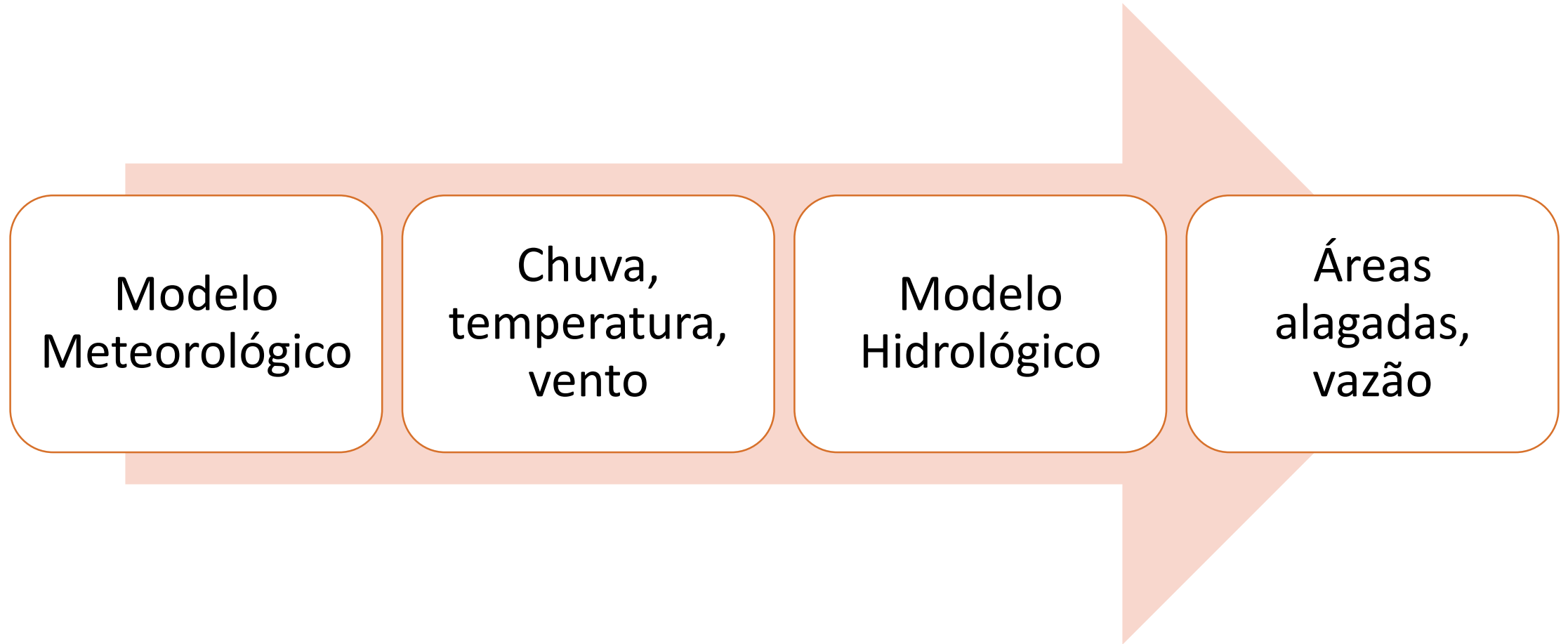


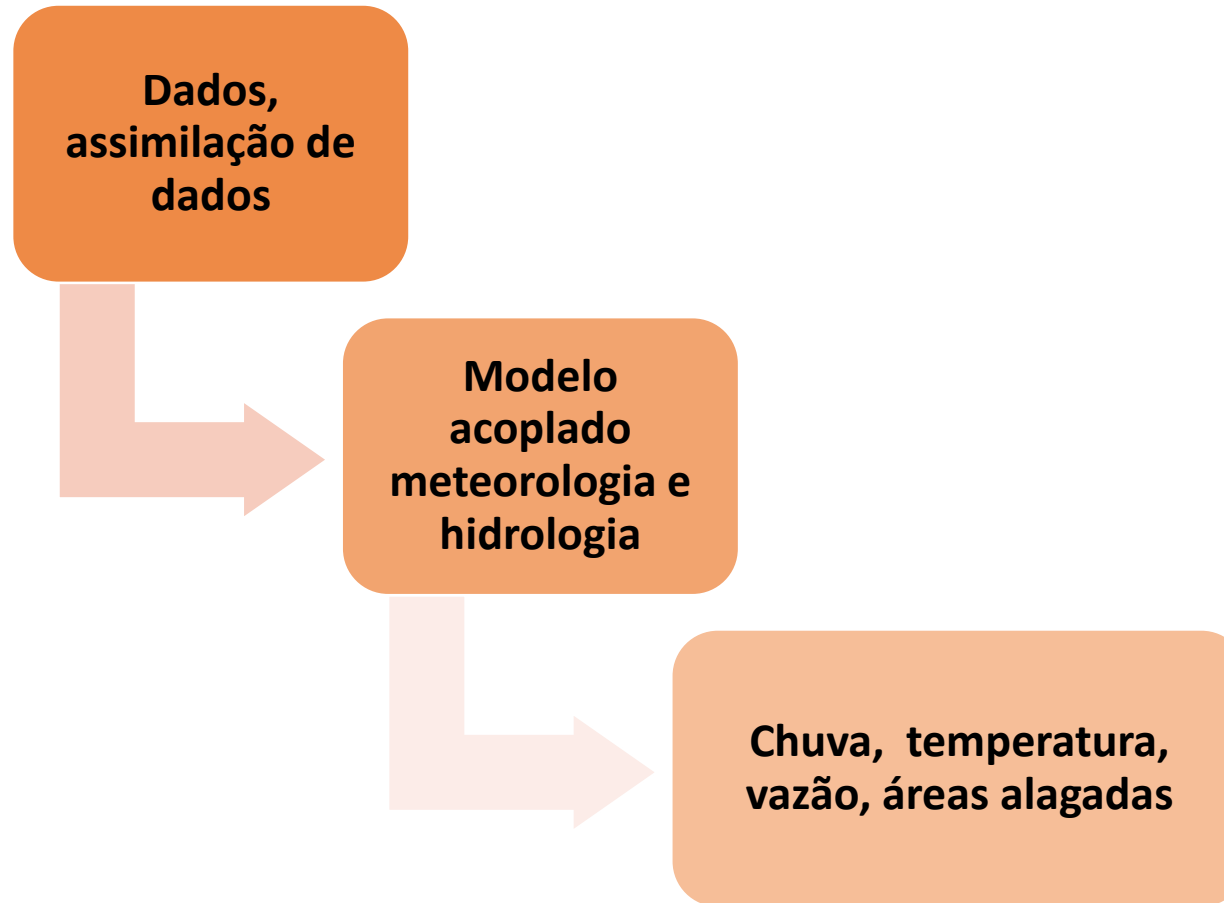
Chuvas e impactos hidrológicos em ambiente de incerteza meteorológica alguns desafios para pesquisas interdisciplinares

Maria Assunção F. Silva Dias
Departamento de Ciências Atmosféricas
Universidade de São Paulo
XXIII Simpósio Brasileiro de Recursos Hídricos
Foz do Iguaçu, 28 de novembro de 2019

Processo geral de previsão:



Processo acoplado de previsão



Seasonal Flooding Causes Intensification of the River Breeze in the Central Amazon

Mercel J. Santos¹ , David Medvigy² , Maria A. F. Silva Dias¹ , Edmilson D. Freitas¹ , and Hyungjun Kim³ 

¹Department of Atmospheric Sciences, University of São Paulo, São Paulo, Brazil, ²Department of Geosciences, Princeton University, Princeton, NJ, USA, ³Institute of Industrial Science, University of Tokyo, Tokyo, Japan

The seasonal flooding alters the surface energy partitioning causing a temperature decrease over the river region and intensification of the river breezes in the daytime. The intensified river breezes propagate more rapidly through the upland region, take longer to dissipate and promote stronger upward vertical motion altering the heat and mass transport.

