



## Impact of ocean observation systems on ocean analyses and subseasonal forecasts

**Aneesh Subramanian** 

with Frederic Vitart, Magdalena Balmaseda, Beena Sarojini, Yosuke Fujii, Yuhei Takaya

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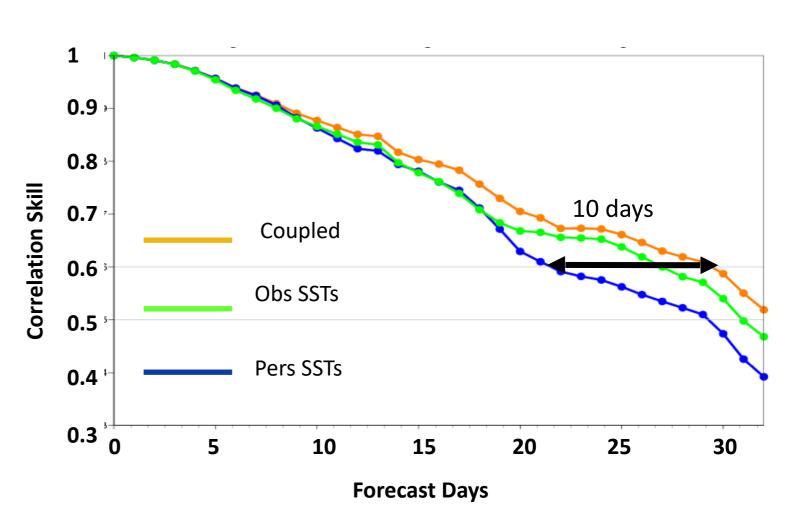






## **Ocean coupling improves MJO predictability**

- Subseasonal forecasts of the MJO benefit significantly from coupling to the ocean (20 years of initialized forecasts)
- Ocean-atmosphere phase locking of anomalies and feedback act as a source of predictability on S2S timescales
- Understand coupled processes better to improve models and predictions on sub seasonal timescales

