Toward the prediction of local-scale rainfall

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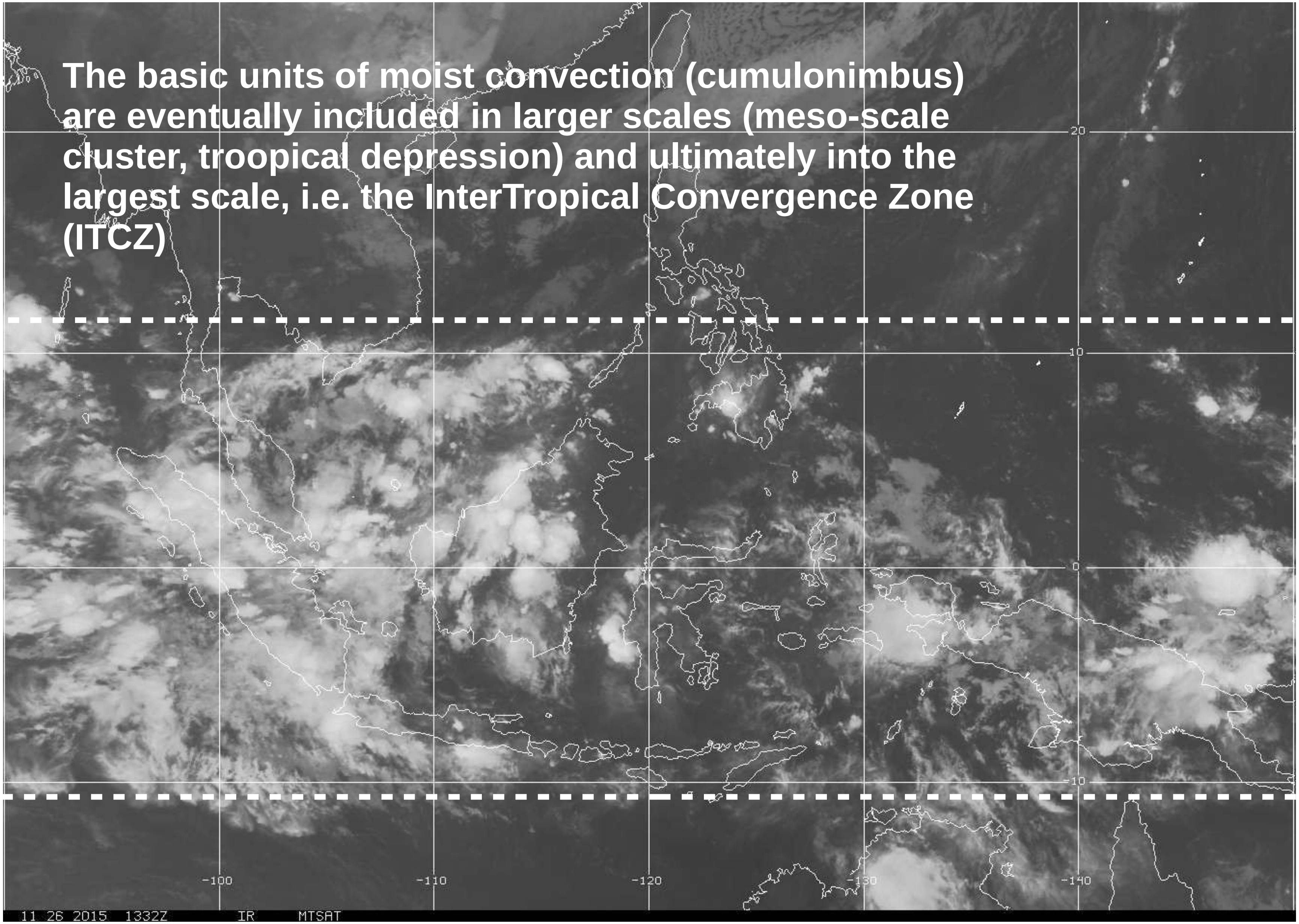
An example of instantaneous rainfall field in a tropical region (through IR proxy)



MSAT IR
26/11/2015
13.32 UTC

http://www.weatheronline.co.uk/weather/satellite/Oceania/Indonesia/Infraredcolor.htm

Scales and predictability

- Local-scale rainfall in the tropical zone (TZ) are mostly of **convective origin**, **phase-locked with the diurnal cycle**, at least over most of the continents, and also with the **annual cycle**, mostly through the meridional shift of the InterTropical Convergence Zone (ITCZ)
- **The diurnal convection is more or less organized by larger phenomena** (Meso-scale clusters, Tropical depression/cyclone, ITCZ) which are themselves **more or less impacted by periodic and quasi-periodic variations** (MJO, annual cycle, ENSO etc.)
- A priori, the deterministic predictability of any local-scale event is limited by chaotic dynamics of the atmosphere, especially when its occurrence/intensity is related to small-scale processes as daily rainfall in the tropics
- **Seasonal amounts at regional scale are more or less predictable** (i.e. Barnston et al., 2010) across the TZ from sea surface temperatures -SST- (including, but not limited to, ENSO), mostly through the coupling between thermal direct circulations (as Hadley or Walker cells) with raw and anomalous SST as well as their gradients (Gill, 1980 ; Lindzen and Nigam, 1987, etc.)
- **Seasonal amounts could be considered as the most « comprehensive » characteristics of a rainy season** since it includes, by definition, all wet events occurring during a 2- to 8-month season

Seasonal amounts vs intra-seasonal characteristics

- The seasonal amount is not necessarily the « optimal » variable despite its « comprehensiveness » due to the fact that **its interannual variability is dominated by few heavy events**, i.e. the wettest day of a season. In other words, it could be heavily contaminated by the small-scale extreme instantaneous events
- A practical limit is the fact that **seasonal amounts are not necessary the most awaited variable by end users**. For example, farmers are usually more interested by the onset date (for sowing purpose), the duration of the rainy season or the mean length of dry spell (for adapting their crop's or variety's choices) than by seasonal amount
- In fact, seasonal amounts include by definition the statistical information about mean length of dry spell, onset date etc. but we can assume that the **same anomaly of a seasonal amount does not necessarily lead to the same intraseasonal scenario of daily rainfall**
- From a theoretical point of view, the relationships between the predictable component associated with regional-scale seasonal amounts and the local and instantaneous scales is still wide open
- This lecture deals with the possible approaches to analyse the predictability of intra-seasonal characteristics (ISC) of regional-scale rainfall based on an example on the Maritime Continent

Outline

1- A typical rainy season in the tropics and possible daily scenarios

2- From seasonal amount to daily rainfall and vice-versa

3- Analytical decomposition of seasonal amounts

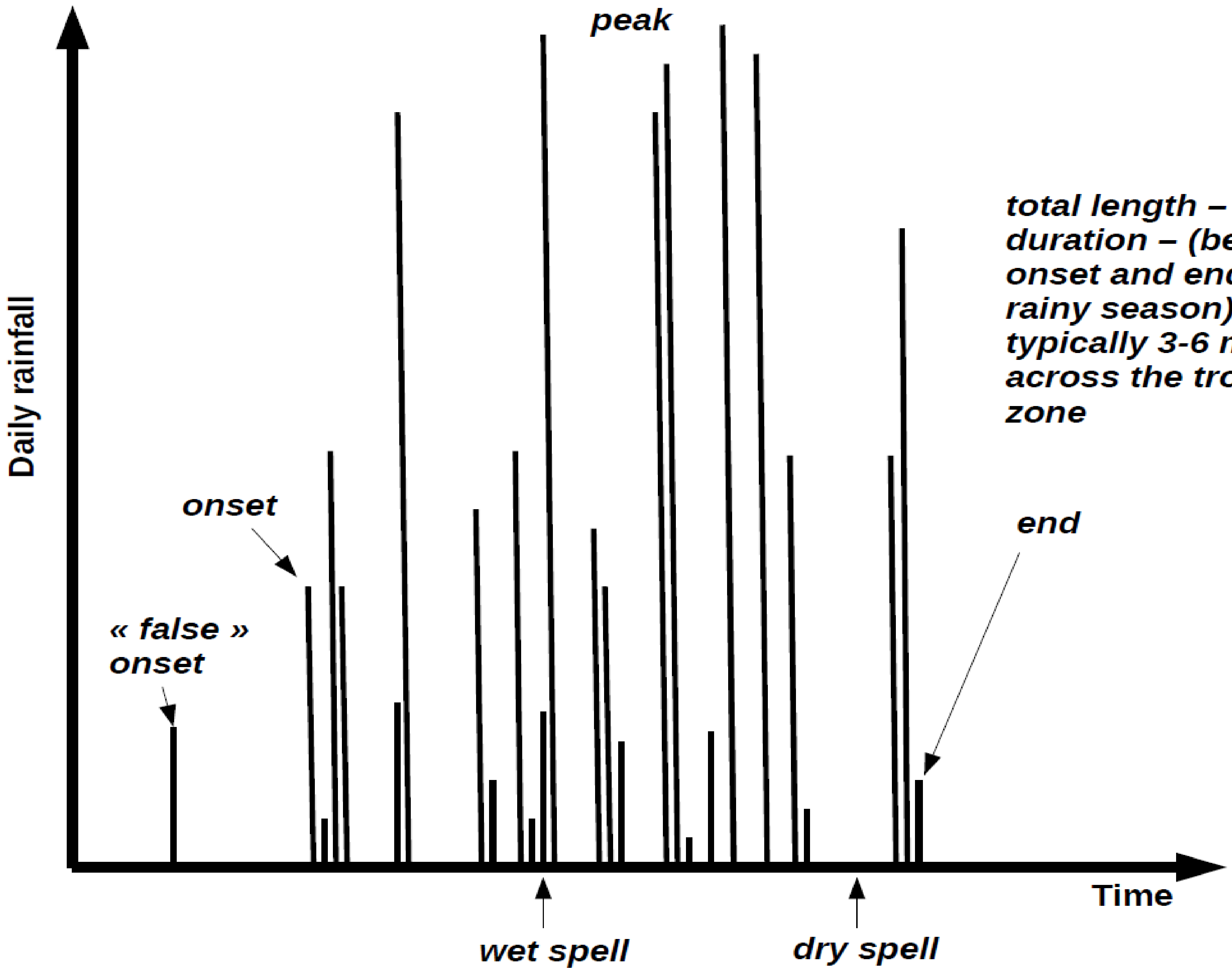
4- An exemple of analytical decomposition of seasonal amounts into ISCs : the onset of austral summer monsoon across the Maritime Continent

5- Extraction of Sub-seasonal Scenarios across the Maritime Continent

6- Concluding remarks

7- References

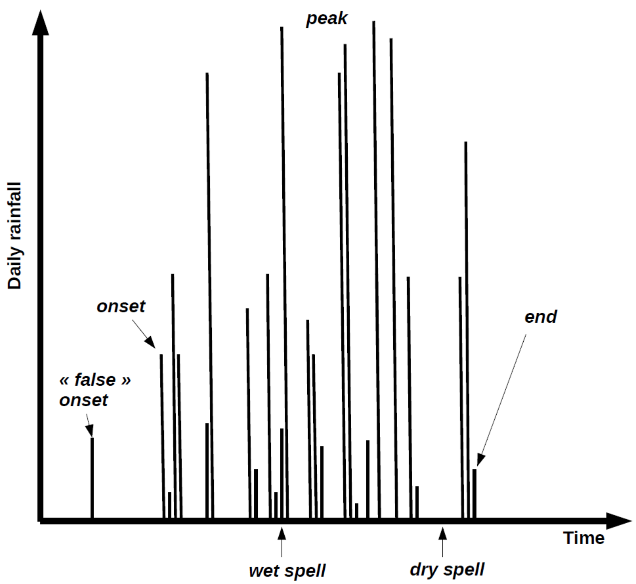
1- A typical rainy season in the tropics

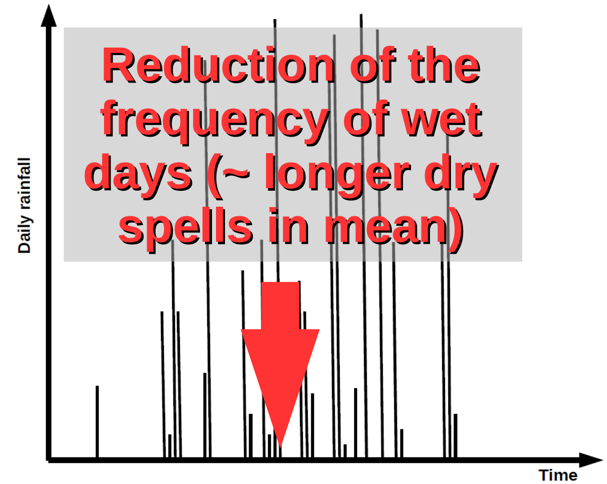


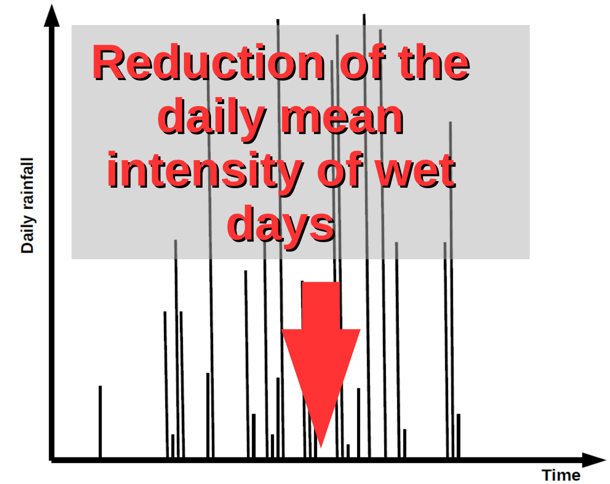
total length – or duration – (between onset and end of the rainy season) lasts typically 3-6 months across the tropical zone

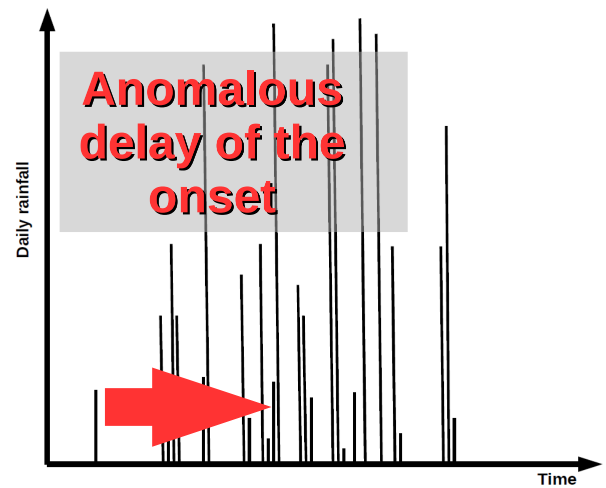
1- Possible changes in daily scenarios

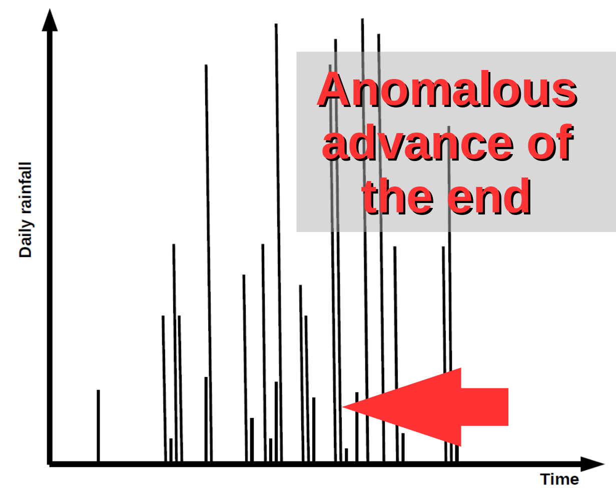
What can be an anomalous dry season from the ISC point of view ?

