1}, mean C_T RMSE ~ 20 μmol kg^{-1}).
4. For both T_A and C_T - Remote sensing salinity driven model performance is near identical to that of in situ salinity in the Caribbean (and to a lesser extent in the Bay of Bengal).
5. For both T_A and C_T – Remote sensing salinity (SMOS) out performs all others for low salinity amazon plume region. (mean T_A RMSE ~ 90 μmol kg^{-1}, mean C_T RMSE ~ 75 μmol kg^{-1}).
6. Now preparing data for public release:
    a. C_T, T_A and corresponding Seacarb derived pH and pCO_2 spatial data for each region in 2010.
    b. A preliminary remotely-sensed upwelling indicator dataset (global coverage, 2010-present day, daily and monthly temporal resolution, Ekman pumping and Ekman transport components).

http://www.pathfinders-oceanacidification.org

Sensitivity of SMOS in Polar waters

- Sensitivity of SMOS brightness temperature to salinity in the Arctic is around 50% of the sensitivity in the tropics.
- Current smallest errors in the tropics are 0.2-0.3 PSU, so errors in Arctic waters are of the order 0.5 PSU
- Error propagation using example TA algorithm from Arrigo et al (2010) gives a sensitivity of 2.7 % PSU^{-1}