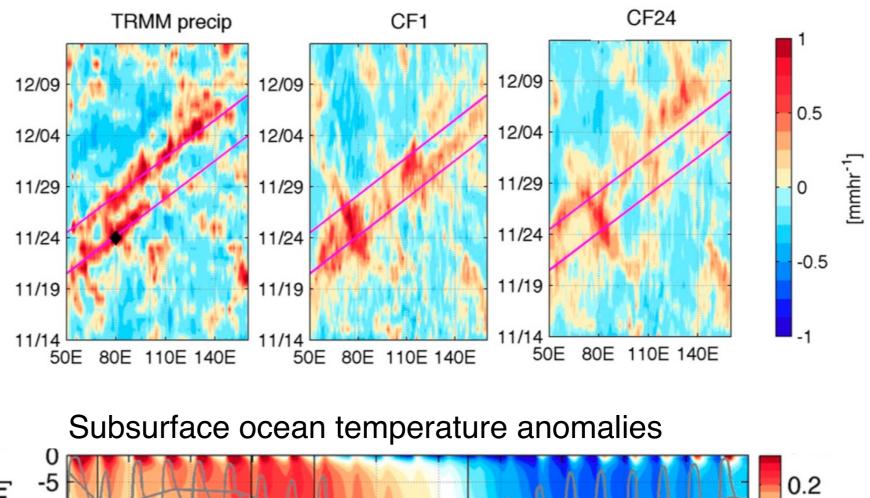


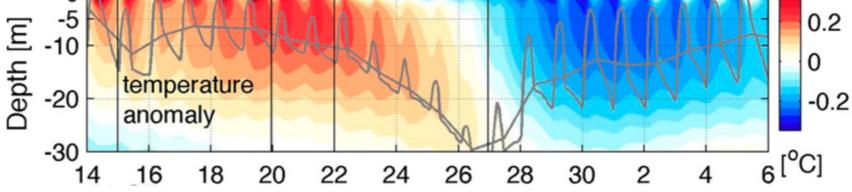
MJO Bivariate Correlation

Subramanian, A., F. Vitart, C. Zhang, A. Kumar and M. A. Balmaseda 2018

## Impact of high-frequency air-sea interactions on MJO

Diurnal coupling in a regional model improves MJO forecast over a 30-day period

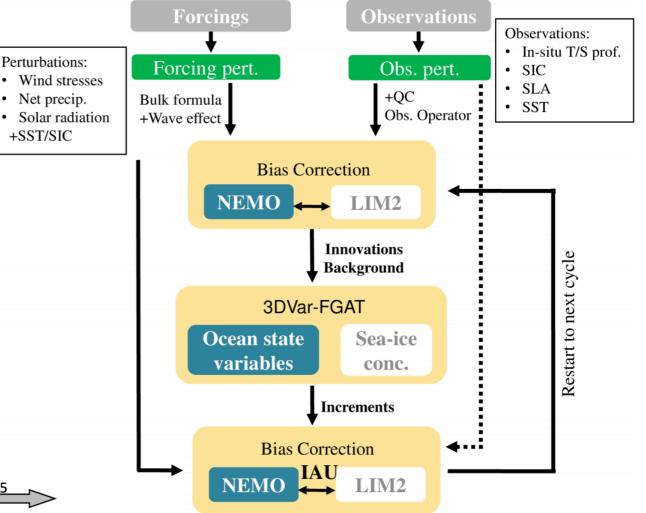


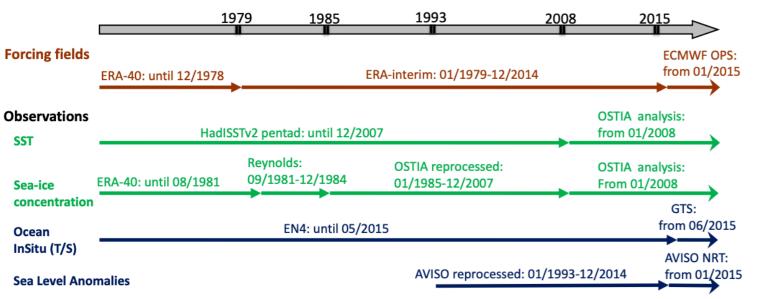


Seo, Subramanian, Miller, Cavanaugh, J. Clim. 2014

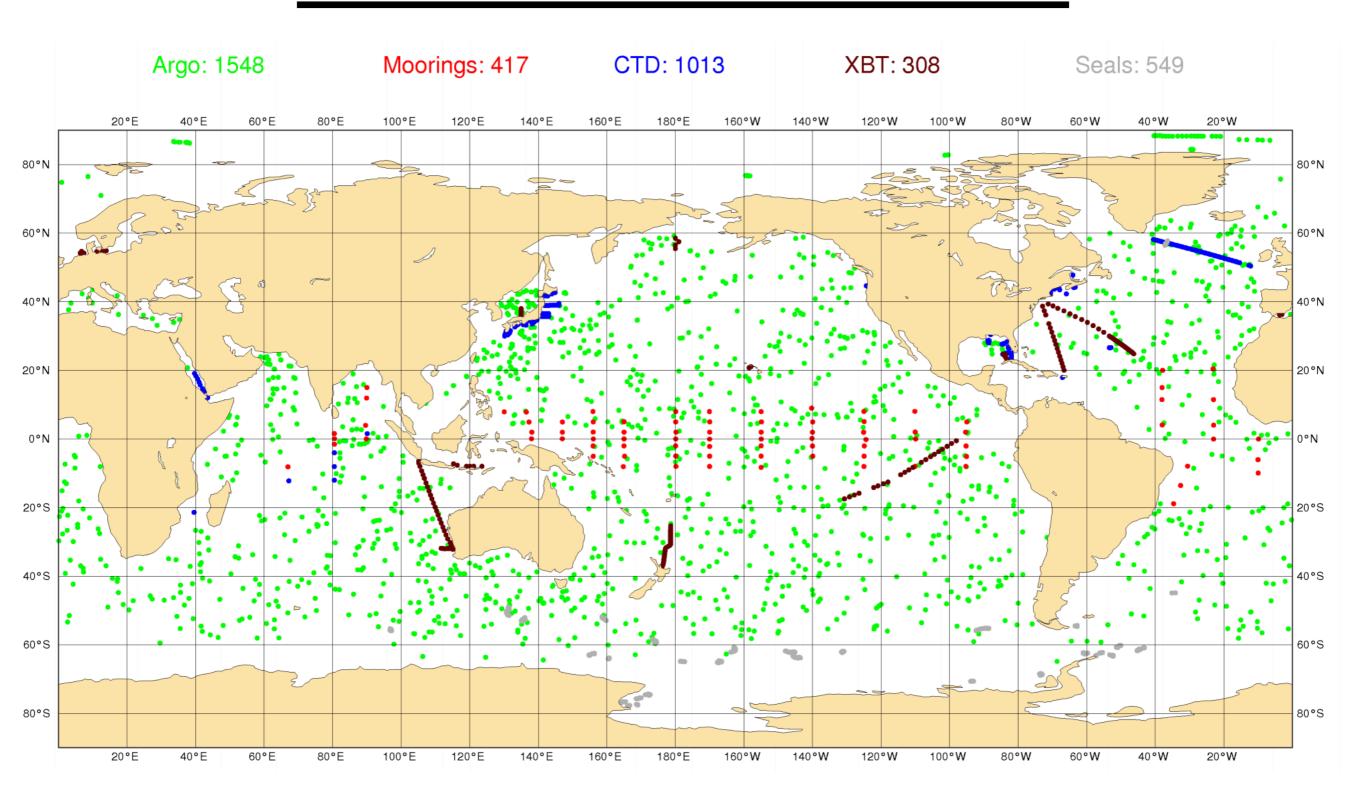
## **ECMWF Ocean ReAnalysis System 5 (ORAS5)**

- ORAS5 is in principle a state of the art ocean reanalysis
- It includes latest observational data sets
- First attempt to use the same SST/SIC in atmos/ocean reanalyses.
- High resolution with sea-ice assimilation





## InSitu observations assimilated in ORAS5: July 2-6, 2010



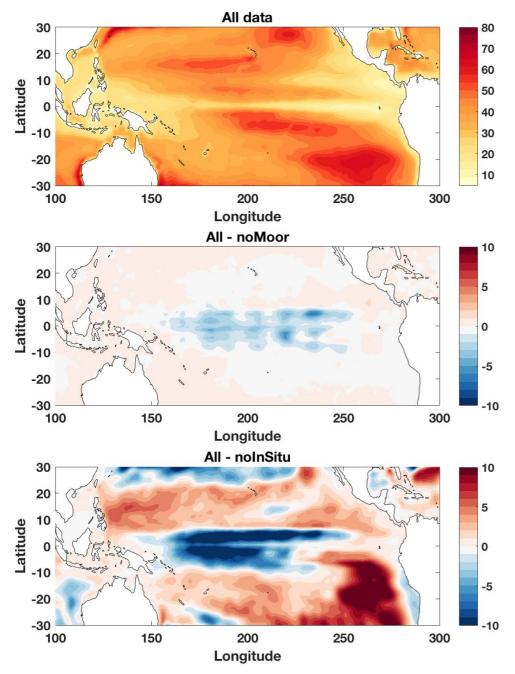
Zuo et al., ECMWF Tech Memo., 2015

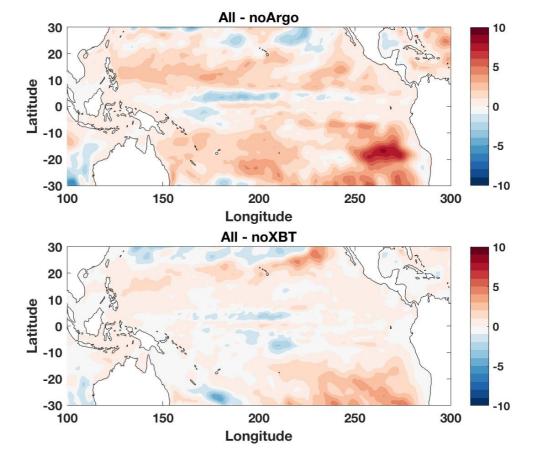
## Sensitivity experiments with ORAS5 at ECMWF