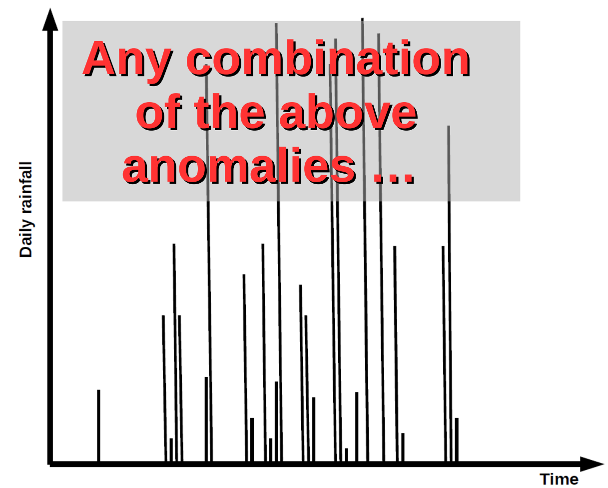




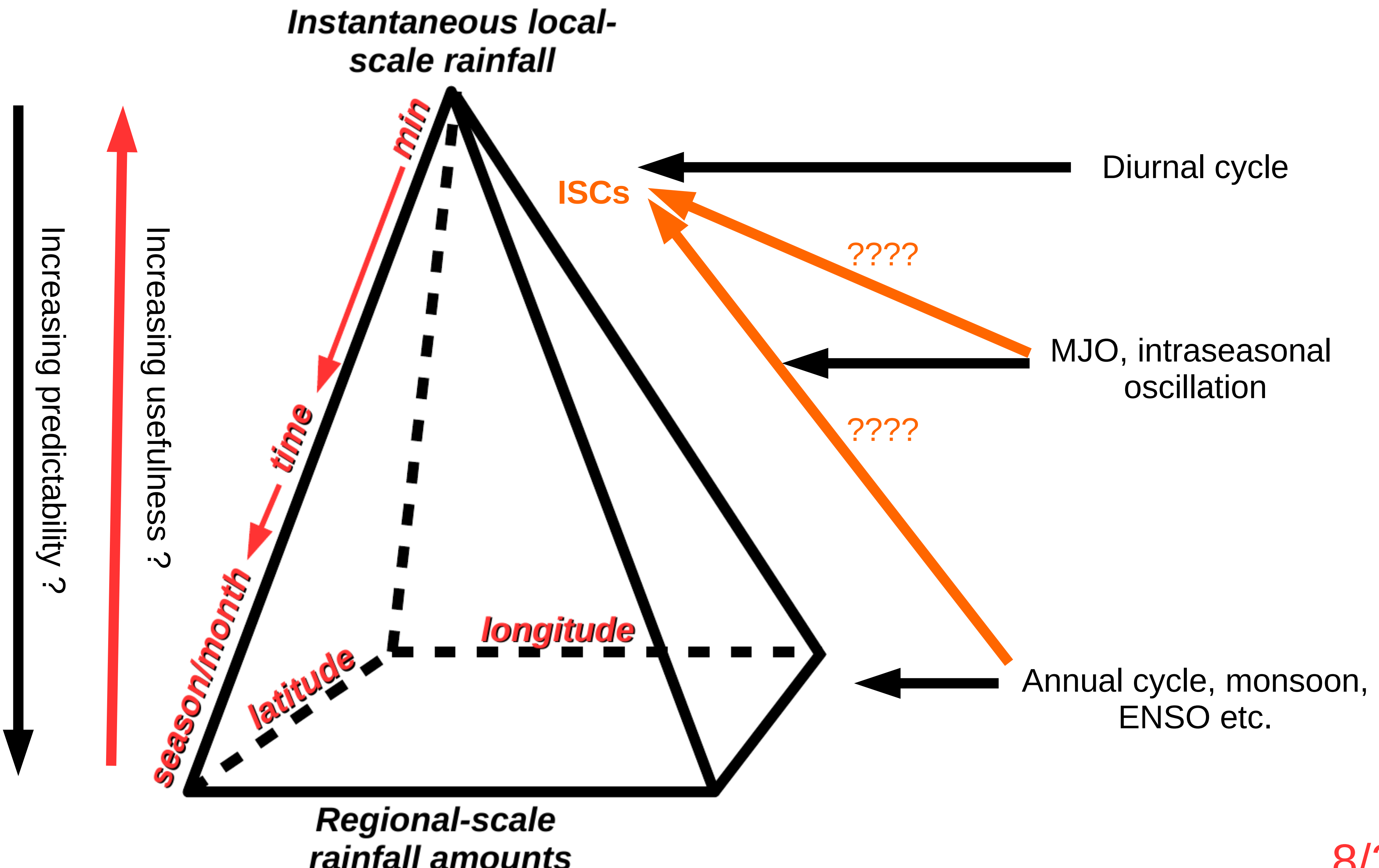




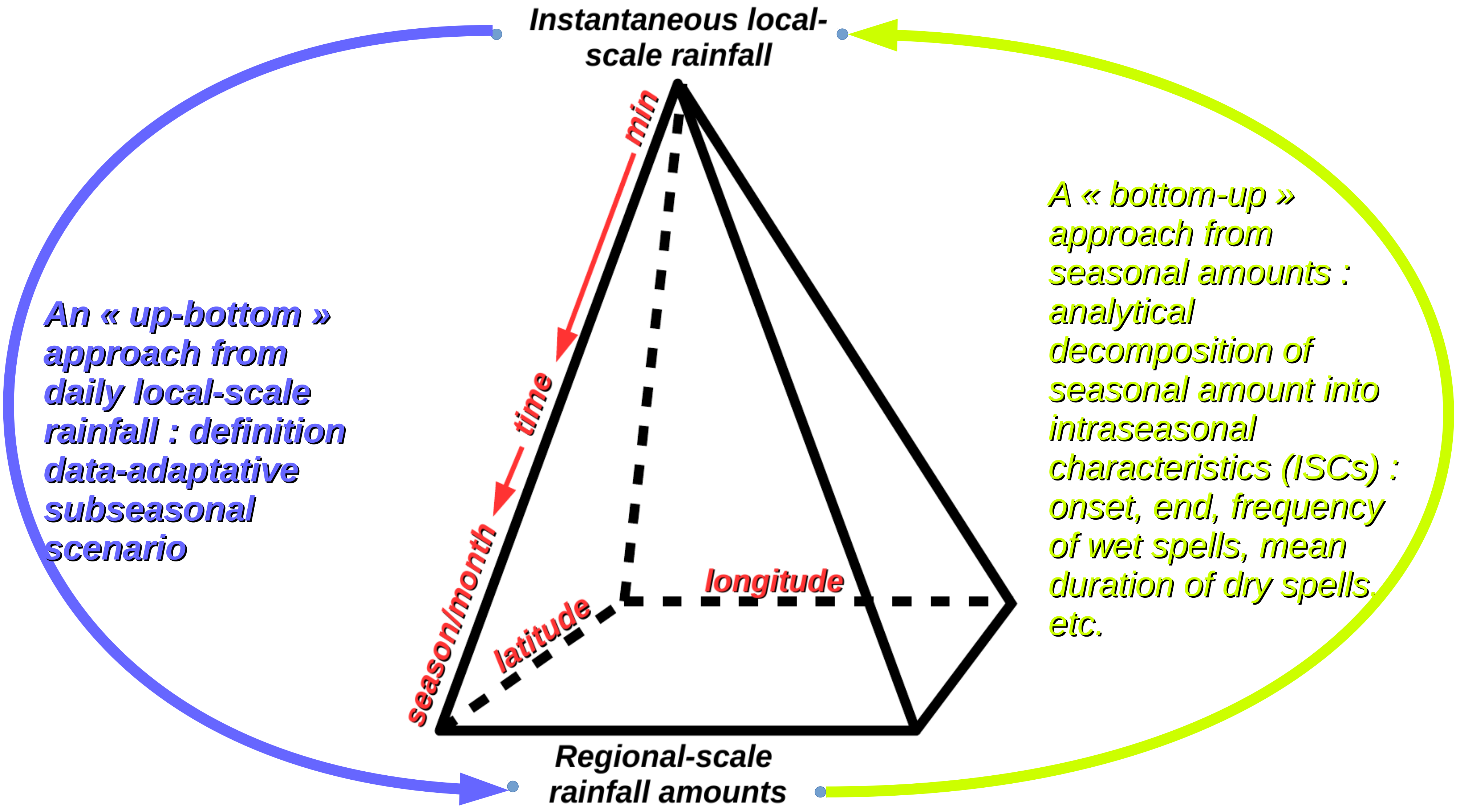




2- Scales and periodic – quasi-periodic forcings



2- Two complementary approaches



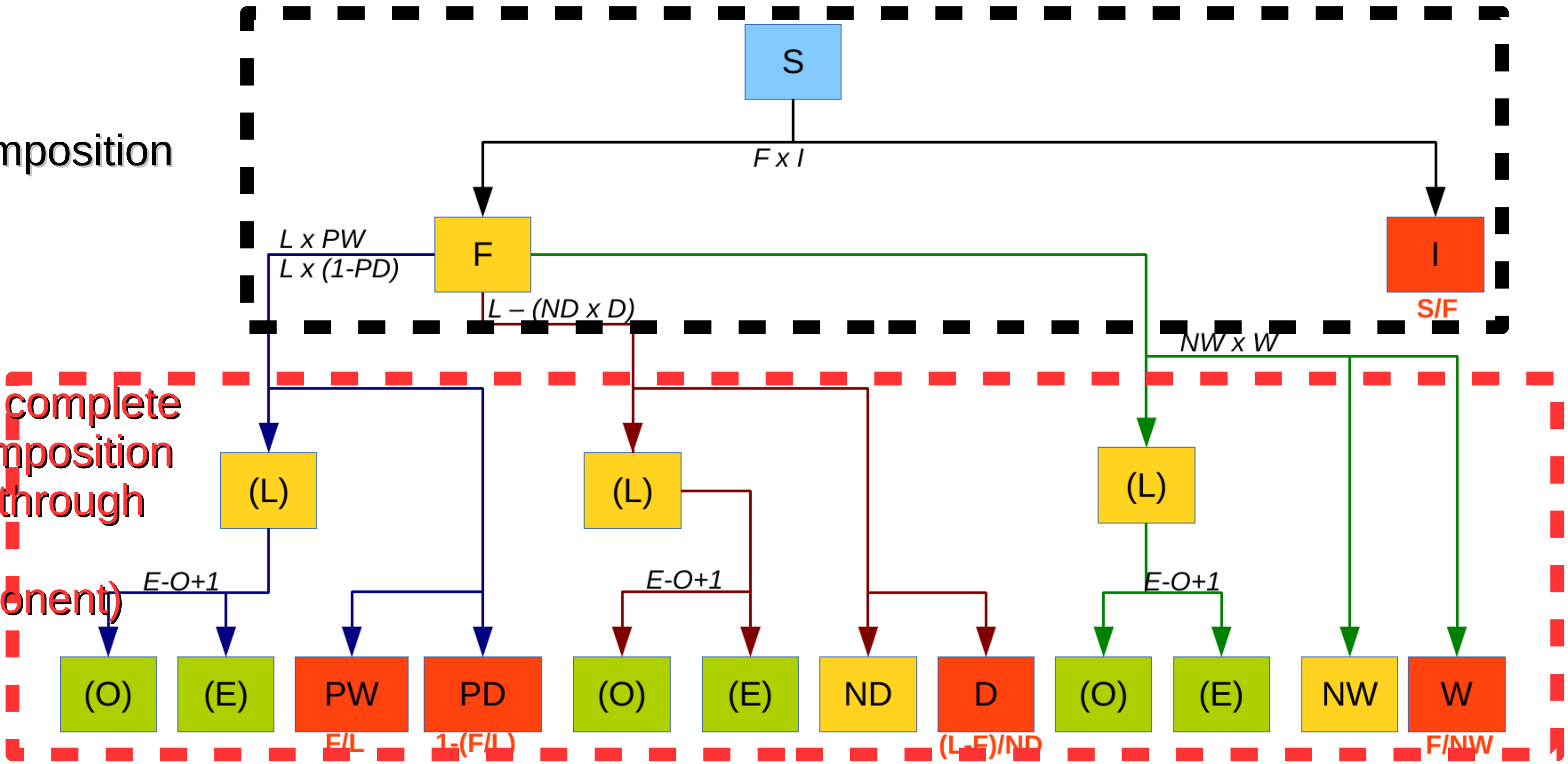
3- Basic & full analytical decomposition of seasonal amount (1)

- First, a basic analytical decomposition of the local-scale seasonal amount (S) considers the product of the number of wet day (N) and the daily mean intensity of rainfall (I) as S = F x I (i.e. Moron et al., 2007)
- By definition the interannual variability of S will be mostly related to the wettest days inside the season and this effect will be relatively dilluted when the rainy season lasts long and/or includes a lot of wet days
- From a dynamical point of view, F is a binary variable (0 or 1) indicating that **moist convection is triggered or not**, while I (a positive definite variable) could be viewed as **an empirical estimate of the intensity of moist convection**
- F could be further analytically decomposed into ISC considering the temporal phase of the monsoon (onset, end, duration) as well as mean length, frequency of dry and wet spells

3- Basic & full analytical decomposition of seasonal amounts (2)

Basic decomposition

More complete decomposition of S (through its F component)

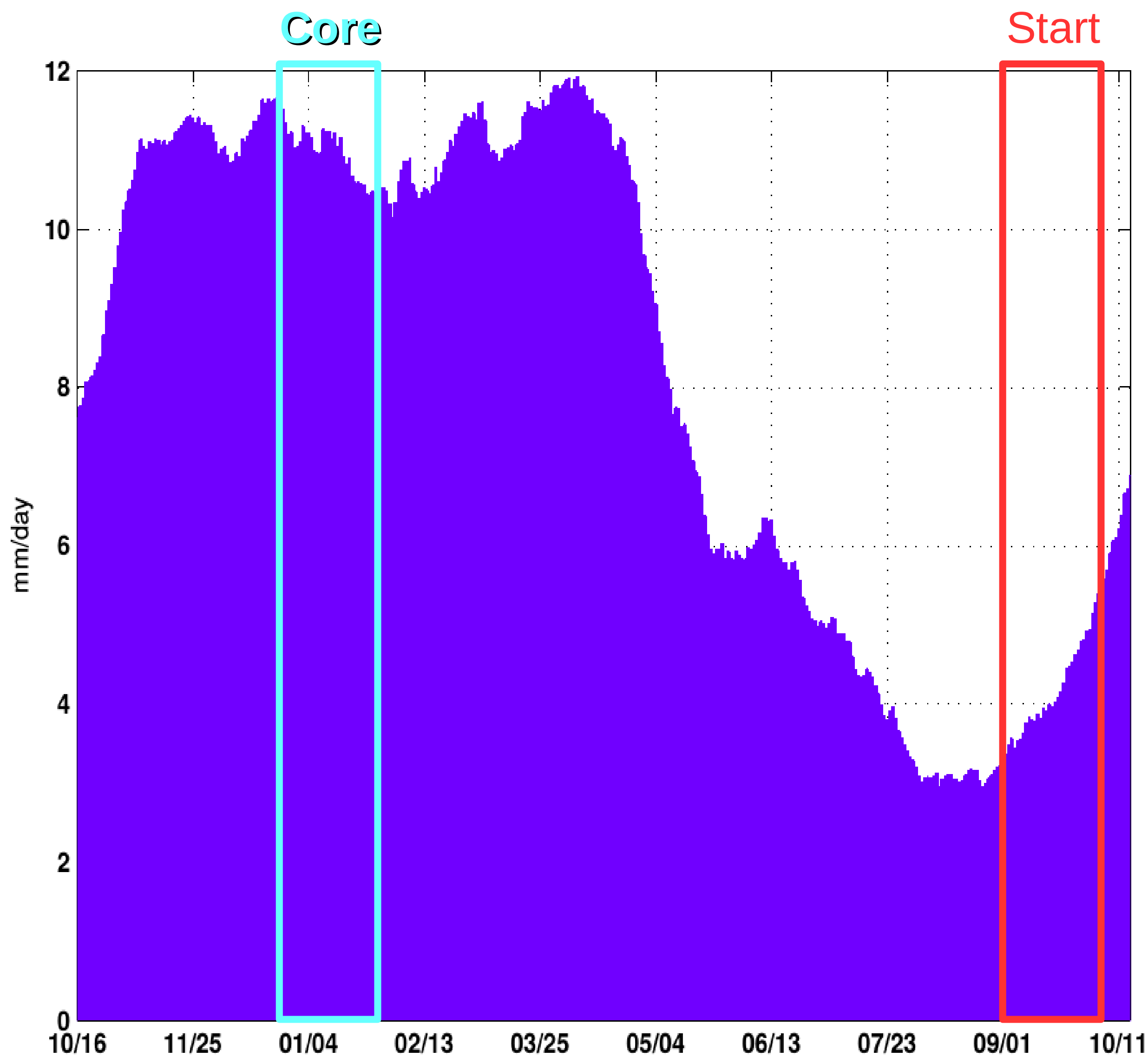


S : **S**easonal amount
F : **F**requency of wet day receiving at least 1 mm
I : mean **I**ntensity of rainfall during wet days
L : **L**ength of the wet season (could be fixed for pre-defined season)
O : **O**nset of the wet season (could be fixed for pre-defined season)
E : **E**nd of the wet season (could be fixed for pre-defined season)
PW : mean **P**robability of **W**et days
PD : mean **P**robability of **D**ry days
ND : total **N**umber of **D**ry spell (= consecutive days receiving less than 1 mm)
D : mean length of **D**ry spell (= consecutive days receiving less than 1 mm)
NW : total **N**umber of **W**et spell (= consecutive days receiving at least 1 mm)
W : mean length of **W**et spell (= consecutive days receiving at least 1 mm)

Variable documenting frequency/count across the rainy season
Variable documenting temporal phase of the rainy season
Variable documenting a mean property across the rainy season, i.e. numerically dependent on two other variables (the parent and another variable : for example I = S/F)

(Moron et al., 2015b)

4- The example of Indonesia



Mean daily rainfall on 114°-115°E, 3°-4°S (SE of Borneo around the city of Bandjarmasin). Data from daily GPCP dataset (from Oct, 1 1996 to Dec, 31 2014.

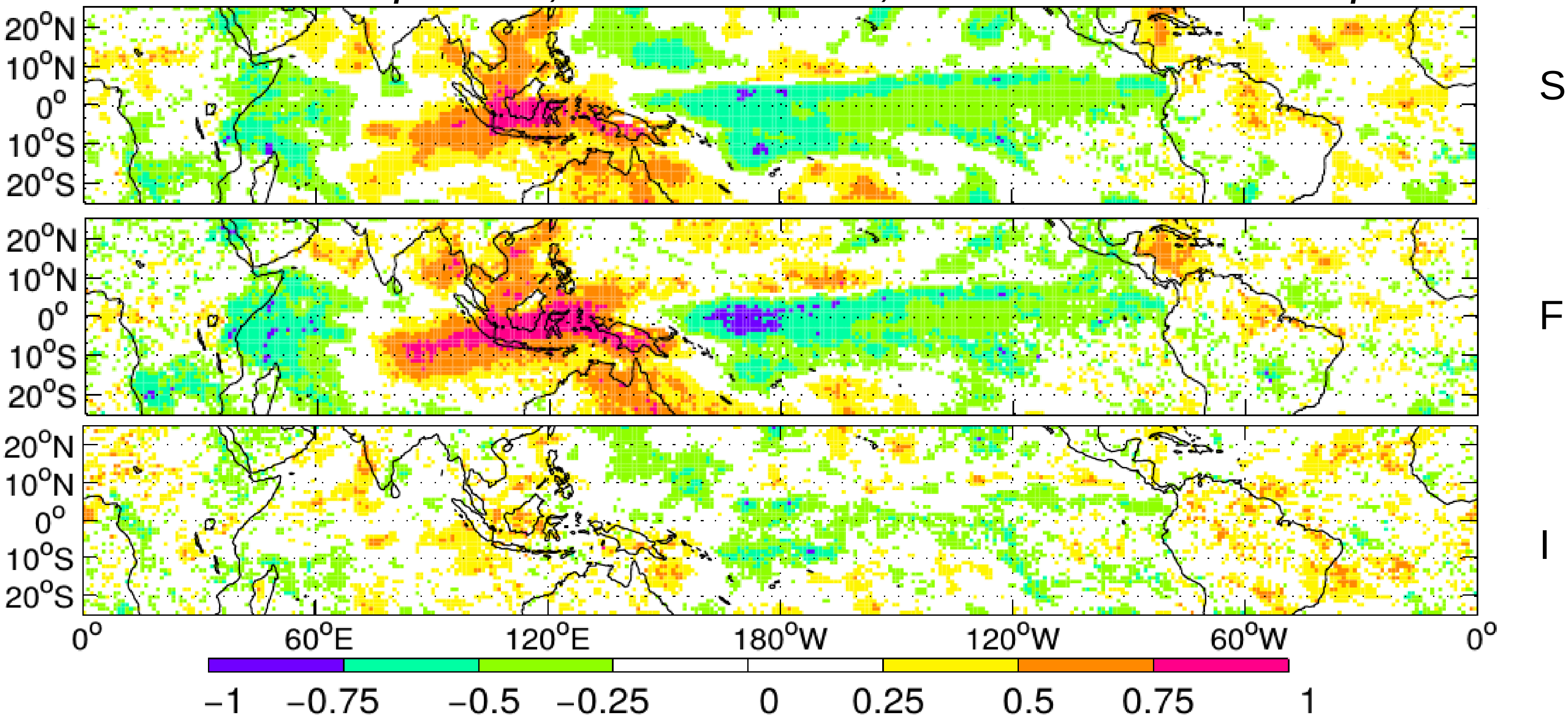
A subequatorial location in Indonesia (around the city of Bandjarmasin) without a real dry season, but a noticeable decrease of rainfall from June to August and an extended wet season from Ocrtober to May

It is assumed that a needed (but not sufficient) **pre-requisite of potential predictability from boundary forcings (including SST) is the regional-scale spatial coherence at interannual time scale** (i.e. Moron et al., 2007)

We will compare the **start of the wet season (~ September)** vs a month in the **core of the wet season (January)**

4- Teleconnection of local-scale rainfall in Southern Borneo in September (~ start of the rainy season)

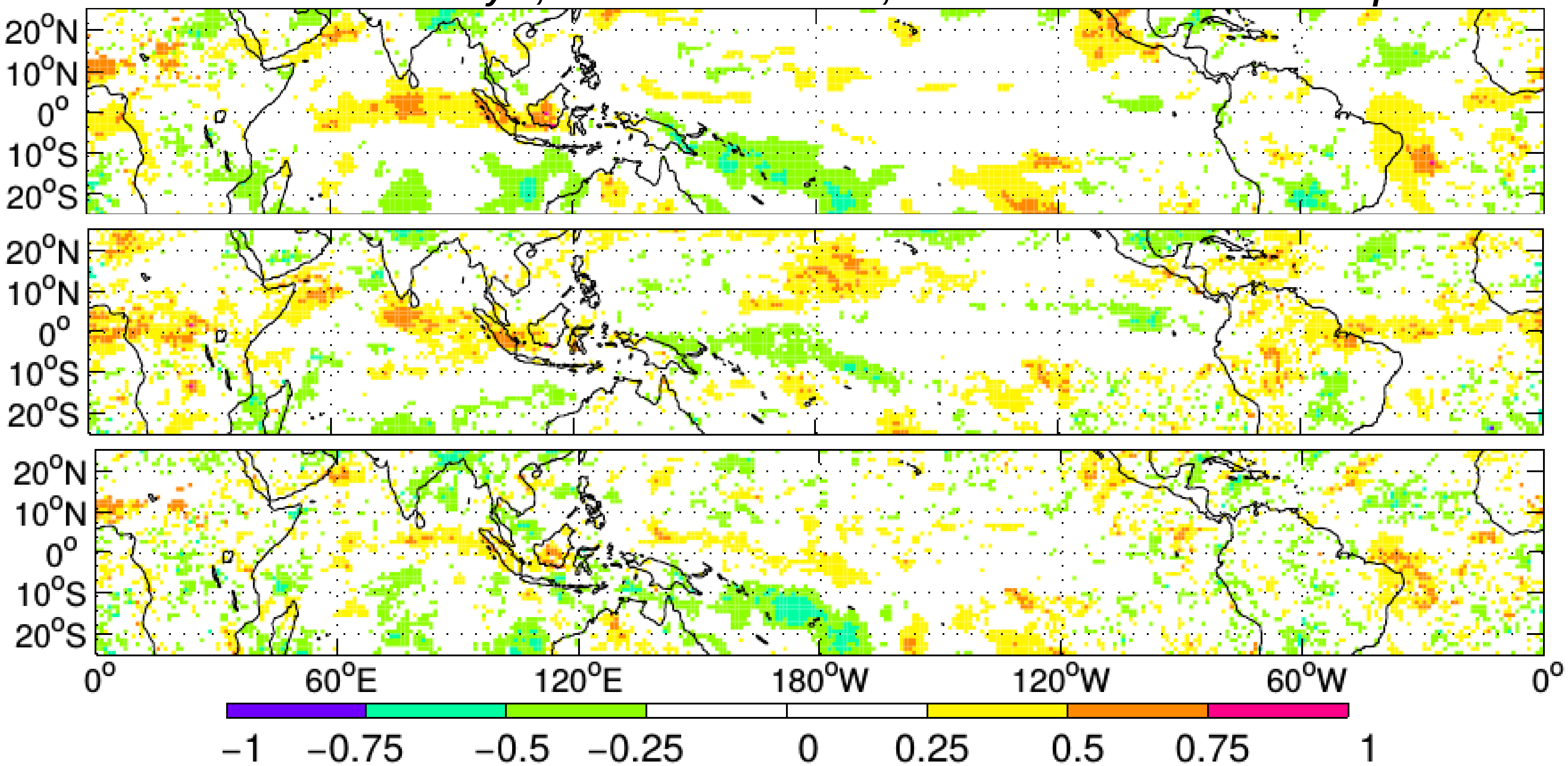
Correlations between September S, F and I at 114°-115°E, 3°S-4°S and the rest of the tropical zone



- Evidence for a large-scale pattern for S, and especially F, between Eastern Indian Ocean and Western Caribbean basin : **the local-scale rainfall variability in southern Borneo is included in a large-scale phenomenon, clearly related to ENSO** (warm ENSO ~ negative rainfall anomalies over the Maritime Continent and most of the Western Pacific and Tropical Eastern Indian ocean)
- I is mostly just a noisy information without a clear spatial structure

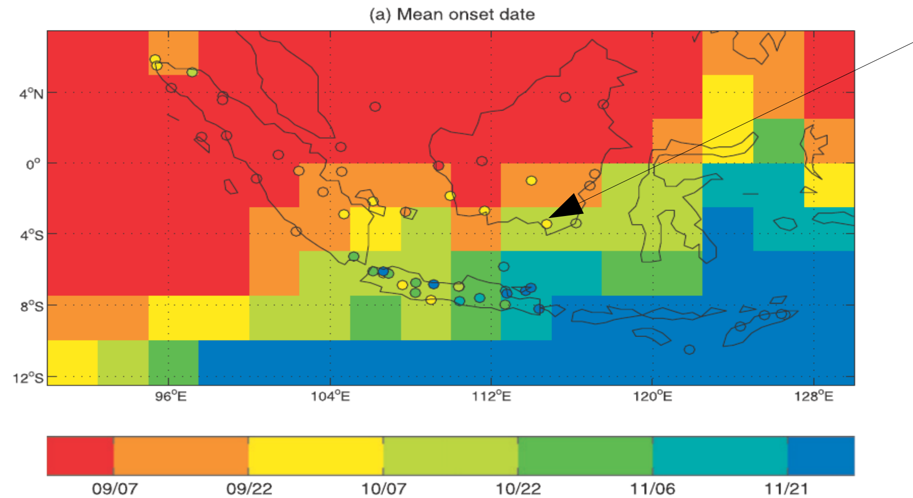
4- Teleconnection of local-scale rainfall in Southern Borneo in January (~ core of the rainy season)

Correlations between January S, F and I at 114°-115°E, 3°S-4°S and the rest of the tropical zone



- The zonal spatial pattern almost vanishes for S and F and now the S pattern is closer to I one than F one: the local-scale rainfall variability is not included in a large-scale mode of variation and the teleconnection with ENSO almost disappears (correlations ~ 0 from Central to Eastern Equatorial Pacific) while ENSO events usually peak thermselves at that time ; **it suggests a poorer predictability (at least linked to ENSO) during the core of the rainy season rather than at the start**

4- Spatial coherence of local-scale onset of austral monsoon



Bandjarmasin

Sept. 1 ……………………………….. Nov. 30

Local-scale onset is defined from rain-gauges and CMAP pentad dataset as the first 5-day (from August 1st) receiving at least 40 mm without 10-day dry spell receiving less than 10 mm in the following 30 days (to avoid « false » onsets). The leading EOF shows a clear synchronization of anomalous onsets at interannual time scale

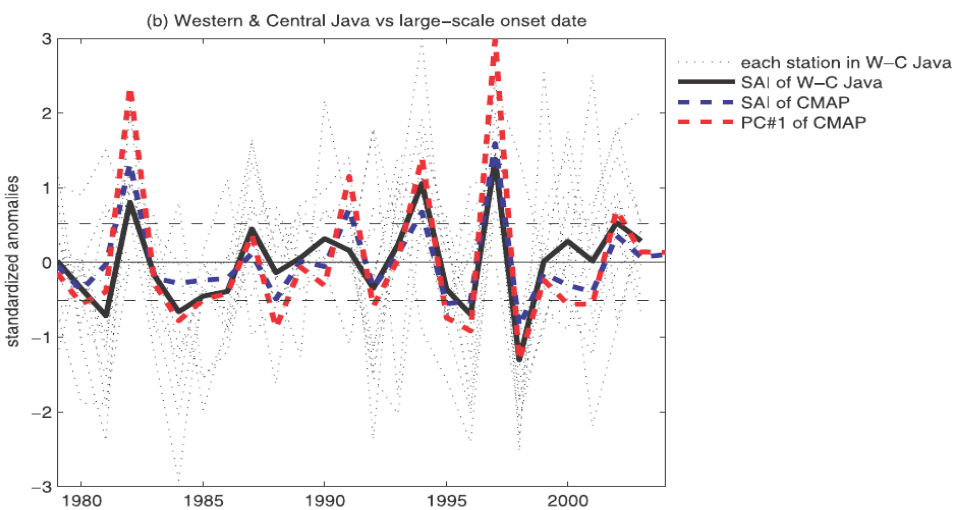


FIG. 1. (a) Mean onset date computed in CMAP (shading) and GSOD (dot) as the first wet day of a 5-day sequence receiving > 40 mm from 1 Aug without a dry 10-day sequence receiving < 5 mm in the following 30 days from onset. (b) Standardized onset date for western and central Java GSOD stations (dotted lines) with the average, i.e., SAI (solid black line), together with the CMAP SAI (blue dashed line) and standardized leading PC time series (red dashed line) computed from all 128 CMAP grid points. The dashed horizontal lines delineate the 95% confidence interval of a set of 14 white noise time series. Note that one std dev corresponds to an averaged deviation of ~20 days for western and central Java.

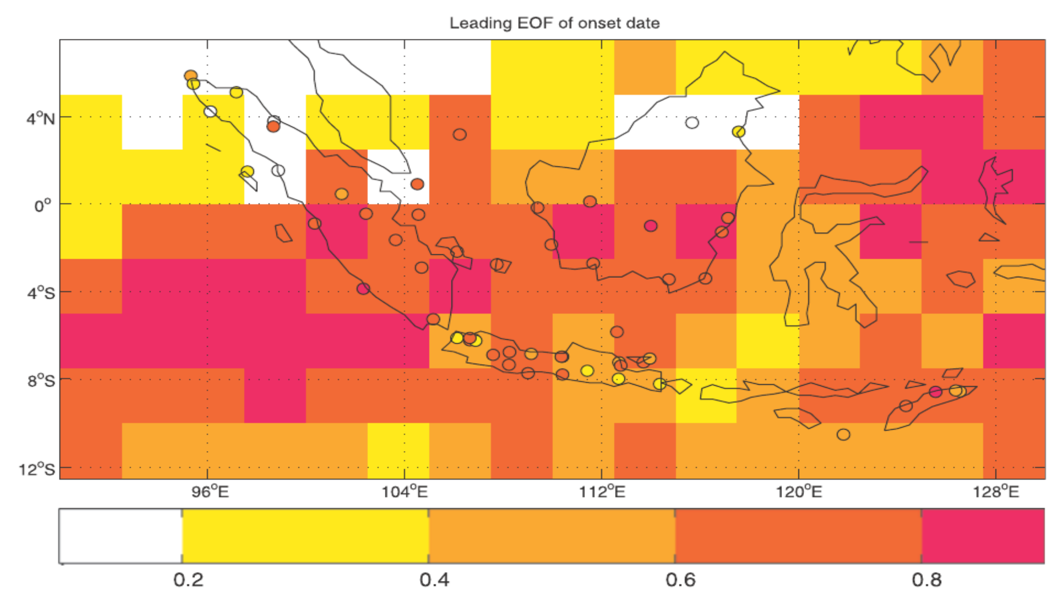


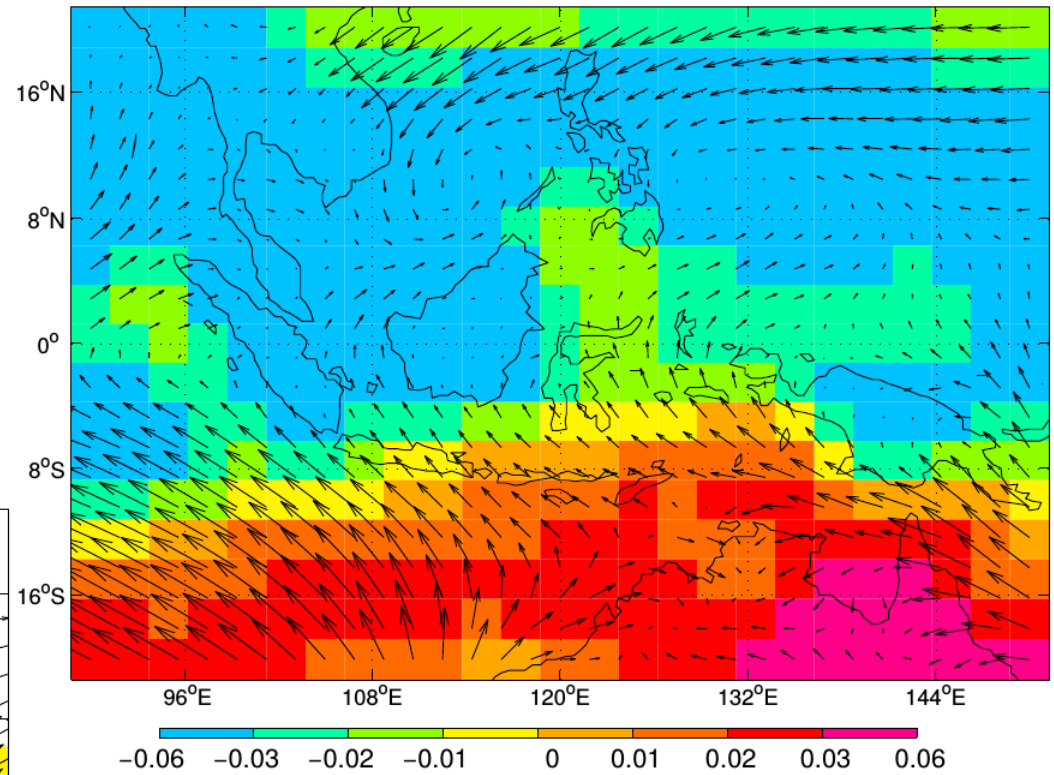
FIG. 2. Leading EOF of CMAP (shading) and GSOD (dot) onset dates, plotted as correlations with the principal component time series. The time series of onset date at each grid point were standardized prior to EOF analysis.

(Moron et al., 2009a)

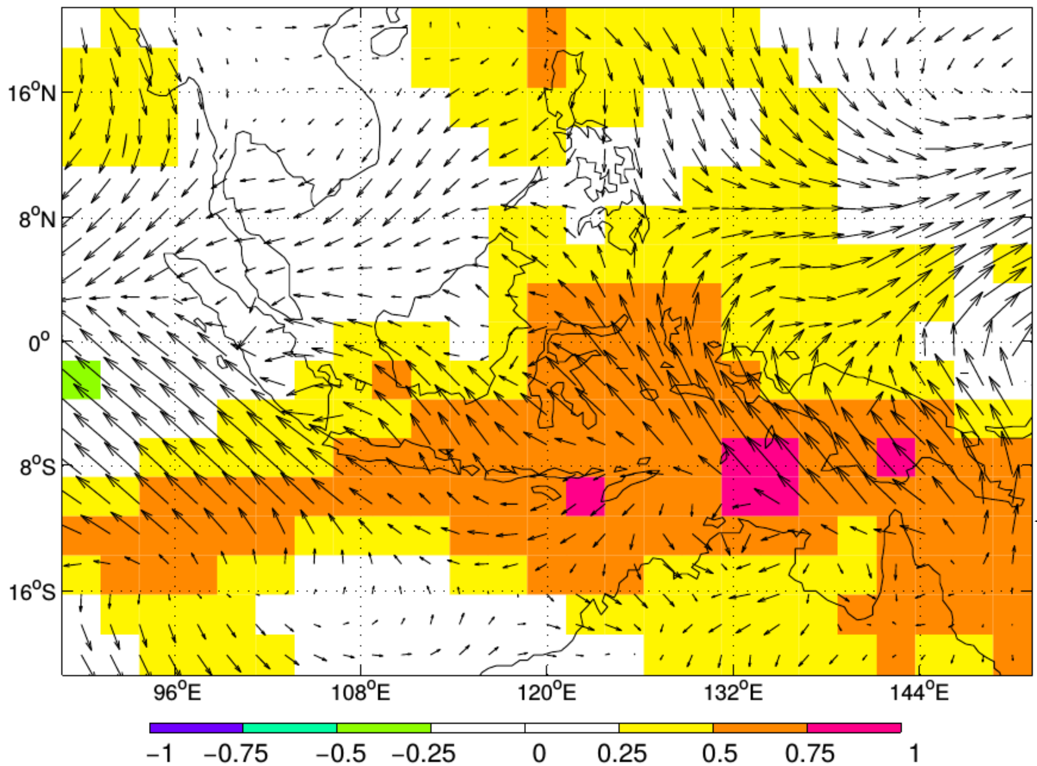
4- Mean impact of ENSO on winds and vertical velocity in Sept.-Nov. (including the local-scale onsets)

Still SE winds S of equator with N-S dipole in ascendance (in the N) and subsidence (in the S)

Mean 10-m winds (vectors) and vertical velocity (shadings) in Pa/s at 500 hPa in Sept.-November



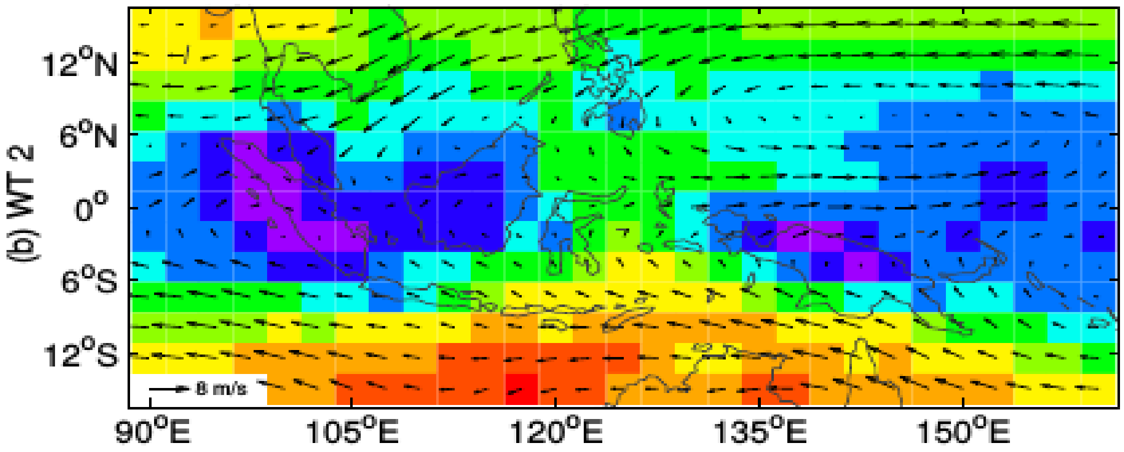
Correlation between Nino 3.4 and mean 10-m winds (vectors) and vertical velocity (shadings) at 500 hPa in Sept.-November