All:	assimilates all in situ observations along with SST (assimilated in all the runs) and altimetry data
noMoor:	excludes mooring data
noXBTCTD:	excludes ship-based observations from XBT(eXpendableBathyThermograph) and CTD (measuring Conductivity, Temperature, and Depth)
noArgo	excludes Argo T/S profiles
noInSitu:	excludes all in situ data

## Impact on the mean mixed layer depth

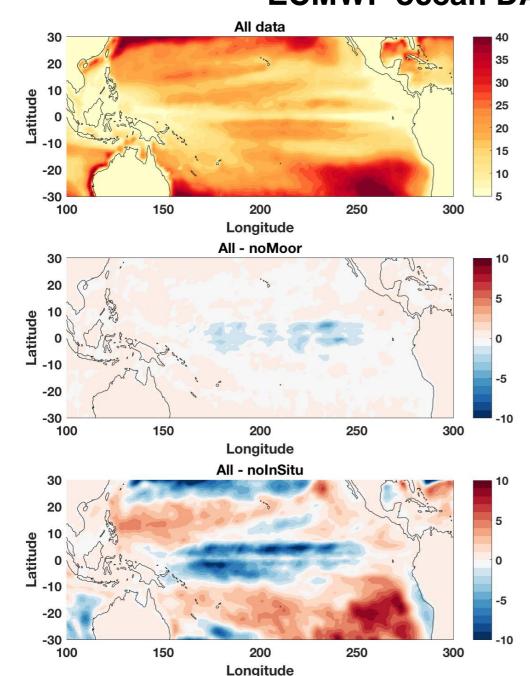
#### ECMWF ocean DA system (same as ORAS5)



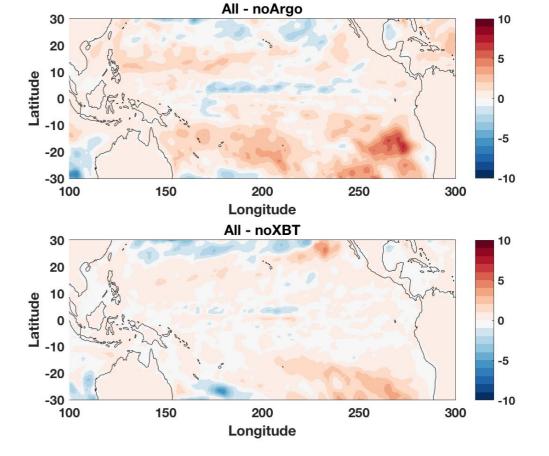


Assimilating in-situ observations in the ocean has a significant impact on the Tropical Pacific mean mixed layer depth. Assimilating TAO moorings reduces mean MLD.

## Impact on the variability in mixed layer depth

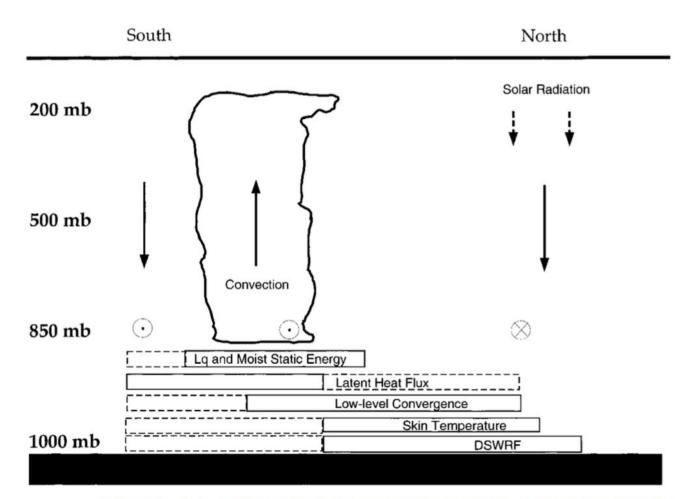


#### ECMWF ocean DA system (same as ORAS5)



TAO moorings mainly impact mixed layer depth locally by reducing the variance in MLD compared to not assimilating mooring data

## Air-sea interaction is key for Monsoon ISOs



Schematic of air-sea interaction in the northward propagation of convective anomalies associated with the BSISO in the Indian and western Pacific Oceans. Dark vertical lines indicate the  $\omega(500 \text{ mb})$  anomaly. The cloud indicates deep precipitating convection. The boxes represent the approximate locations of anomalies relative to the convection. Solid box indicates a positive anomaly, and dashed box indicates a negative anomaly. Circles indicate direction of 850-mb zonal wind anomaly with the  $\otimes$  ( $\odot$ ) representing easterlies (westerlies).

PBL convergence maximum north of the convection maximum leads to feedbacks that propagate the system poleward. Kemball-Cook and Wang (2001)

## Ocean data assimilation impact: Precipitation in MISO predictions

#### **ECMWF** sub seasonal forecast system

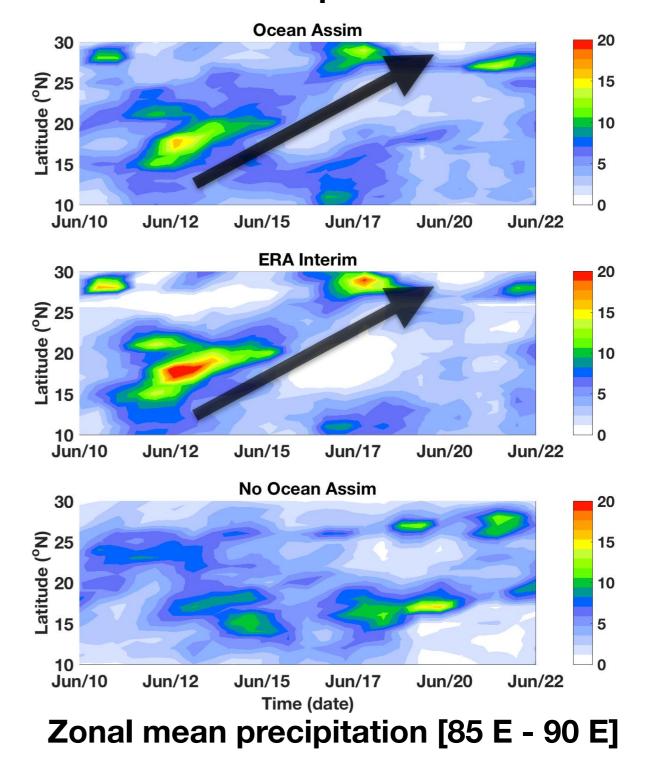
All ocean observations assimilated prior to hindcast initialization  $\Rightarrow$  **more** 

coherent MISO propagation

Reanalysis

No ocean DA prior to hindcast initialization

Subramanian et al. (2019, In Prep.)



#### **2013 June: Precipitation Hovmöller**

## Ocean data assimilation impact: LH Flux anomalies in MISO predictions

#### **ECMWF** sub seasonal forecast system

All ocean observations assimilated prior to hindcast initialization  $\Rightarrow$  **more** 

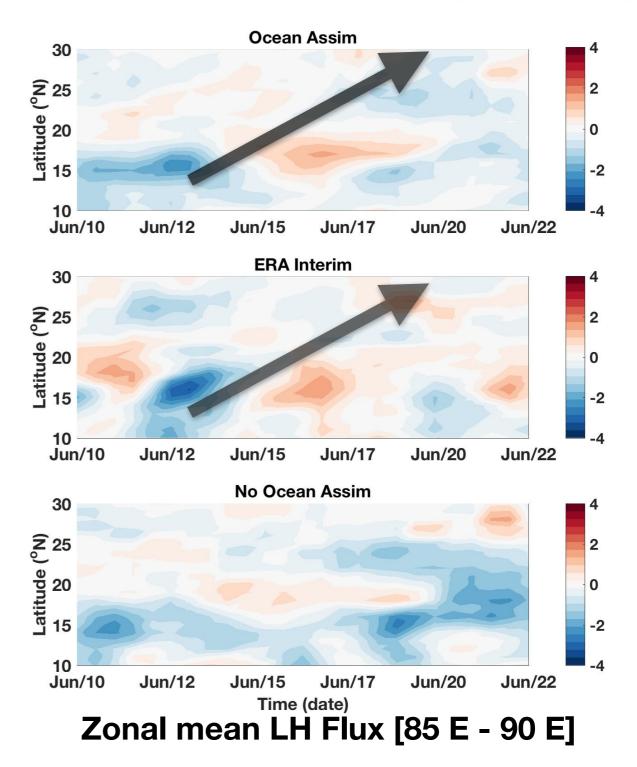
consistent surface flux anomalies

Reanalysis

No ocean DA prior to hindcast initialization

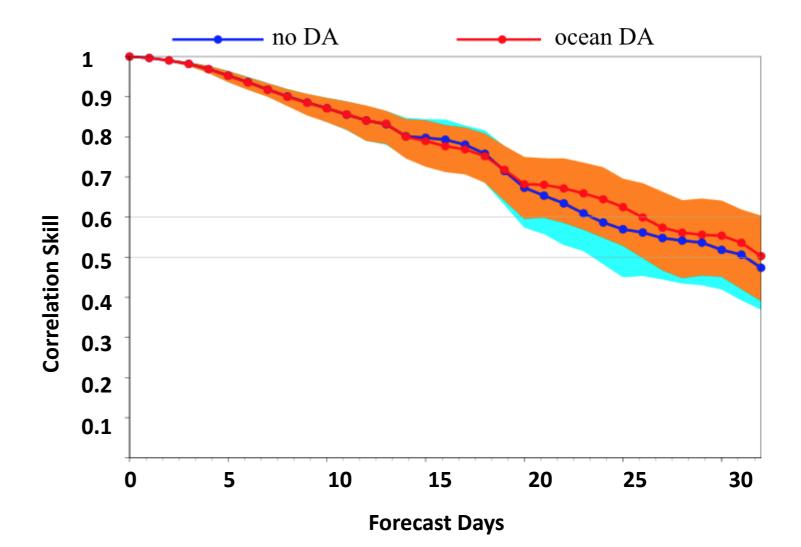
Subramanian et al. (2019, In Prep.)