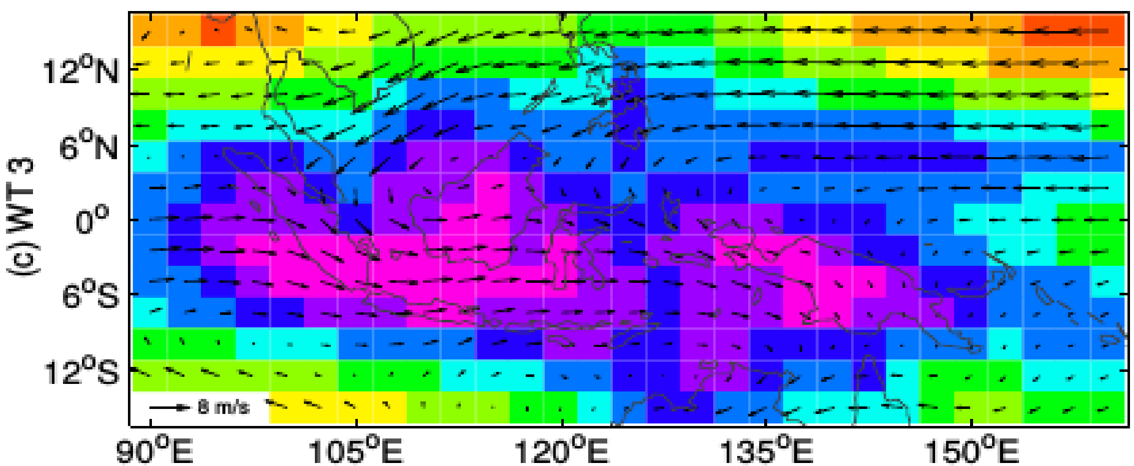


Warm ENSO = SE anomalies (= reinforcing the mean state, thus cooling inner seas) + anomalous subsidence mostly S of equator = delaying the usual NW-SE shift of the start of the rainy season

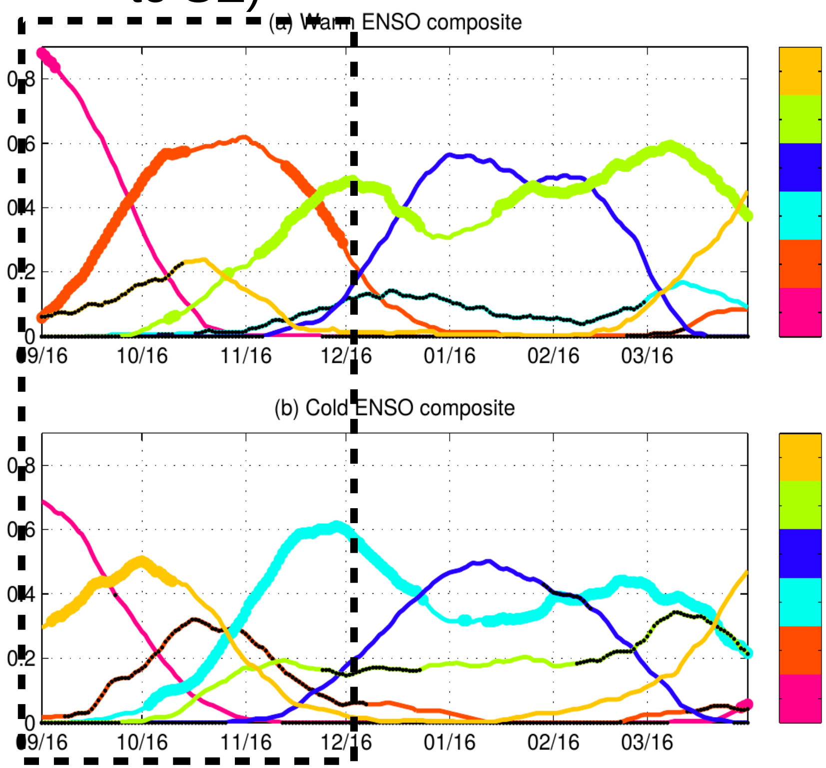
4- Mean impact of ENSO on weather types around the local-scale onsets

OLR (shadings) and 925 hPa winds (vectors) in 2 weather types (amongst a total of 6) with their frequency in warm and cold ENSO events





Onset (from NW to SE)



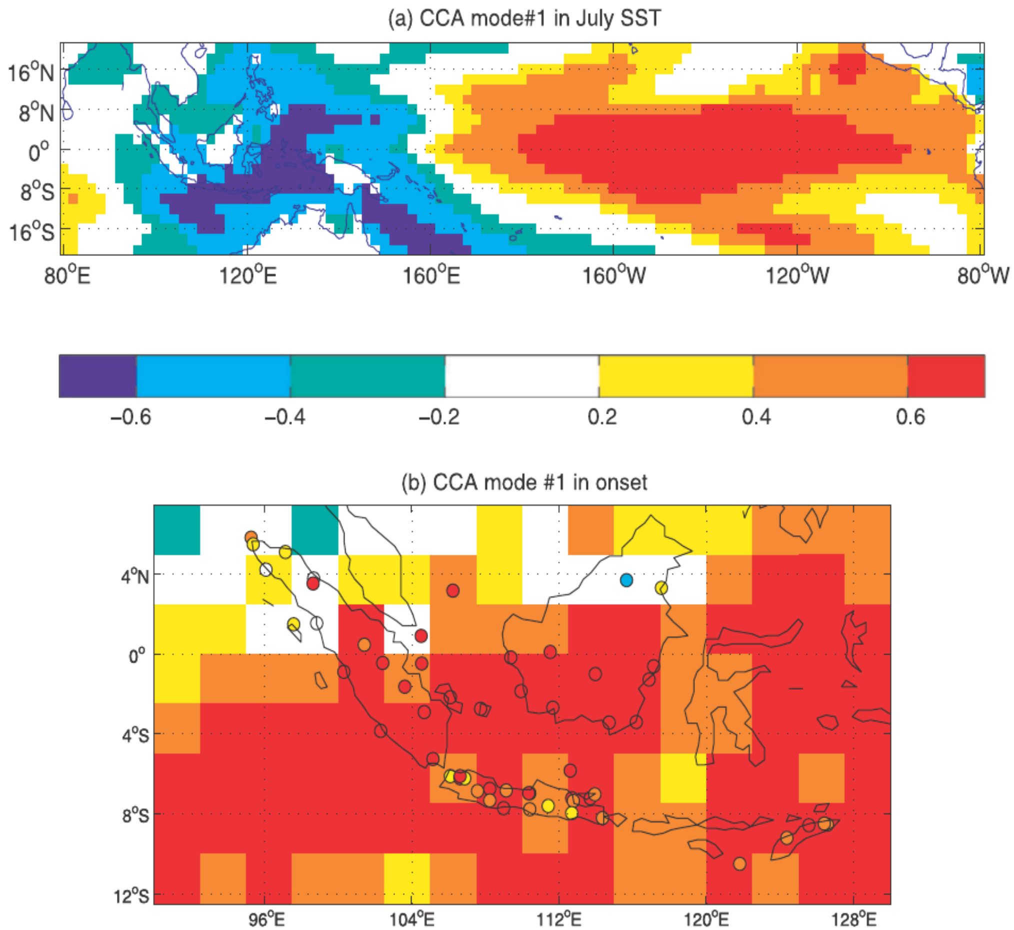
(Moron et al., 2015a)

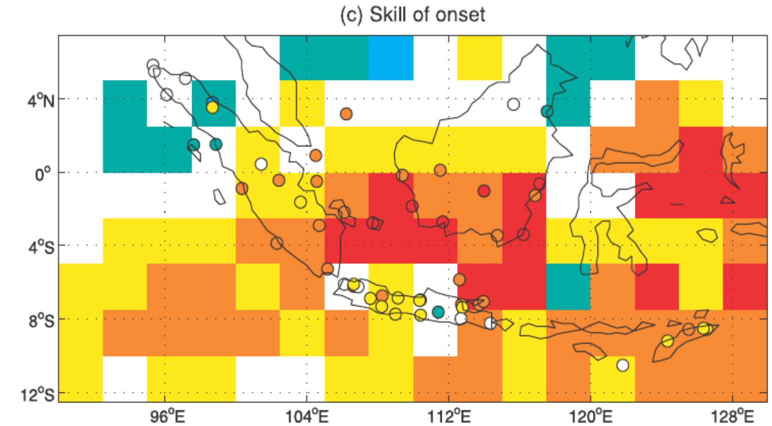
- Warm ENSO events = too many WT #2 days (still E-SE south of equator and weak convection confined to Sumatera-Borneo and Western Pacific)
- Cold ENSO events = an early and massive transition to WT #3 (low level W + deep convection across Indonesia)

4- Infering the predictability of the local-scale onsets

- Analysis of spatio-temporal variability of local-scale onsets that **they onset to be homogeneously delayed or advanced across most of the Maritime Continent**
- Synchronous correlations between ENSO and 10-m winds and 500 hPa vertical velocity helps to interpret the anomalous delays in warm ENSO phases ; they induce **large-scale subsidence at 500 hPa, especially south of Equator and low-level easterlies** (corresponding to WT 2) which increase the usual trades (and thus cool inner sea since the wind speed is increased)
- **As the ENSO are already in warm or cold state in boreal summer**, local-scale onsets could be accurately predicted from June-August SST in the tropical Pacific
- It could be done with any statistical method linking the predictors (SST in boreal summer) and predictand (local-scale onsets from September to early December)
- An example is shown here using Canonical Correlation Analysis -CCA- (Barnston and Ropelewski, 1992) : CCA seeks linear combinations of variables from two fields (here SST and local-scale onsets) maximising the correlation between the corresponding temporal scores. As any retrospective prediction, it should be done in cross-validation by separating strictly training and verification. This exercise could be easily done using CPT from IRI

4- The skill of local-scale onsets across the Maritime Continent





5. Homogeneous correlation maps of (a) SST, and (b) onset date from CMAP g) and GSOD (circles), of the leading canonical correlation analysis (CCA) mode (c) kill (i.e., correlation between observed and hindcast onset date) associated with the CCA mode between July SST and onset dates.

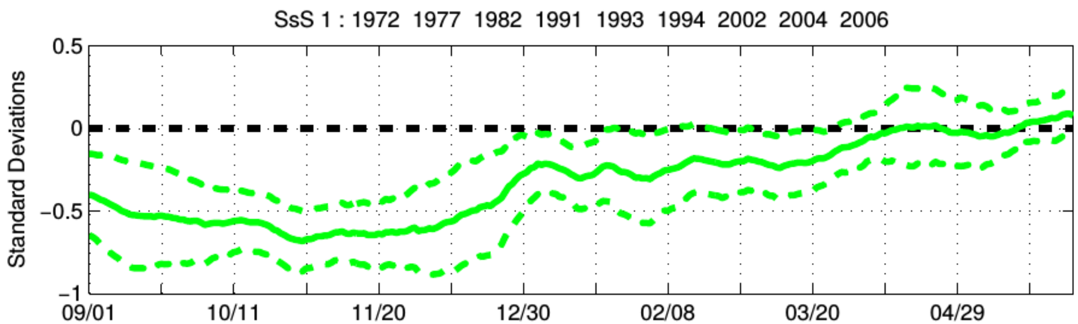
(Moron et al., 2009a)

It illustrates the fact that **a local-scale event could be predicted as soon as (1) it is indeed included in a spatially-consistent mode at regional-scale** and (2) **it is physically related to a large-scale and predictable phenomena**. In this case, warm ENSO delays the usual southeastward shift of the ITCZ and thus impacts locally the temporal phase of the onset of austral summer monsoon. Note that the case of MC is not unique (at least Philippines in May, East Africa in Feb-March)

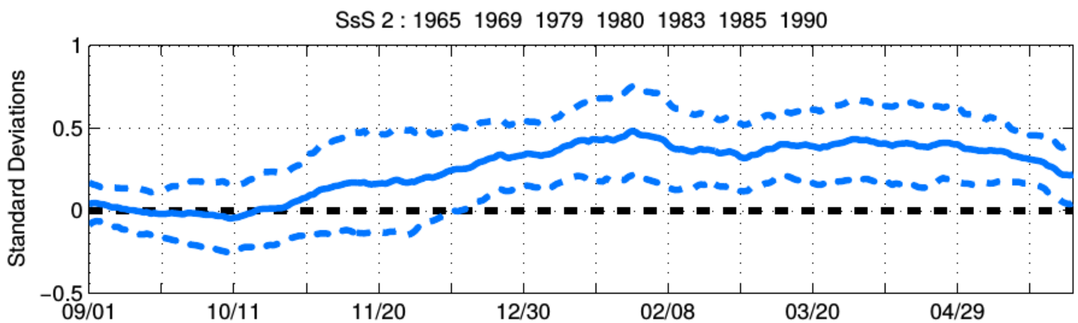
5- An « up-bottom » approach : the subseasonal scenario (SsS)

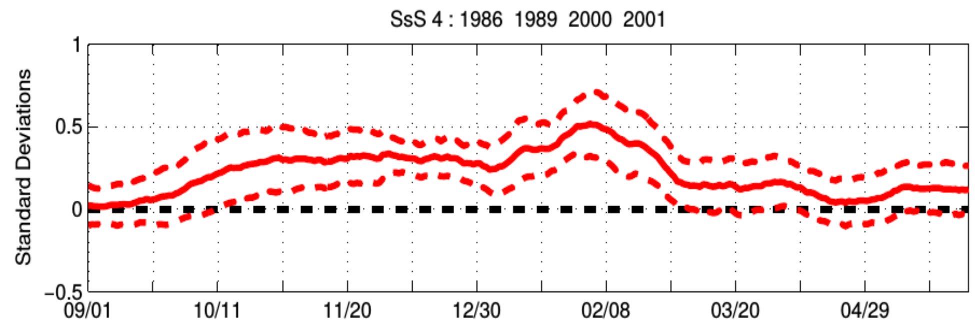
- SsS is an attempt to extract the **spatially-consistent signals across the rainy seasons at regional-scale without any a priori decomposition of seasonal amounts**
- Daily amounts (from 0.5° x 0.5° Aphrodite dataset from 1961 to 2007) of rainfall are averaged on running 31-day windows
- The 31-day amounts are square rooted to reduce the skewness
- The 31-day square-rooted amounts are normalized using the running means (but not standardized to keep the largest anomalies when it rains)
- These anomalies are standardized using the standard deviation of the whole available period and concatenated so that observations are years and variables are stations (or grid-points) and intra-seasonal time steps
- An time-lagged EOF is performed to extract the leading PCs
- The SsS are extracted with a fuzzy k-means (Mc Bratney and Moore, 1985). Fuzzy clustering (i.e. when membership of observations is between 0 and 1) is by definition more flexible than « hard » clustering (i.e. membership of observations is either 0 or 1). This property is important since SsS classify few years (47 in our example) with potential large spatial and intra-seasonal dimensions
- **SsS are then typical scenarios of low-pass rainfall anomalies with the largest mean amplitudes recorded when they are spatially consistent at regional-scale. SsS consider also explicitly the temporal consistency across the season**

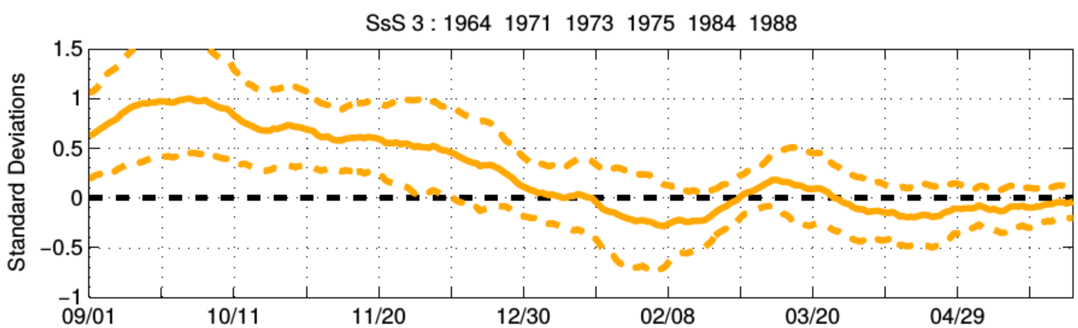
5- The Sub-seasonal Scenarios (SsS)

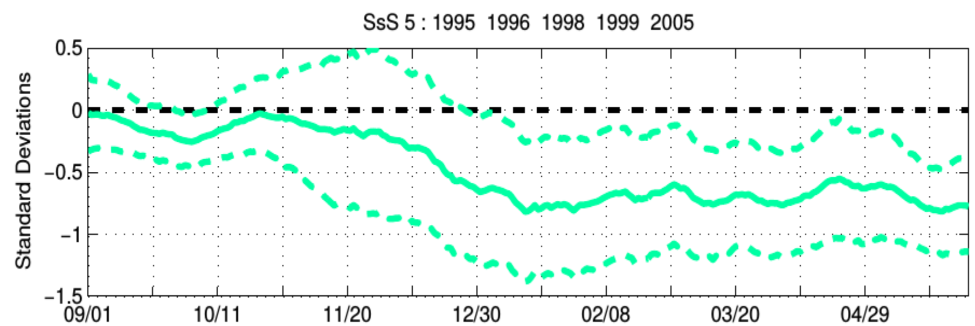


5 SsS of rainfall anomalies of continent (95°E-140°E, 0°-10°S) from Aphrodite dataset (749 grid-points). Full line = spatial average ; dashed line = spatial average ± 1 standard deviation. Years with a membership > 0.5 are indicated on the top. The date in abcissa are centers of running 31-day windows



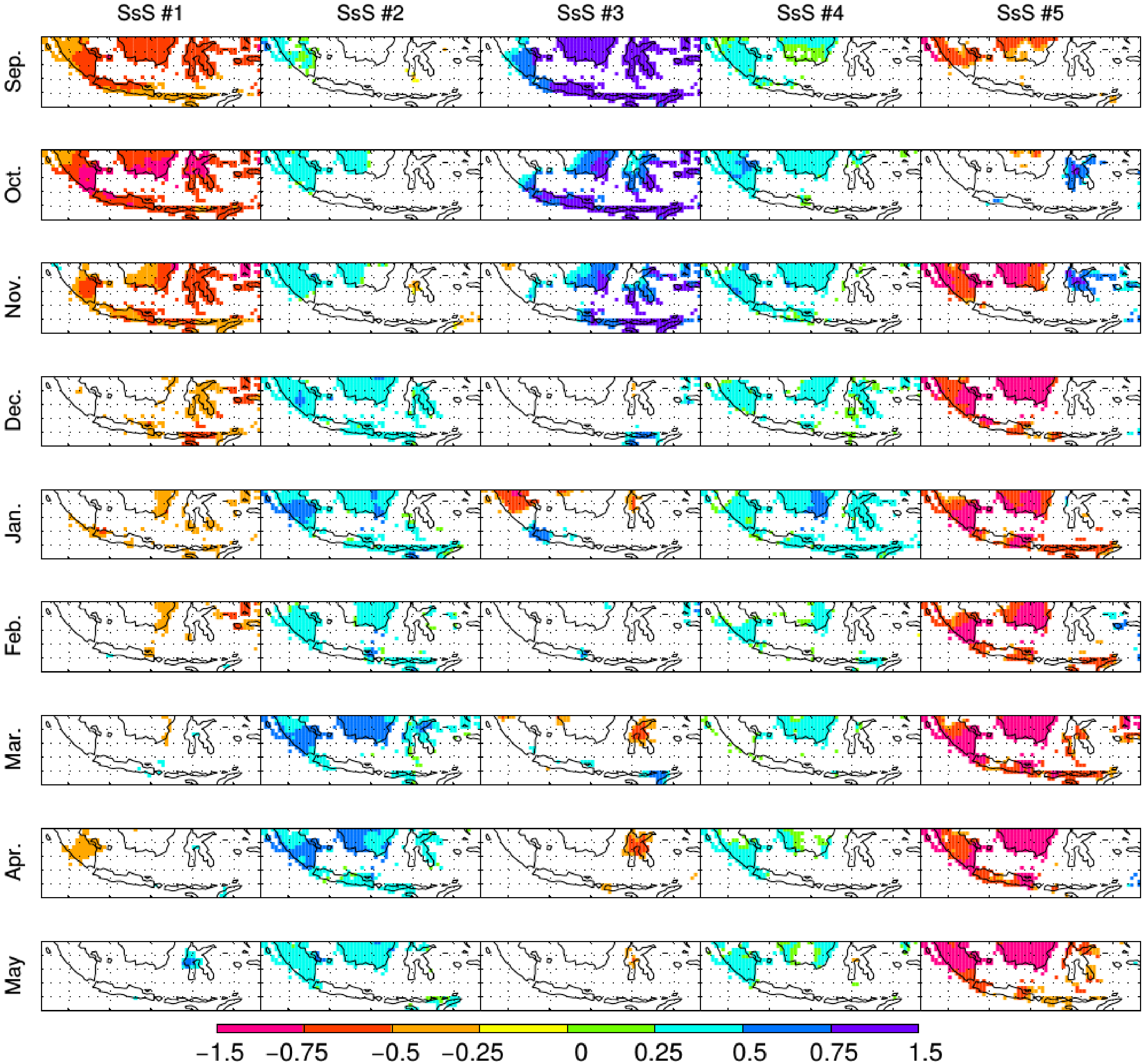






- SsS #1 / #3 : delayed (advanced) onset then weakly negative rainfall anomalies from late December
- SsS #2 : positive rainfall anomalies from early November
- SsS #4 : positive rainfall anomalies during most of the season, largest from October to February
- SsS #5 : close to normal rainfall around the onset, then large negative rainfall anomalies (but with a large spatial spread)

5- Monthly rainfall associated with SsS



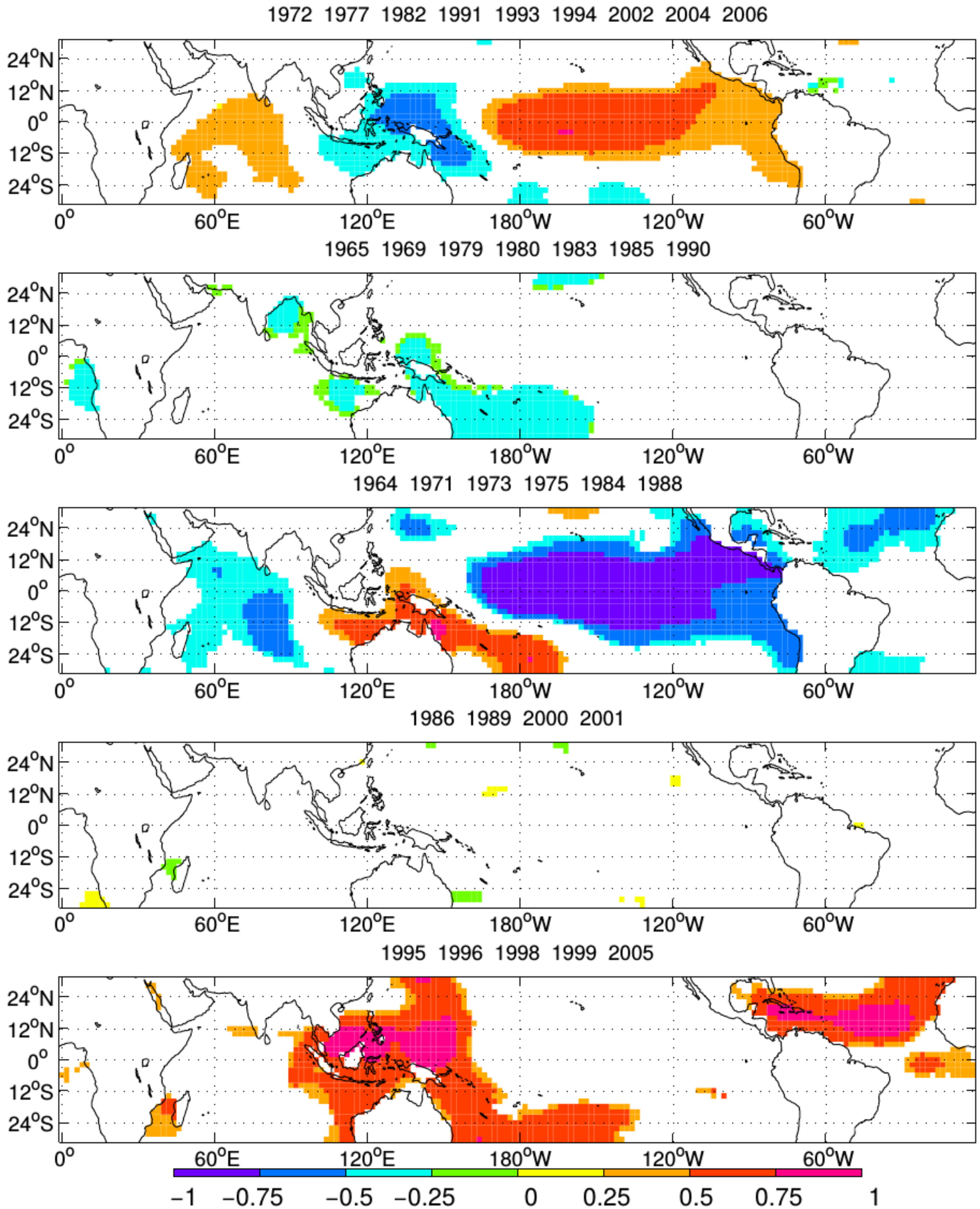
Monthly standardized rainfall anomalies (sig. at the two-sided 90% level) weighted by the memberships of 5 sub-seasonal scenarios

SsS #1 is out-of phase with SsS #3 (largest anomalies near the onset of austral monsoon)

SsS #2 is broadly out-of phase with SsS #5 (largest anomalies during and at the end of the austral monsoon)

The rainfall anomalies are usually weak near the peak of the monsoon (except for the dry SsS #5)

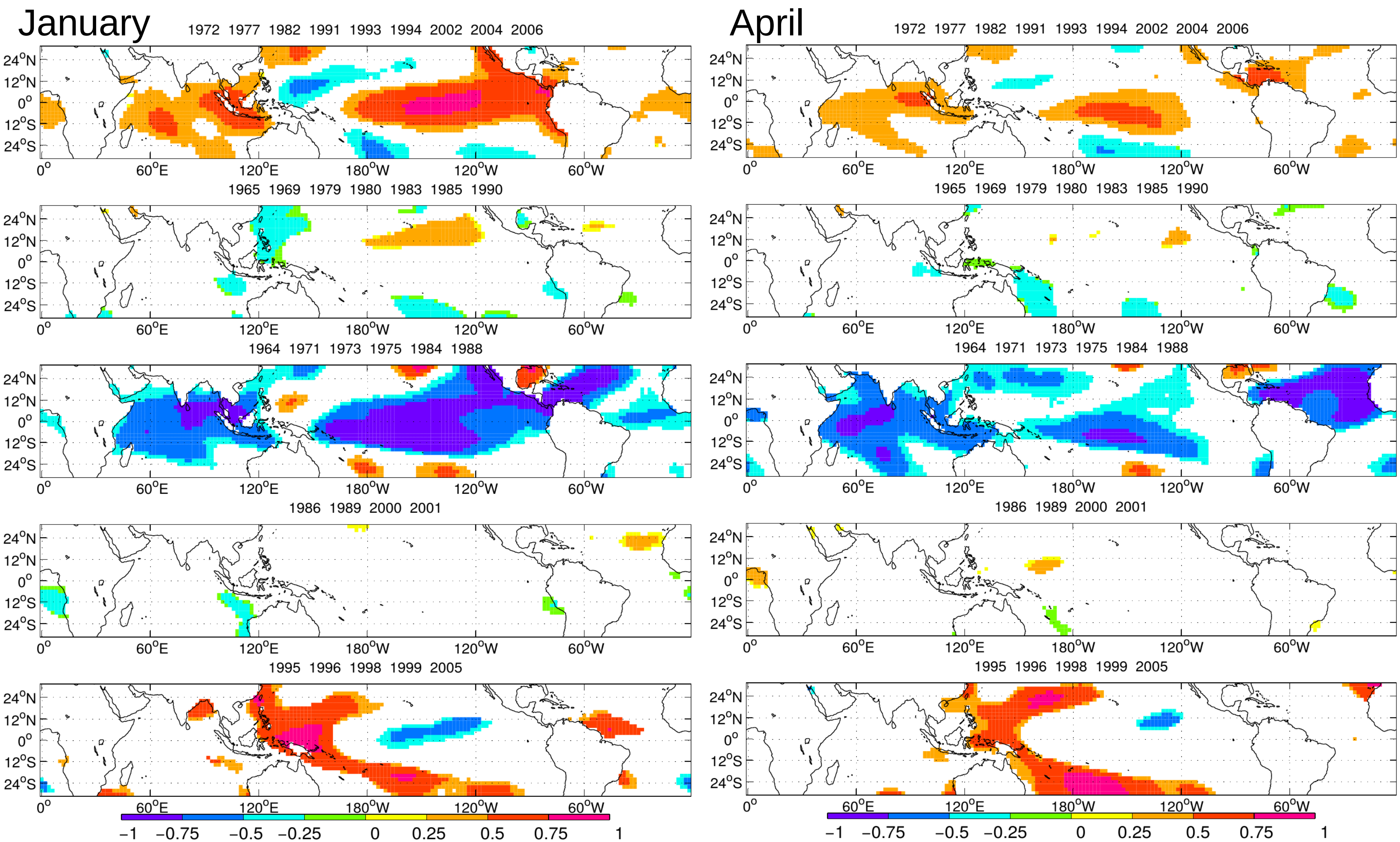
5- SsS vs sea surface temperatures in August



Standardized SST anomalies (sig. at the two-sided 90% level) in August weighted by the memberships of 5 sub-seasonal scenarios

- SsS #1 ~ warm ENSO
- SsS #3 ~ cold ENSO
- SsS #2 & #5 mostly refer to the long-term trend especially around Western Pacific (+ Tropical Northern Atlantic in SsS #5) ; SsS #5 = fingerprints of global warming ???
- SsS #4 is related to near-normal SST in mean

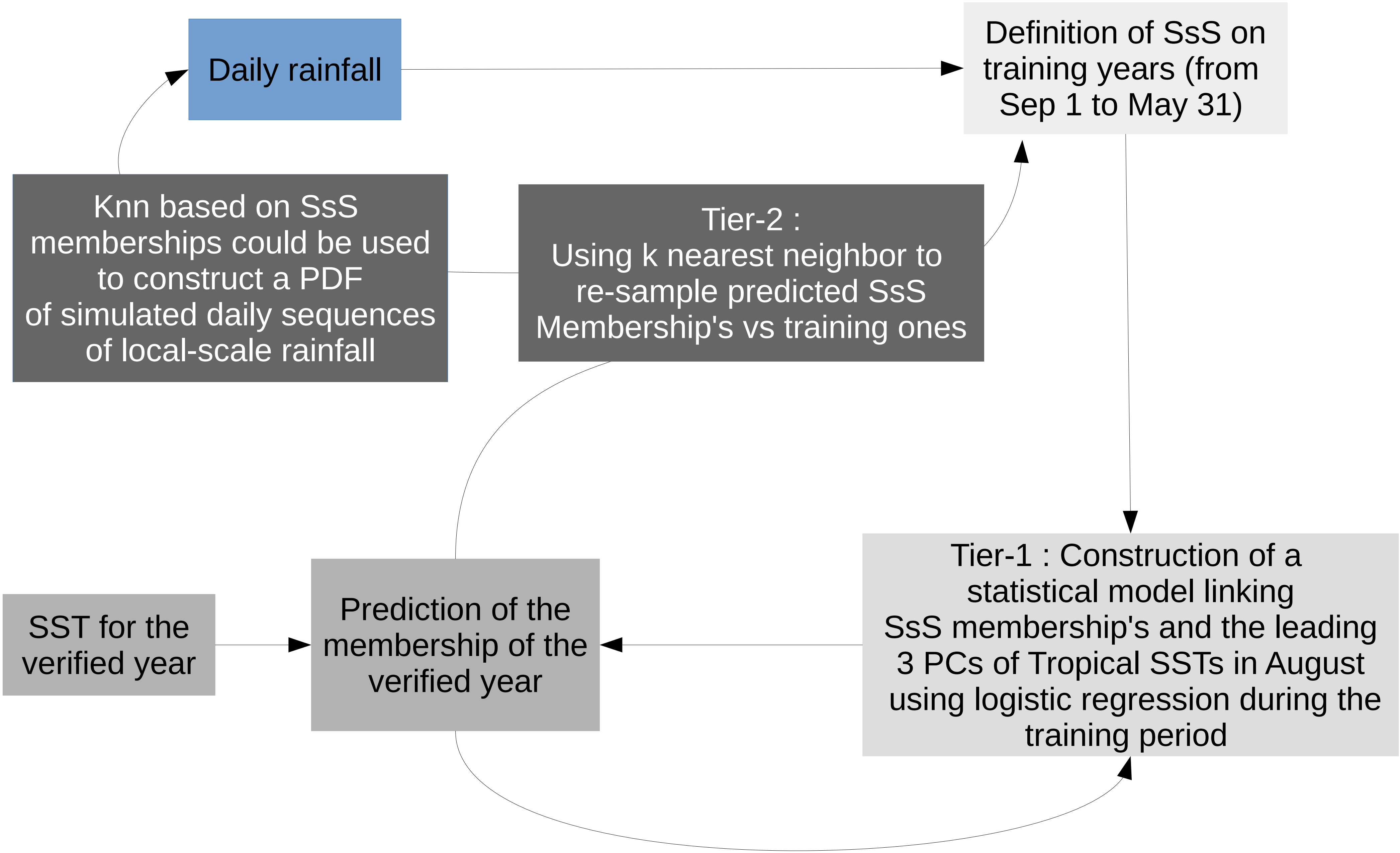
5- SsS vs sea surface temperatures in January & April



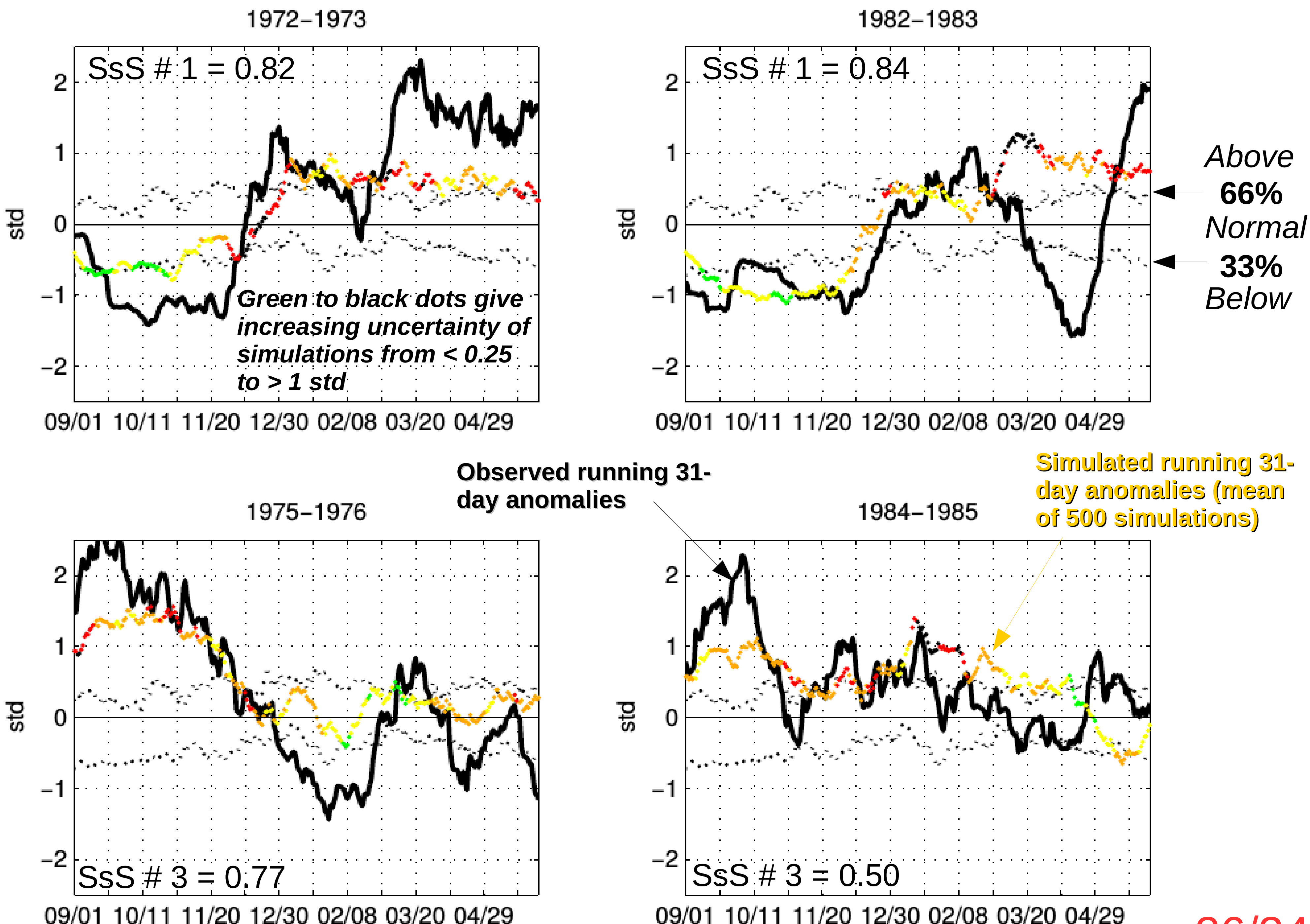
Standardized SST anomalies (sig. at the two-sided 90% level) in Jan. and April weighted by the memberships of 5 SsS

SsS #1 (~ warm ENSO) and SsS #3 (~ cold ENSO) show a clear intraseasonal modulation of SST anomalies over the inner seas (warming during warm ENSO events and cooling during cold ENSO events due to interaction of low-level wind anomalies couteracting -warm ENSO- and reinforcing -cold ENSO- climatological W-NW winds) (i.e. Hendon, 2003). This modulation could explain, at least partly, the intraseasonal modulation revealed by the SsS