#### 2013 June: Latent Heat Flux (x10<sup>3</sup> kJ m<sup>-2</sup>)



## **Ocean DA and MJO forecast skill**

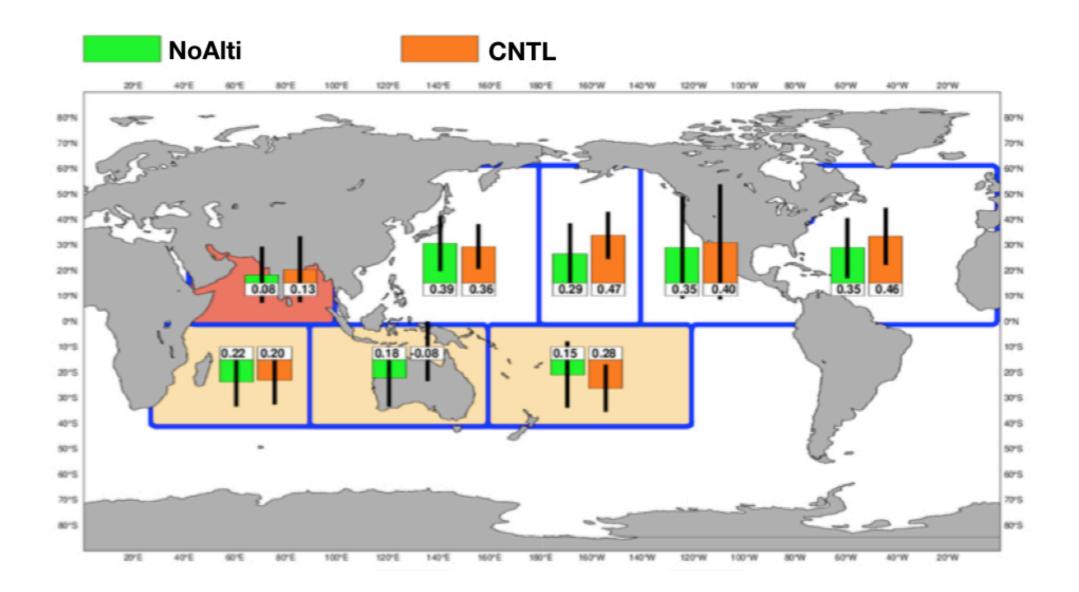
- Subseasonal forecasts of the MJO benefit modestly from ocean initialization in coupled forecasts
- Week-3 and beyond show improved skill of a day or two
- Forecast skill improvement is within uncertainty and more diagnostics need to be performed to understand the differences



MJO Bivariate Correlation

Figure courtesy: Frederic Vitart (ECMWF)

## **Ocean DA and Tropical Cyclone forecast skill**



- Anomaly correlation skill of forecast of tropical cyclone energy at days 16-45 days from two experiments with different ocean initialization
- •TC forecast skill is improved in most basins (orange better than green) for the week 2-4 lead time forecast

#### Subramanian et al., (2019)

## **International S2S Prediction Project: Phase II**

PROPO	OSAL F	OR S2S PHASE II	7
3.1	S2S d	atabase enhancement	7
3.2	Resea	rch activities	7
	3.2.1	MJO prediction and teleconnections	7
	3.2.2	Land initialization and configuration	10
	3.2.3	Ocean and sea ice initialization and configuration	11
	3.2.4	Ensemble generation	13
	3.2.5	Atmospheric composition	14
	3.2.6	Stratosphere	17

3.

- Promote improved sub-seasonal predictions through improved initialization of the oceansea ice state and depiction of key ocean and sea-ice processes that provide predictability at sub-seasonal timescales.
- The project will also promote improved understanding and prediction of subseasonal variations of the ocean and sea ice, including marine heat waves and seaice extremes.

WWRP 2018 - 4 WCRP Report No. 11/2018

WWRP/WCRP Sub-seasonal to Seasonal Prediction Project (S2S) Phase II Proposal

(November 2018–December 2023)