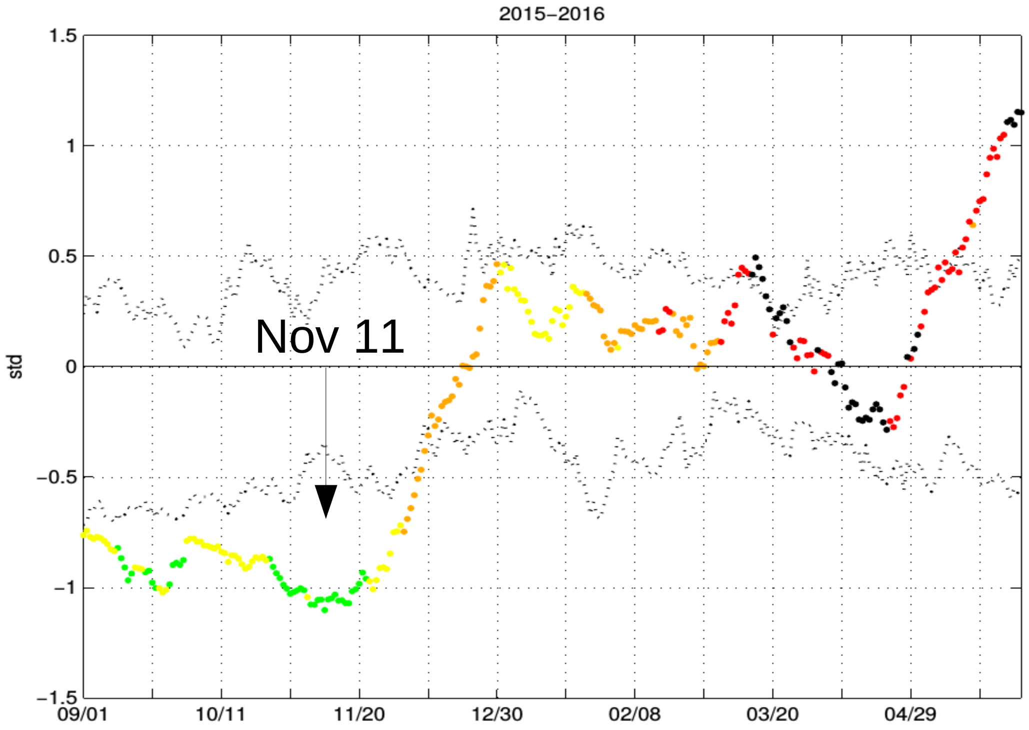
5- Predicting SsS and re-sampling local-scale rainfall using a 2-tiered cross-validated (XV) approach



5- Retrospective XV predictions at Bandjarmasin

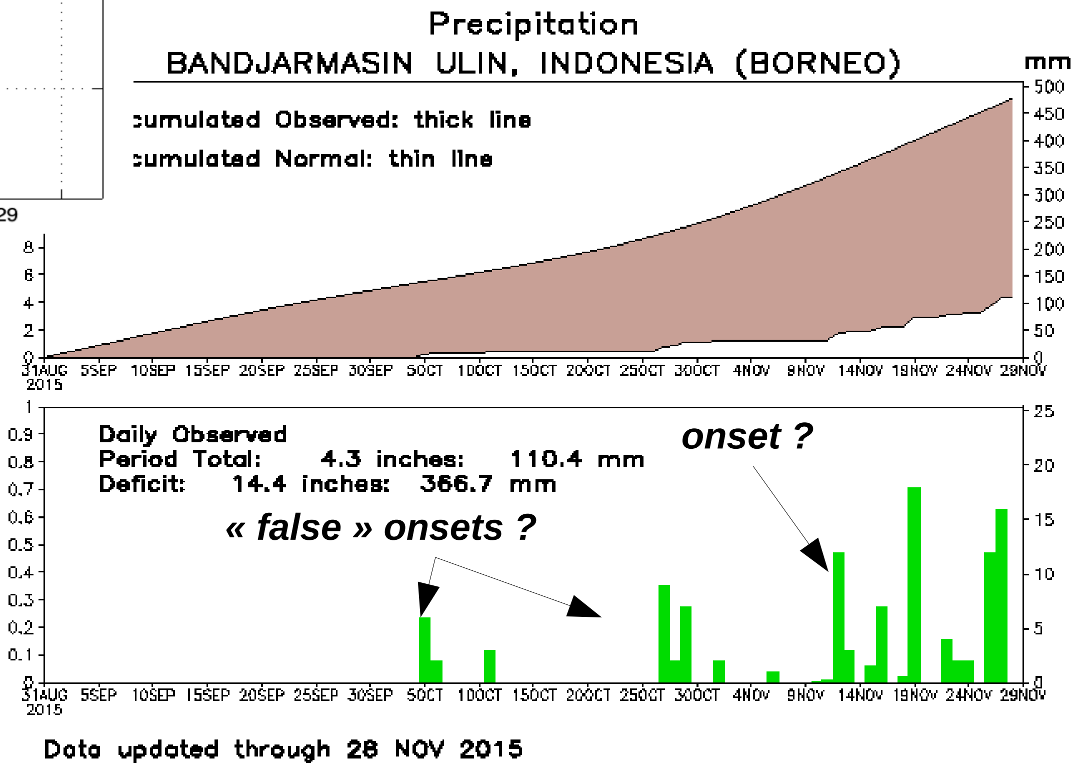


5- An attempt to predict the 2015-2016 season from August SST at Bandjarmasin



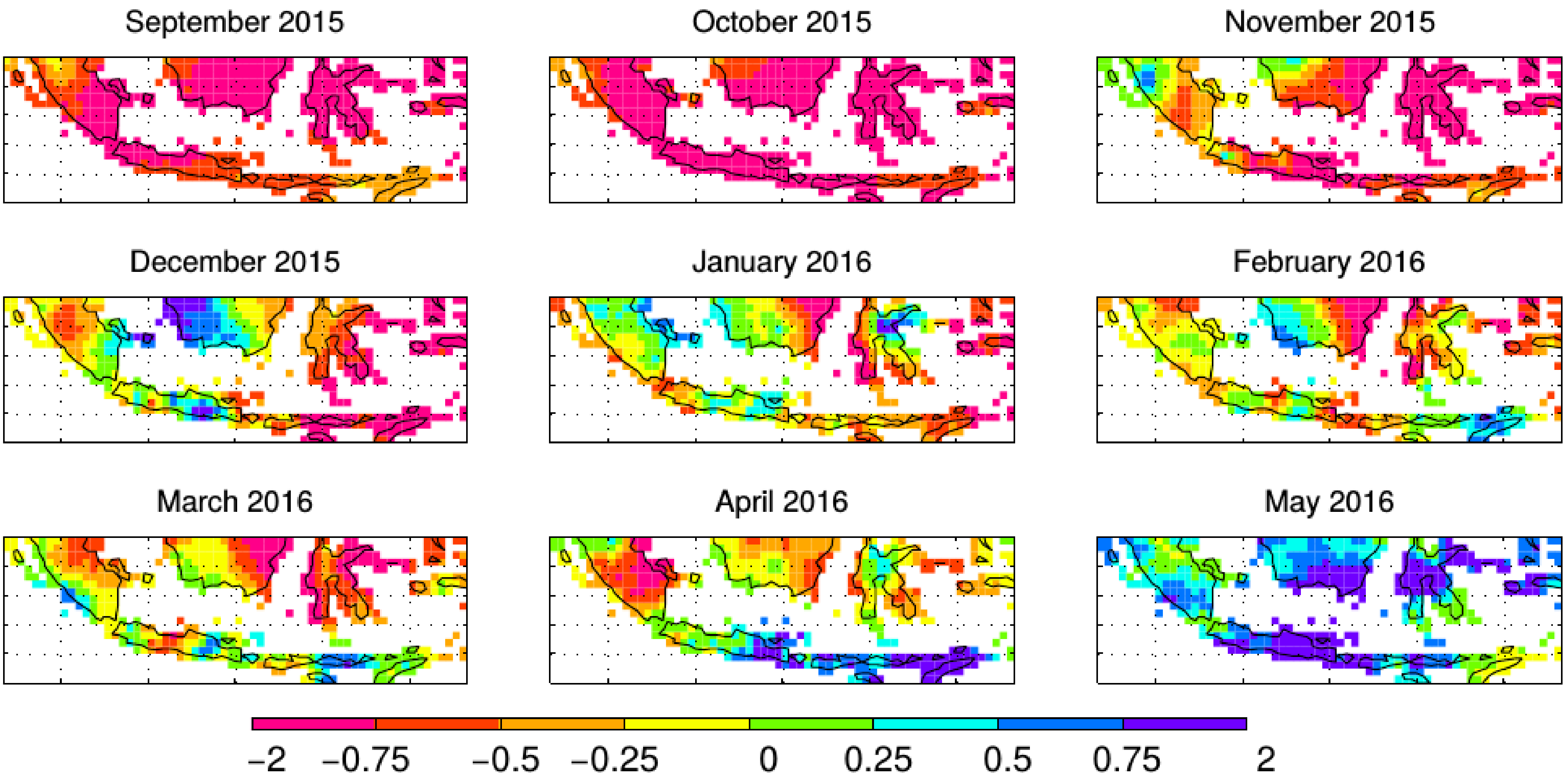
Negative anomalies till mid November, with onset delayed to late November or so. The uncertainty is < 0.75 std till late January and increases thenafter

Predictions of running 31-day rainfall standardized anomalies at Banjarmasin based on the two-tiered simulation approach vs observed daily rainfall till Nov 25 and the cumulative rainfall since Sep 1



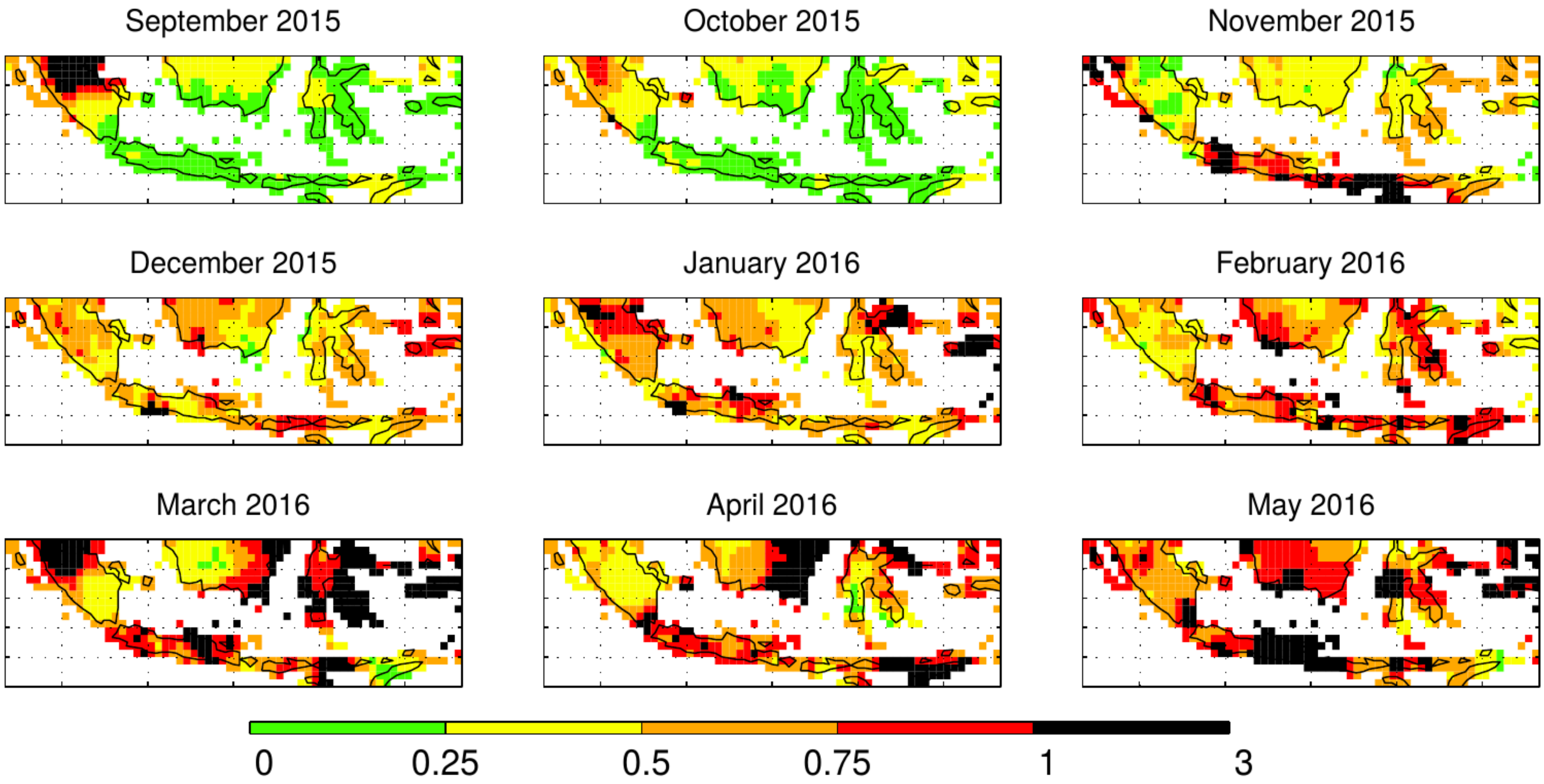
http://www.cpc.ncep.noaa.gov/products/global_monitoring/precipitation/sn96685_90.gif

5- Predictions of mean monthly rainfall



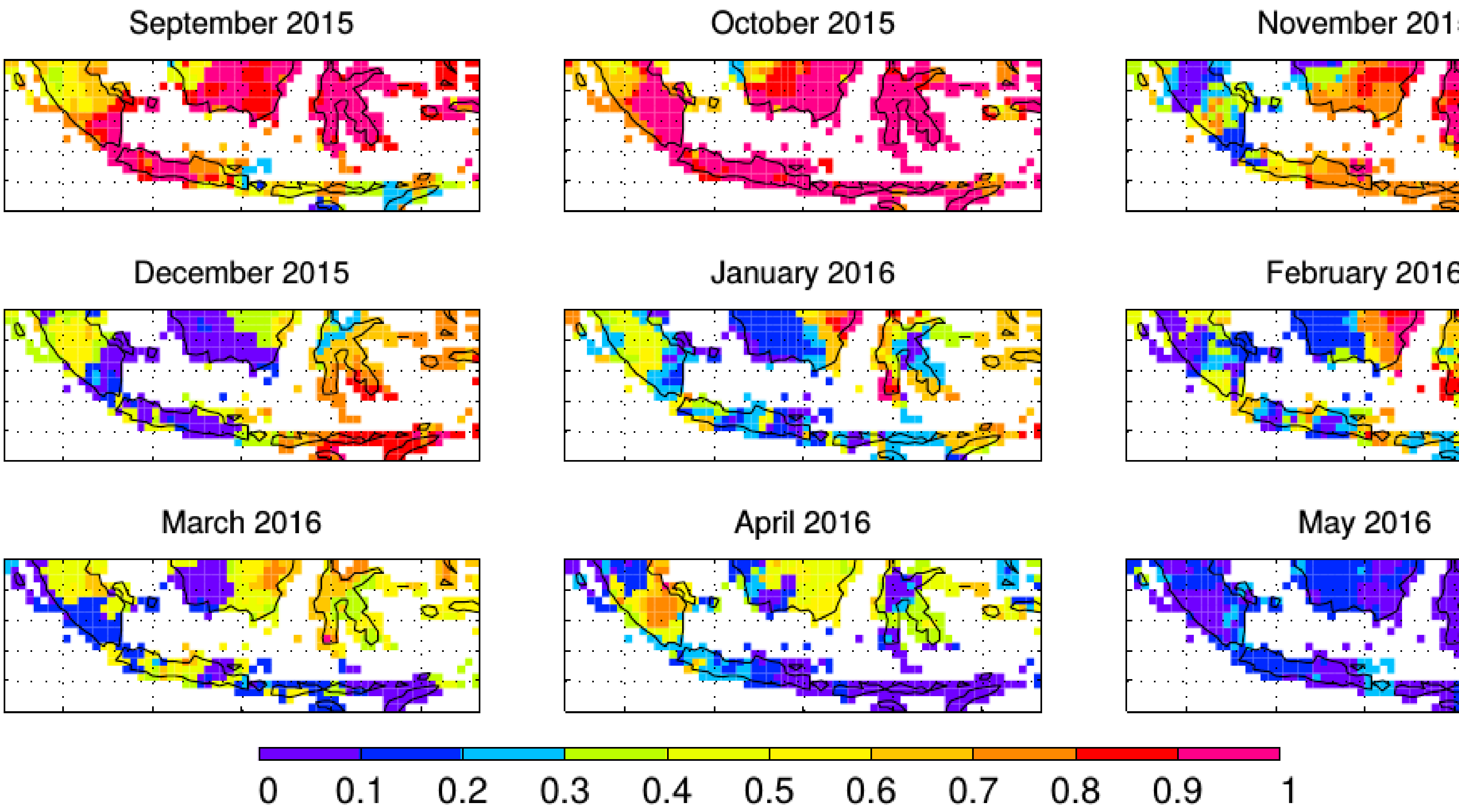
Mean predictions of monthly standardized anomalies of rainfall on the 0.5° x 0.5° grid. The anomalies are computed vs the 1961-2007 mean and standard deviation and based on the two-tiered simulation approach

5- Monthly predictions : uncertainty



Std of predictions of monthly standardized anomalies of rainfall on the 0.5° x 0.5° grid. The anomalies are computed vs the 1961-2007 mean and standard deviation and based on the two-tiered simulation approach

5- Monthly predictions : probability of below normal amounts



It is rather clear that the driest anomalies tend to match the usual NW-SE shift of the local-scale onsets from September-October (Western Indonesia) to December (south of Sulawesi and Sunda islands)

Probability of monthly rainfall below the first tercile on the 0.5° x 0.5° grid. The terciles are computed on the 1961-2007 period and the predictions are based on the two-tiered simulation approach

6- Concluding remarks (1)

- Local-scale instantaneous rainfall are mostly associated with deep convective systems, which are, by definition, **unpredictable at interannual time scale**
- Properties of these local-scale rainfall events are in fact synchronized ; (1) a *synchronization of « first » kind* is the instantaneous integration of rainfall into larger scales from MCC to ITCZ ; (2) *a synchronization of « second » kind* is related to systematic modulation of properties (phase, frequency, sequentiality and mean intensity) through the scales of motion at the interannual time scales by climatic modes of variation which include slow boundary forcings (SST, but it could be also continental surfaces through its temperature and/or moisture content).
- Current seasonal forecasts are made on fixed 3-month amounts of rainfall and deal mostly **with the synchronization of second kind quoted above**
- **Seasonal amounts could be heavily dominated by few wet events**. It could decrease the spatial coherence of seasonal amount and blur their potential predictability. Seasonal amounts are also not necessarily the optimal target for end-users
- Looking at ISC or subseasonal scenarios targets the same goal : **analyzing the potential predictability (PP) beyond the seasonal amounts**

6- Concluding remarks (2)

- The advantage of these approaches is to get specific information more tightly targeted to end-users and also to consider the possibe intraseasonal modulation of PP
- The inconvenient is that as soon as we go toward the local and instantaneous time scales, we move from the seasonal predictability toward unpredictable noise but this shift is probably not a linear decrease of predictability from the former to the latter scales
- The example of Indonesia shows that **a near local-scale and almost instantaneous event (= the phase of the onset of austral summer monsoon) is indeed predictable at seasonal time scale** due to the fact that this local-scale event is synchronized at interannual time scales by a large-scale phenomenon (= ENSO). Other examples are also promising across the tropics as the onset in the Philippines in May (Moron et al. 2009b) or Kenya in March (Camberlin et al. 2009 ; Moron et al. 2013).The predictability of ISC is not identical across the TZ : onset seems poorly predictable from SST across the Sahelian belt for example. In Sahel (but also in India, the spatial coherence peaks at the end of the rainy season, but the annual peak seems largely incoherent)
- Generally, **it seems that frequency of wet days (F) is far more spatially consistent than daily mean intensity of rainfall (I) but that there is no global agreement about the spatial coherence and PP of ISCs related to F across the tropical zone**

6- Concluding remarks (3)

- **Analytical decomposition of seasonal amounts into ISCs is simple to implement and does not need a lot of parametrization** (except for the threshold to define a wet day, but a threshold of 1 mm is a good compromise). A more important issue is to define onset and withdrawal of the rainy season but several solutions exist to enhance the signal-to-noise ratio (i.e. Boyard-Micheau et al., 2013)
- **SsS appears to be a flexible tool to diagnose and predict daily sequences at local-scale**. Two parameters are needed : the fuzziness parameter (= 1 for an hard clustering ; > 1 = fuzzy clustering) and the number of clusters. Several preliminary analyses over the MC indicate that the skill of rainfall is very robust vs these parameters. A more important issue is the length of available records since the diagnostic and the simulation are entirely based on past available data. A solution would be to train SsS on coupled simulations but it raises the issue of the simulation of daily rainfall at « local » scale in the tropics
- **Sources of intraseasonal modulation of spatial coherence and potential predictability** could be related to local and remonte ocean-atmosphere couplings and especially the triggering of positive/negative feedbacks but also to continent-atmosphere couplings which could be triggered during the rainy season itself (for example, stochastic wet events would be able to homogeneize progressively after some time the temperature and moisture conditions at regional-scale)

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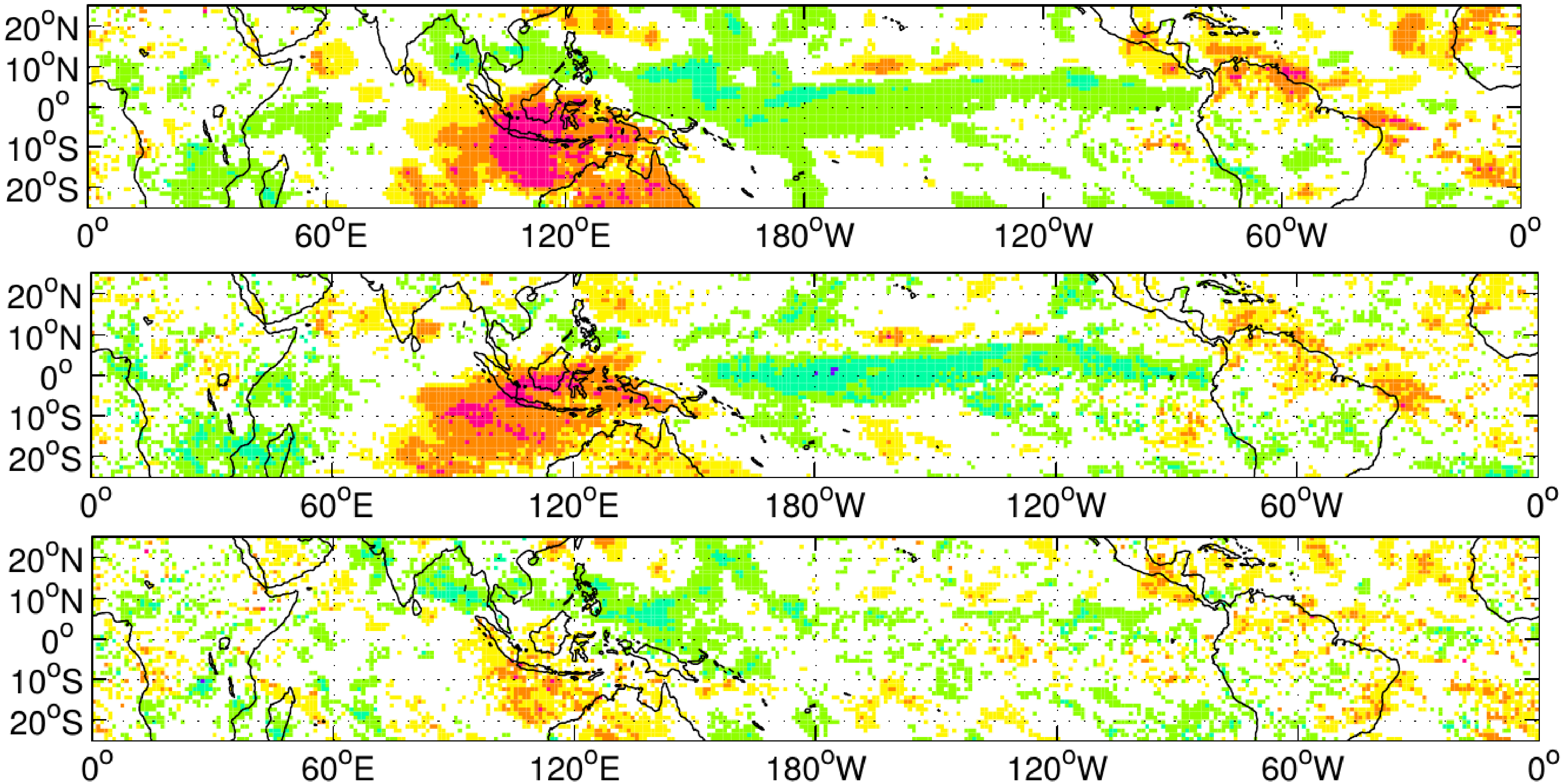
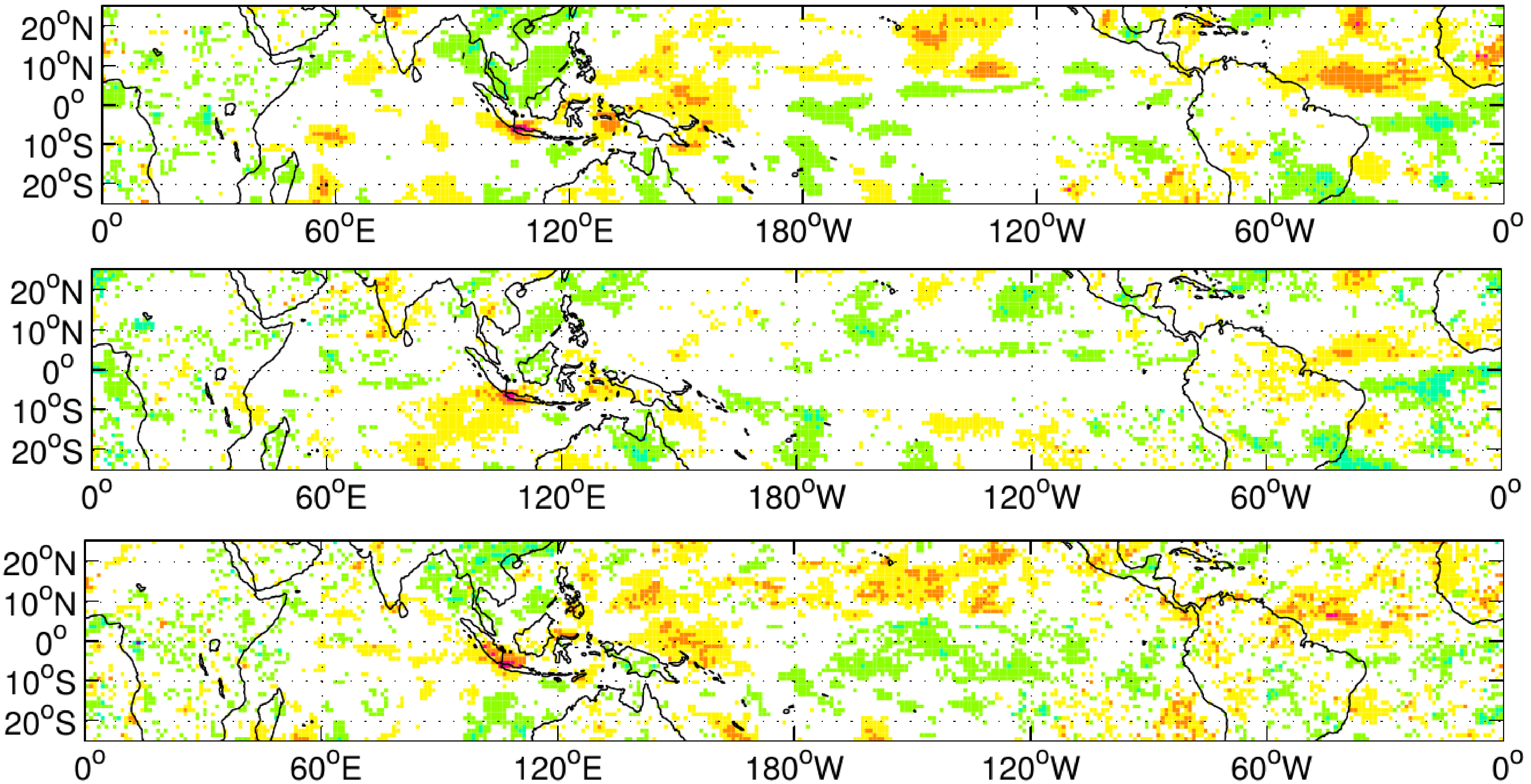
Additional slide (1)



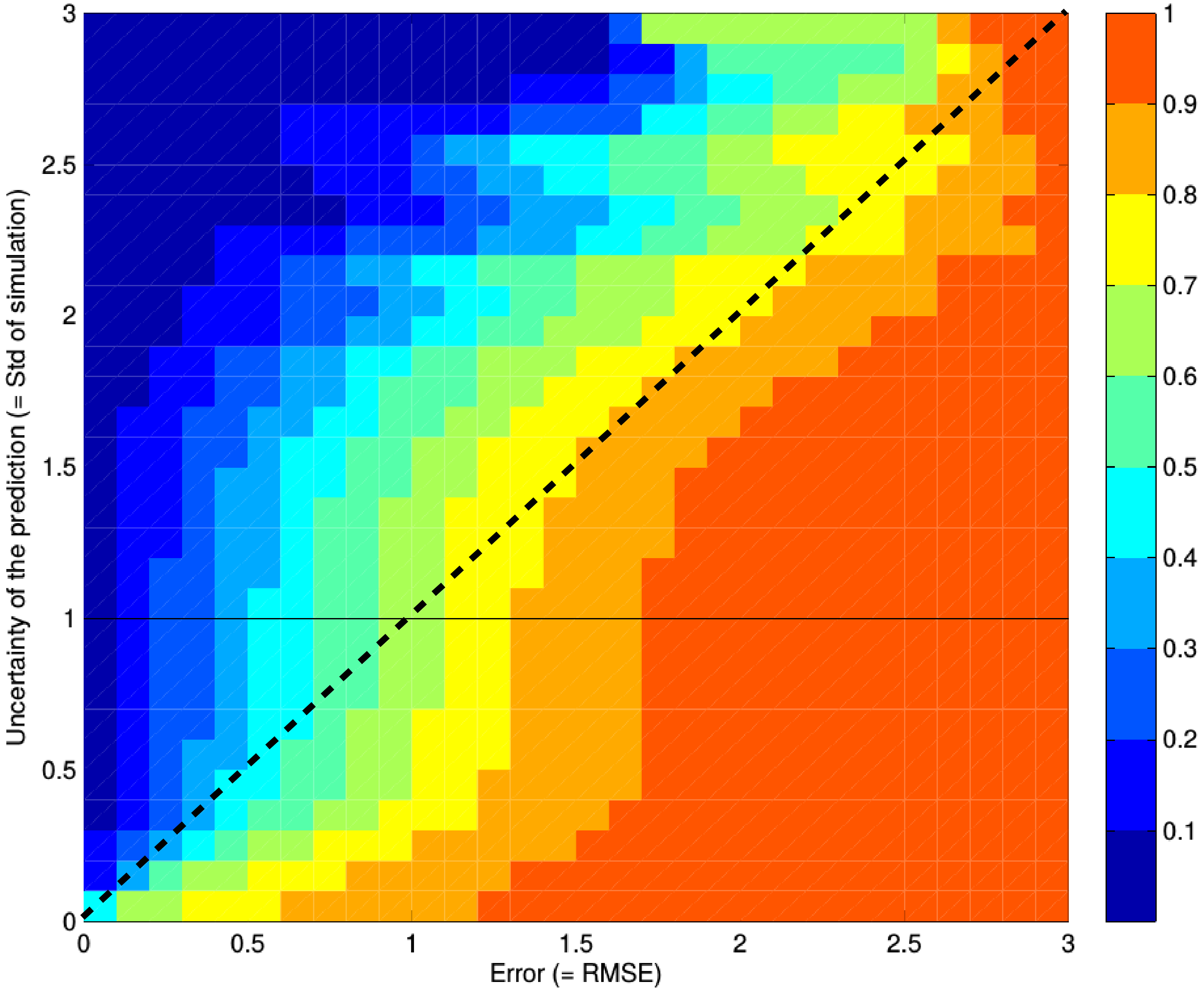
Correlations between September S, F and I at 106°-107°E, 6°S-7°S (~Djakarta) and the rest of the tropical zone

Additional slide (2)



Correlations between January S, F and I at 106°-107°E, 6°S-7°S (~Djakarta) and the rest of the tropical zone

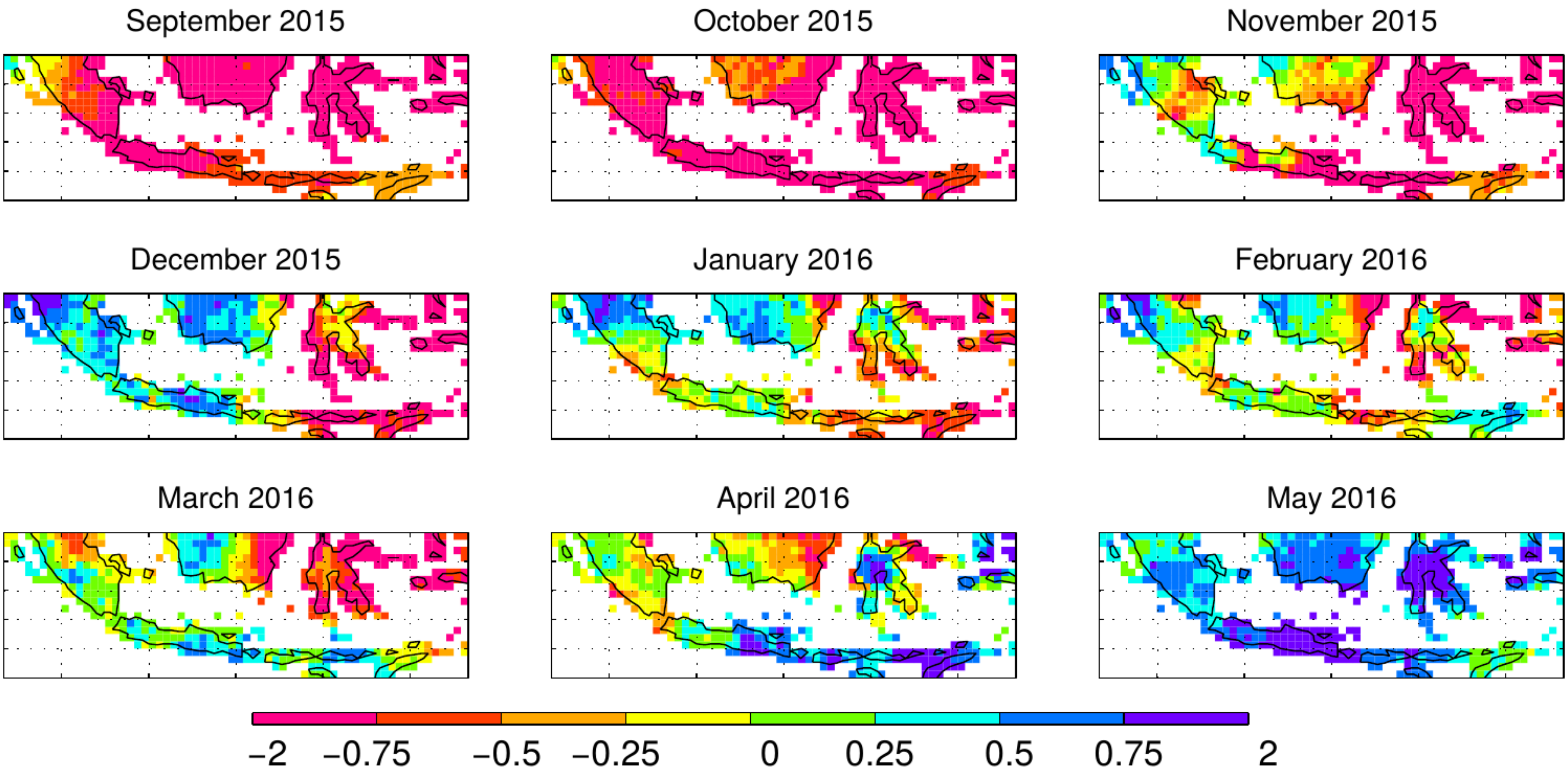
Additional slide (3)



Proportion of error (= RMSE between observed and simulated running 31-day anomalies of 0.5° rainfall). The simulations is done by re-doing extraction of SsS and predicting the membership with the 3 leading EOFs of August tropical SST using logistic regression in cross-validation (1 year left out at each turn). Rainfall fields are re-sampled from the predicted memberships using a k nearest neighbor approach (500 simulations) of the training sequences. This method can be used for any other target