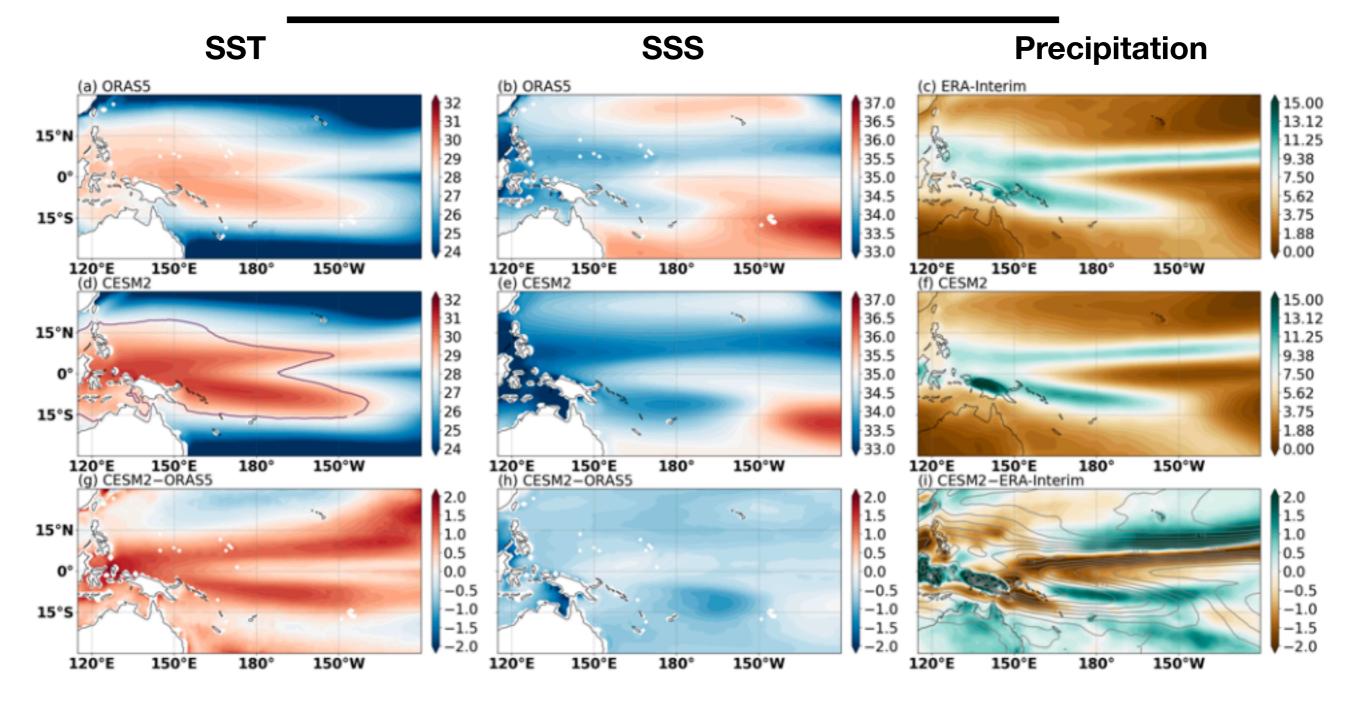
#### WORLD METEOROLOGICAL ORGANIZATION





## **Analyzing Tropical Pacific biases in CESM2**

Work lead by Ho-Hsuan Wei (Post-Doc at CU Boulder)



We identify biases at the surface and in the sub-surface Tropical Pacific ocean. These biases (like barrier layer thickness) lead to erroneous feedbacks in ENSO evolution

Our next goal is to analyze initialized CESM2 forecasts to study how these biases develop and what role do different ocean observing systems play in constraining these subsurface biases.

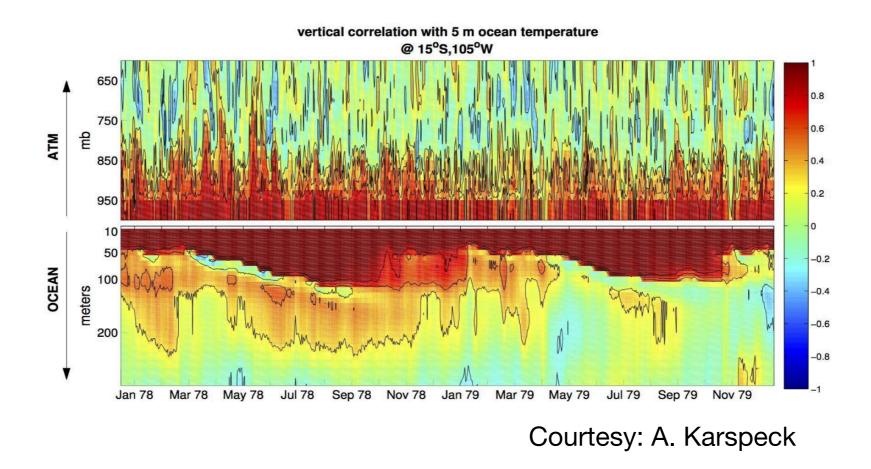
## **Summary of Results**

- Preliminary results from new ocean DA system at ECMWF shows overall positive impact from assimilation of TAO mooring and Argo (in-situ) data in ocean analyses
- Ocean in-situ observations have significant impact on mean and variability representations of subsurface ocean variables
- Ocean DA helps improve forecast skill of some atmospheric variables on sub seasonal timescales
- JMA has completed oceanDA vs noDA S2S experiments. Analysis yet to be completed.
- Further analysis is required (including CESM2) to understand the systematic impact of ocean observations on improved process understanding and forecast skill for S2S timescales



## Ocean observations to improve our understanding, modeling, and forecasting of subseasonal-to-seasonal variability

Aneesh C. Subramanian<sup>1\*</sup>, Magdalena A. Balmaseda<sup>2</sup>, Rajib Chattopadhyay<sup>3</sup>, Luca Centurioni<sup>4</sup>, Bruce D. Cornuelle<sup>4</sup>, Charlotte DeMott<sup>5</sup>, Thomas M, Hamill<sup>6</sup>, Harry Hendon<sup>7</sup>, Ibrahim Hoteit<sup>8</sup>, Maria Flatau<sup>9</sup>, Donata Giglio<sup>1</sup>, Yosuke Fujii<sup>10</sup>, Sarah T. Gille<sup>4</sup>, Arun Kumar<sup>11</sup>, Jae-Hak Lee<sup>12</sup>, Andrew J. Lucas<sup>4</sup>, Mio Matsueda<sup>13</sup>, Amala Mahadevan<sup>14</sup>, SungHyun Nam<sup>15</sup>, Sastri Paturi<sup>16</sup>, Stephen G. Penny<sup>17</sup>, Adam Rydbeck<sup>9</sup>, Rui Sun<sup>4</sup>, Amit Tandon<sup>18</sup>, Yuhei Takaya<sup>10</sup>, Robert E. Todd<sup>14</sup>, Frederic Vitart<sup>2</sup>, Dongliang Yuan<sup>19</sup>, Chidong Zhang<sup>20</sup>



**Improve coupled data assimilation** methods in coupled forecasting systems to best utilize these high-resolution ocean observations.

# Thank you

Monsoon clouds over Bangladesh. Courtesy: NASA

# Thank you

Monsoon clouds over Bangladesh. Courtesy: NASA

#### Impact on atmospheric biases : 1993-2015 (left)

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#### 2005-2015 (right)

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505	•	▼	▼			▼	▼		505	•	•	•	•	•	▼	▼	•
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#### Slide courtesy: Beena Sarojini (ECMWF)