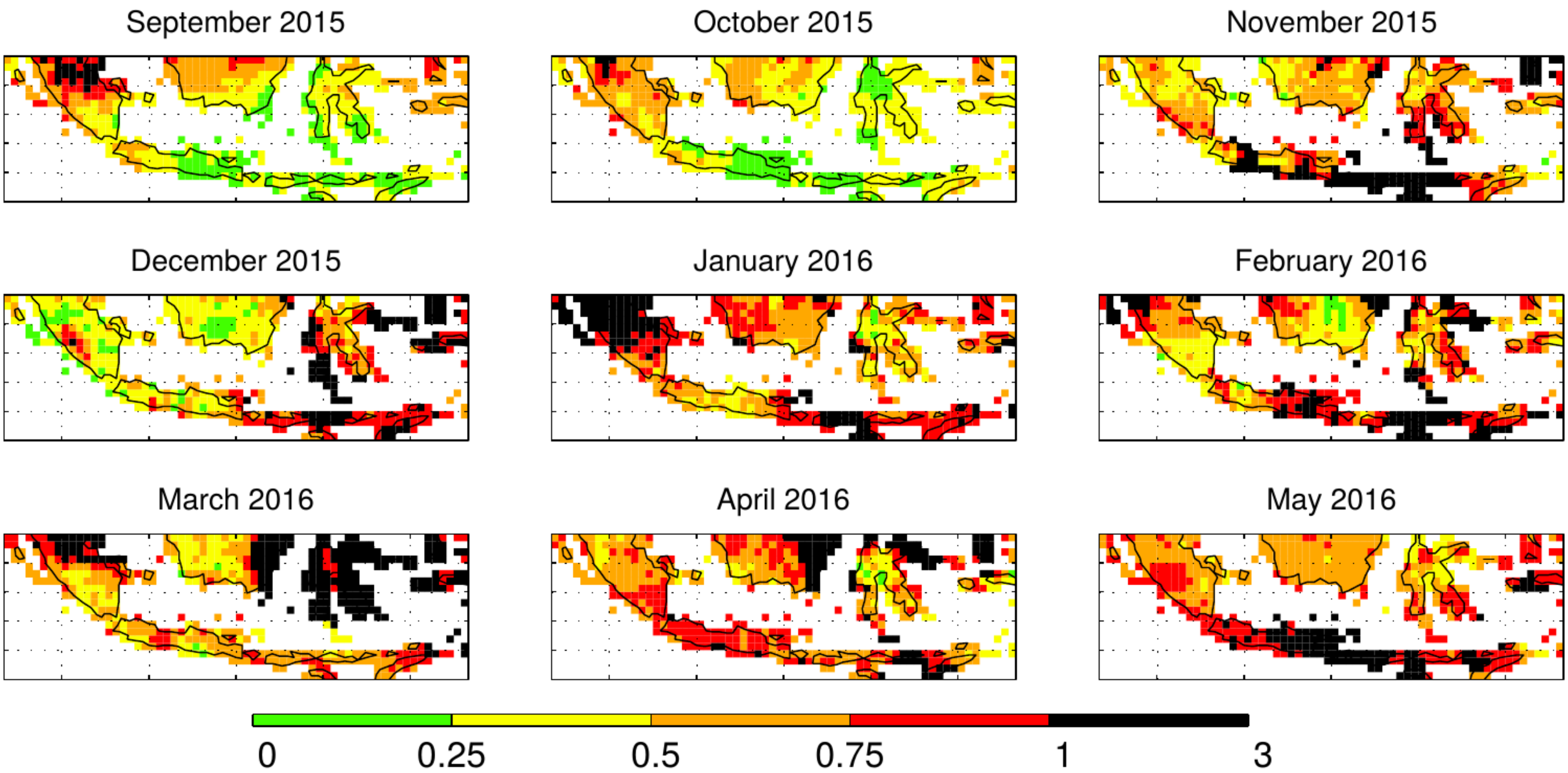
In general, reduced uncertainty is associated with reduced error with a stabilization of error between an uncertainty between 0.5 and 1 ; uncertainty < 1 sd = > 80 % of cases (grid-points x 31-day x years) = error < 1 sd in 65% of cases & error < 1.65 sd in 90% of cases.

Additional slide (4)



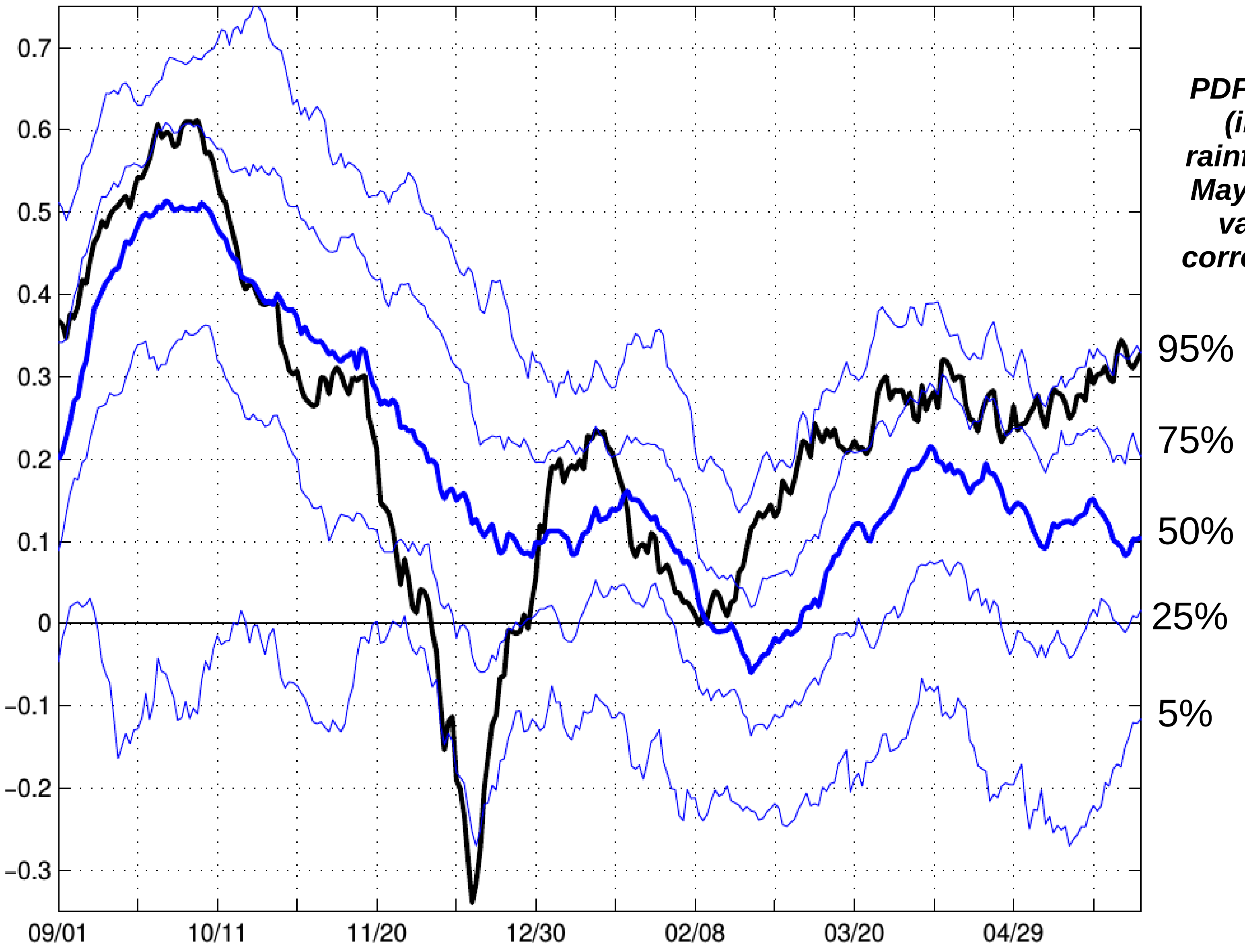
Mean predictions of monthly standardized anomalies of frequency of wet days > 1 mm on the 0.5° x 0.5° grid. The anomalies are computed vs the 1961-2007 mean and standard deviation and based on the two-tiered simulation approach

Additional slide (5)



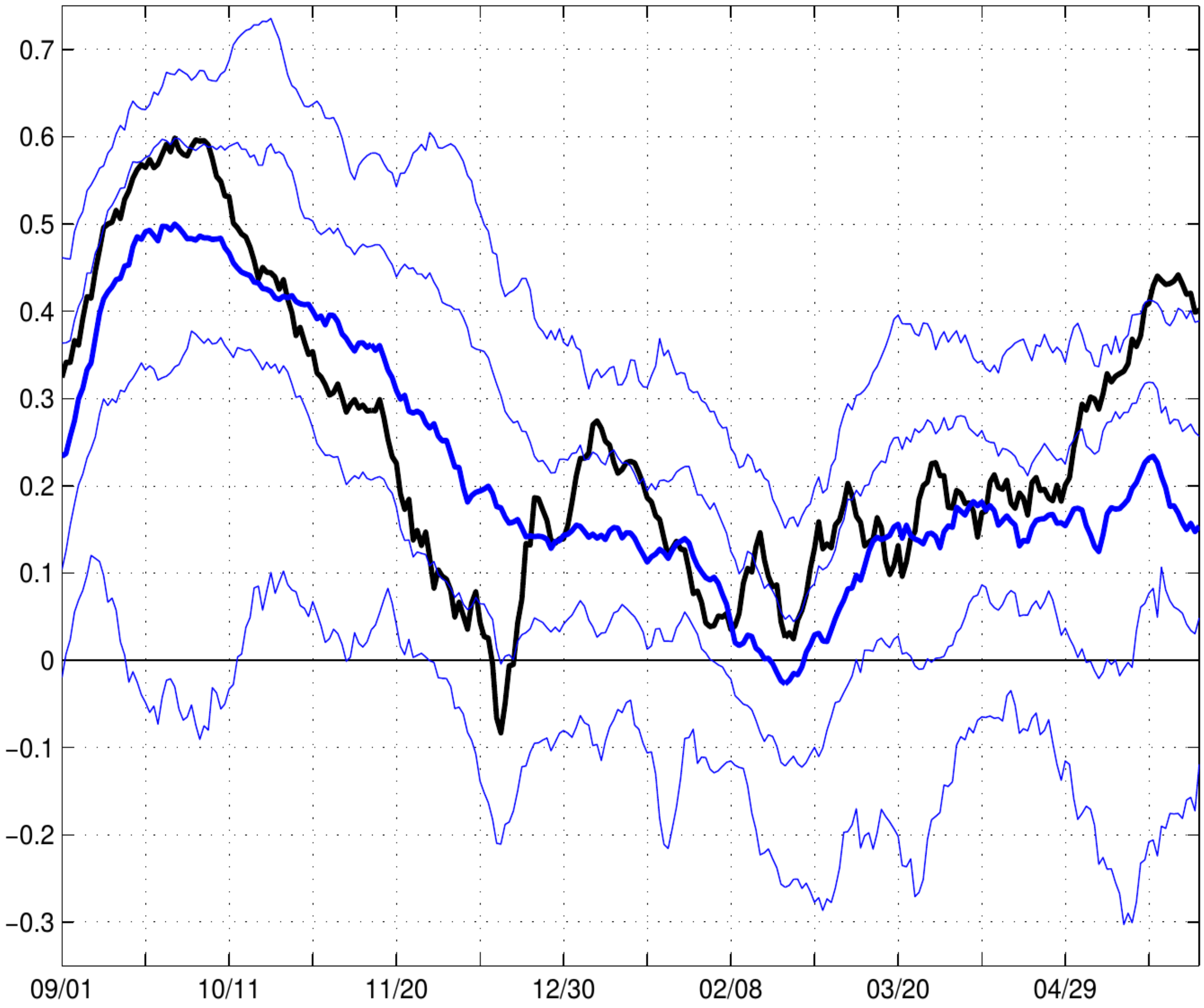
Std of predictions of monthly standardized anomalies of frequency of wet days > 1 mm on the 0.5° x 0.5° grid. The anomalies are computed vs the 1961-2007 mean and standard deviation and based on the two-tiered simulation approach

Additional slide (6)



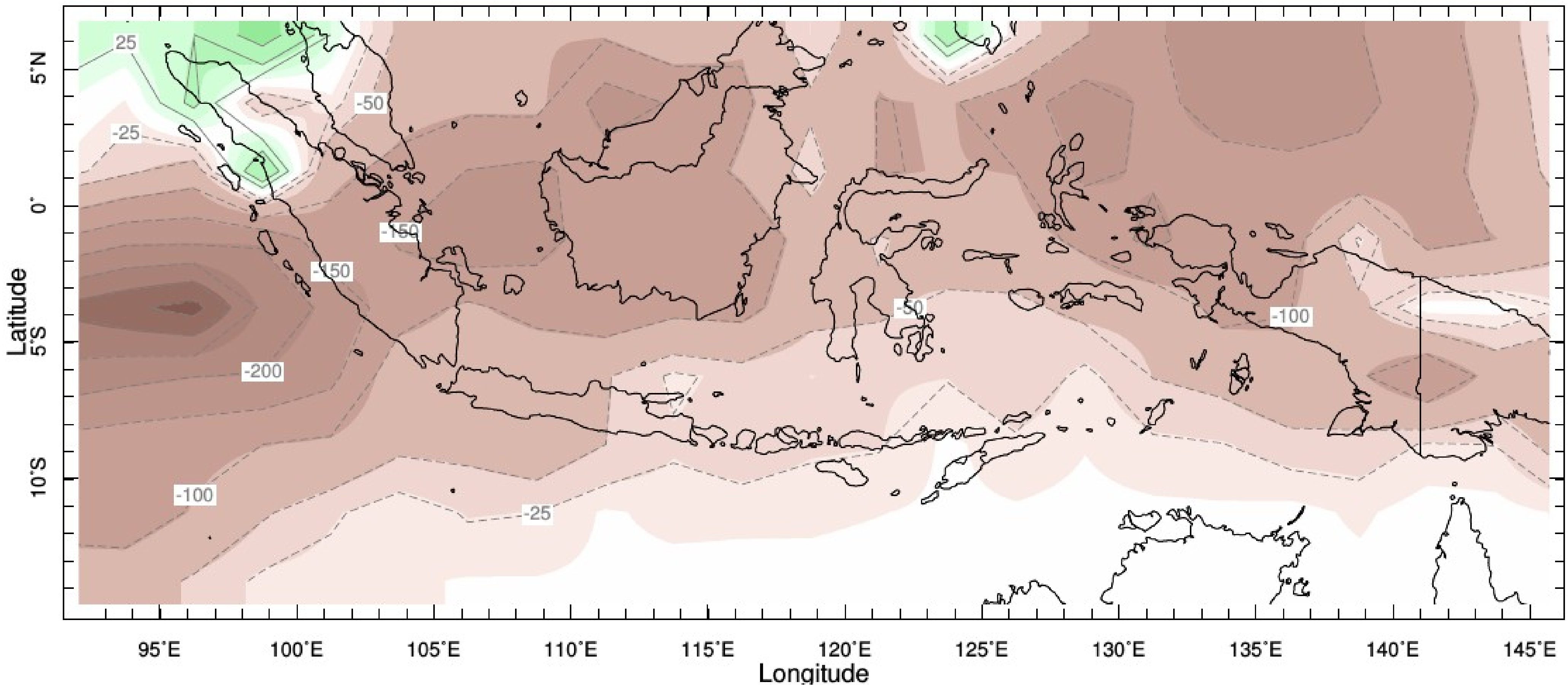
PDF of the cross-validated skill (in blue) of running 31-day rainfall anomalies from Sep 1 to May 31. The skill in black is the value for the 0.5° grid-point corresponding to Bandjarmasin

Additional slide (7)



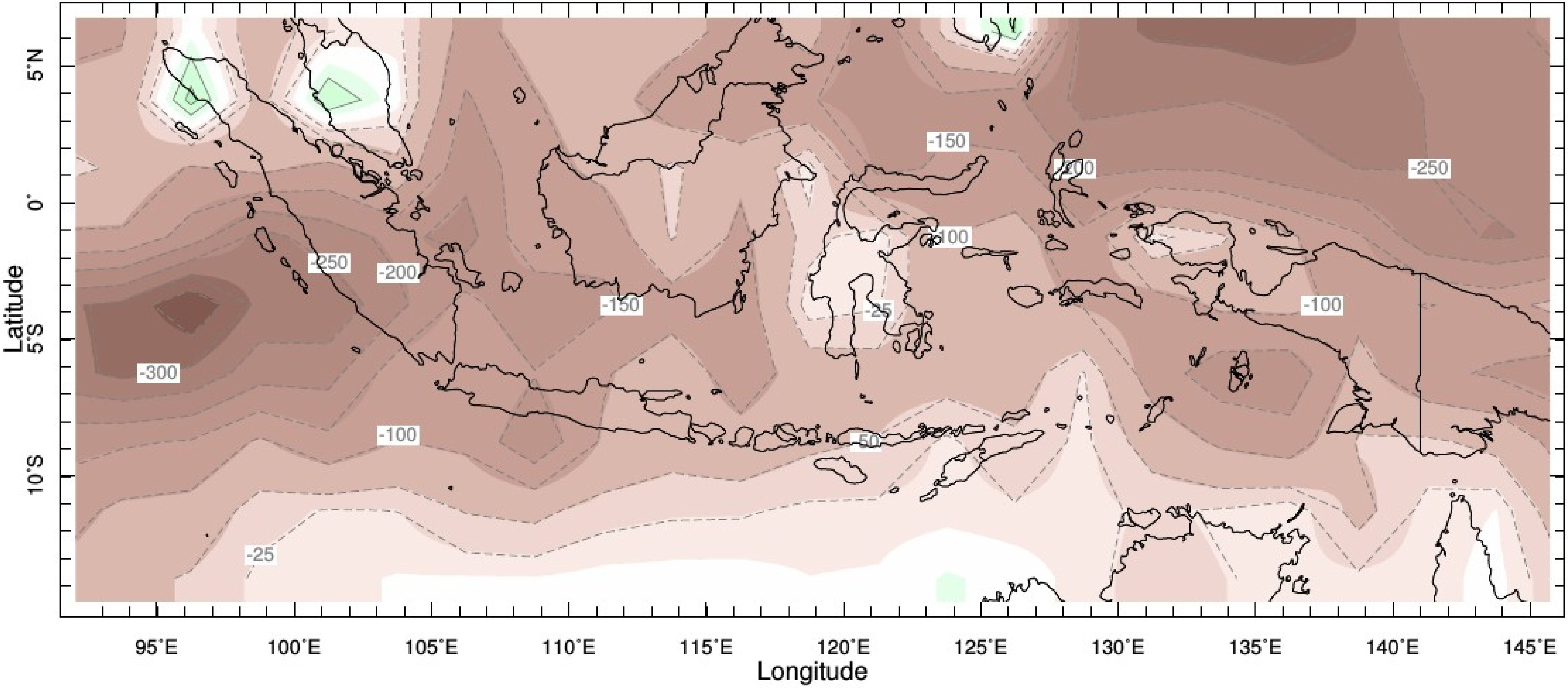
PDF of the cross-validated skill (in blue) of running 31-day frequency of wet days > 1 mm anomalies from Sep 1 to May 31. The skill in black is the value for the 0.5° grid-point corresponding to Bandjarmasin

Additional slide (8)



Observed rainfall anomalies (in mm) observed in September 2015 (IRI)

Additional slide (9)



Observed rainfall anomalies (in mm) observed in October 2015 (IRI)