## **Ocean DA and forecast skill scorecard**

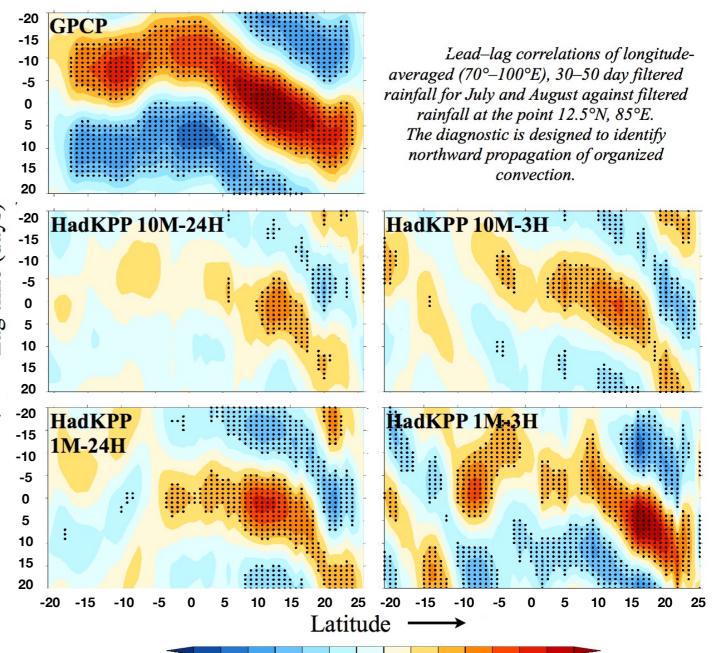
- Difference of weekly CRPSS skill scores
- Skill improvements are much larger in the Extratropics, with a clear degradation in the no DA experiments
- Upper atmosphere as well as surface skill scores are better in ocean DA experiments

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		N.H	lem.			Tro	Tropic			
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## Impact of high-frequency air-sea interactions on MISO

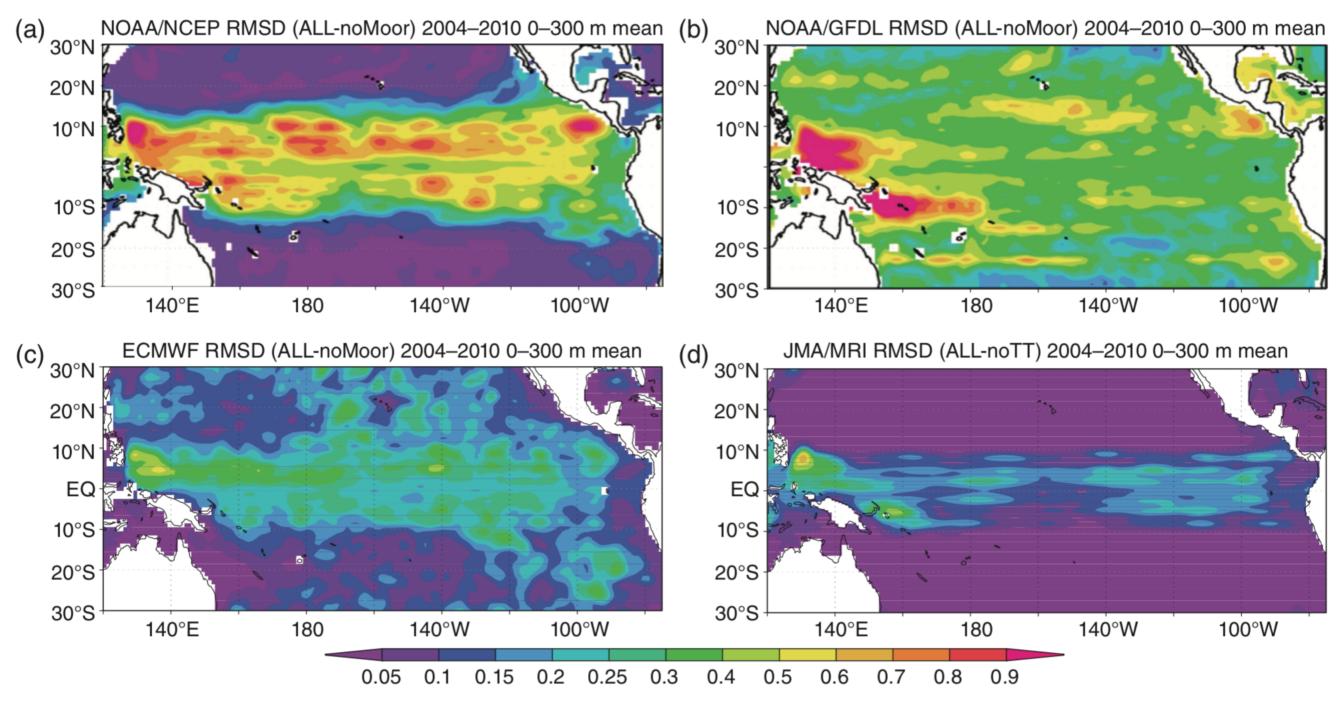
Higher vertical resolution in the upper ocean and resolving the diurnal cycle in coupling helps improve the representation of MISO.

Klingaman et al., 2010



-0.7 -0.6 -0.5 -0.4 -0.3 -0.2 -0.1 0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7

### Impact of assimilating Tropical Pacific observations



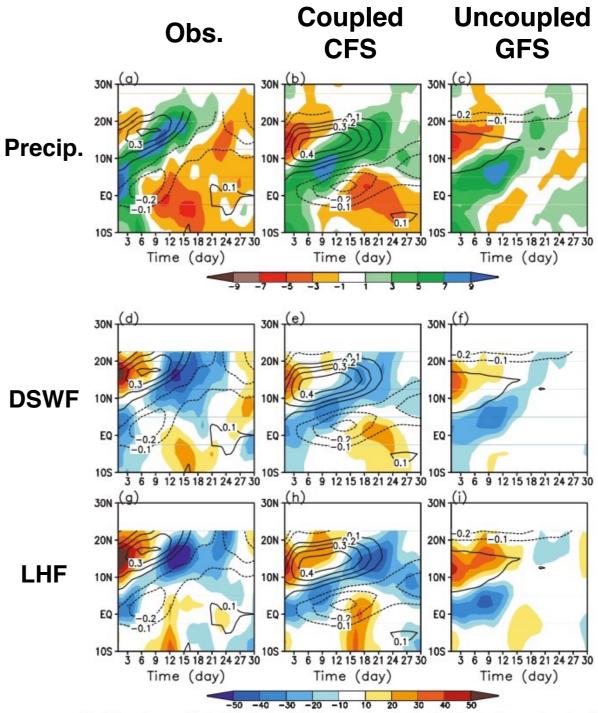
RMS difference of temperature (°C) in upper ocean

Statistics from 2004-2011

Fujii et al., (2015)

## **Air-sea interaction for MISO forecasts**

During MISO propagation, the observed phase relation between latent heat flux, SST and SW radiation is better represented in coupled NCEP forecasts compared to uncoupled forecasts.



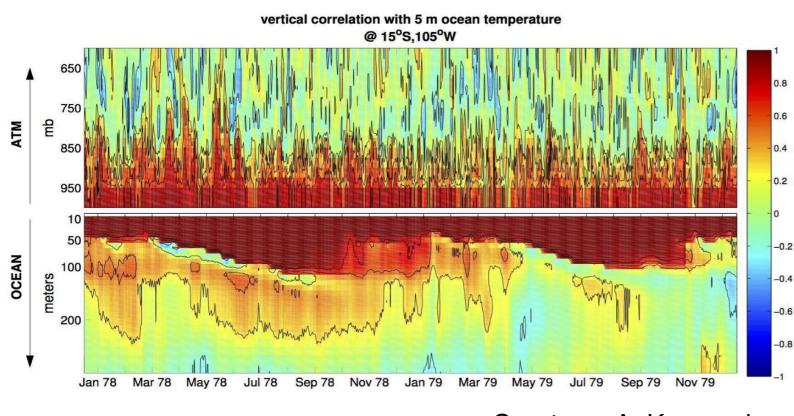
Wang et al. 2009

Composite anomalies. (top) Precipitation (shaded starting at 1 mm day<sup>-1</sup>, with a 2 mm day<sup>-1</sup> contour interval) and SST (contours starting at  $\pm 0.1$  K, with a 0.1-K contour interval, negative values dashed) averaged between 65° and 95°E. (middle) Same as the top row, except that the shading is for downward surface solar radiation (starting at  $\pm 10$  W m<sup>-2</sup>, with a 10 W m<sup>-2</sup> contour interval). (bottom) Same as the middle row, except that shading is for downward latent heat flux. (left) Observation, (middle) CFS forecast, and (right) GFS forecast.

## **frontiers** OceanObs'19

## Ocean observations to improve our understanding, modeling, and forecasting of subseasonal-to-seasonal variability

Aneesh C. Subramanian<sup>1\*</sup>, Magdalena A. Balmaseda<sup>2</sup>, Rajib Chattopadhyay<sup>3</sup>, Luca Centurioni<sup>4</sup>, Bruce D. Cornuelle<sup>4</sup>, Charlotte DeMott<sup>5</sup>, Thomas M, Hamill<sup>6</sup>, Harry Hendon<sup>7</sup>, Ibrahim Hoteit<sup>8</sup>, Maria Flatau<sup>9</sup>, Donata Giglio<sup>1</sup>, Yosuke Fujii<sup>10</sup>, Sarah T. Gille<sup>4</sup>, Arun Kumar<sup>11</sup>, Jae-Hak Lee<sup>12</sup>, Andrew J. Lucas<sup>4</sup>, Mio Matsueda<sup>13</sup>, Amala Mahadevan<sup>14</sup>, SungHyun Nam<sup>15</sup>, Sastri Paturi<sup>16</sup>, Stephen G. Penny<sup>17</sup>, Adam Rydbeck<sup>9</sup>, Rui Sun<sup>4</sup>, Amit Tandon<sup>18</sup>, Yuhei Takaya<sup>10</sup>, Robert E. Todd<sup>14</sup>, Frederic Vitart<sup>2</sup>, Dongliang Yuan<sup>19</sup>, Chidong Zhang<sup>20</sup>



Courtesy: A. Karspeck

- Establish co-located ABL+flux/ subsurface measurements by moored buoys or other sustained platforms in tropical and midlatitude oceans to benefit S2S forecasts significantly by improving the coupled initial conditions
- Support emerging observing technology with the promise of innovative devices (e.g., Autonomous Surface Vehicles (ASV)) that can supplement the conventional platforms to fill gaps of ocean observations for S2S prediction with the support of the international operational forecasting centers and observational communities.
- Improve coupled data assimilation methods in coupled forecasting systems to best utilize these high-resolution ocean observations.

## **Lots of Process Studies!**



#### **ASIRI-OMM and MISO-BOB**

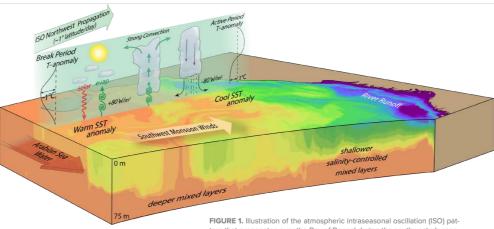
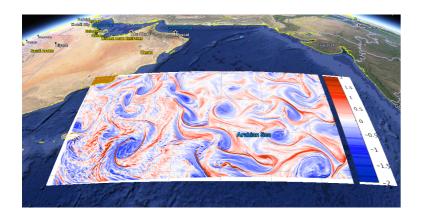


FIGURE 1. Illustration of the atmospheric intraseasonal oscillation (ISO) pattern that propagates over the Bay of Bengal during the southwesterly monsoon season. Color in the ocean represents salinity, and was produced using the HYbrid Coordinate Ocean Model, or HYCOM (Cummings and Smedstad, 2013, http://dx.doi.org/10.1007/978-3-642-35088-7\_13). Schematic drawing by Emily Shroyer and produced by David Reinert, Oregon State University.

#### BoBBLE



#### Years of Maritime Continent



**NASCar** 