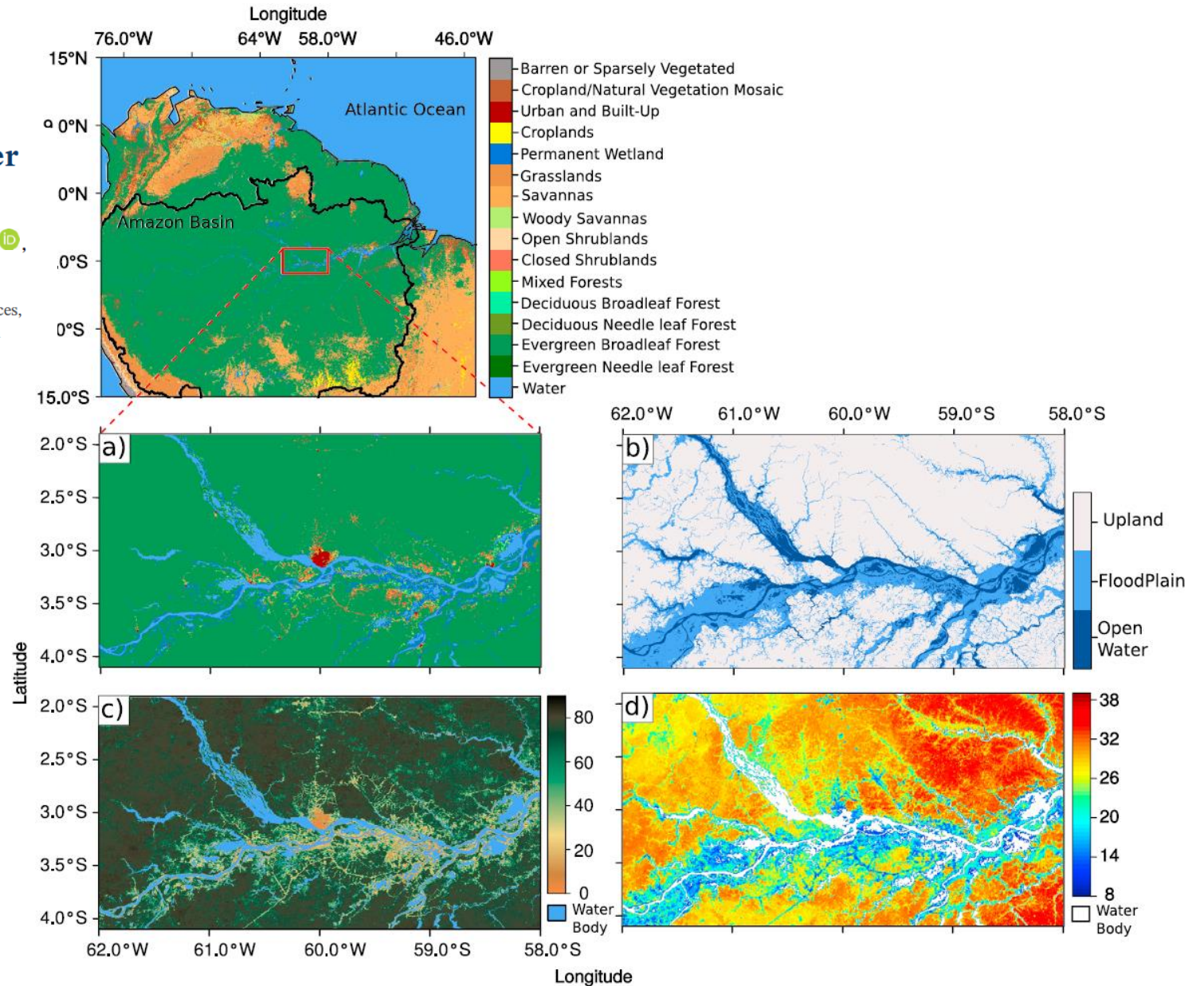


Figure 1. Environmental data for the central Amazon. (a) Moderate Resolution Imaging Spectroradiometer Land cover map (Product MCD12Q1), (b) Floodplain extent (Hess et al., 2003), (c) Maximum Green Vegetation Fraction (Broxton et al., 2014), and (d) Forest canopy height (Simard et al., 2011).

Catchment-Based Macro-scale Floodplain (CaMa-Flood) model
(Yamazaki et al, 2009, 2011, 2013)

Ocean-Land-Atmosphere Model (OLAM) (Walko and Abissar, 2008)



CaMa-Flood

OLAM

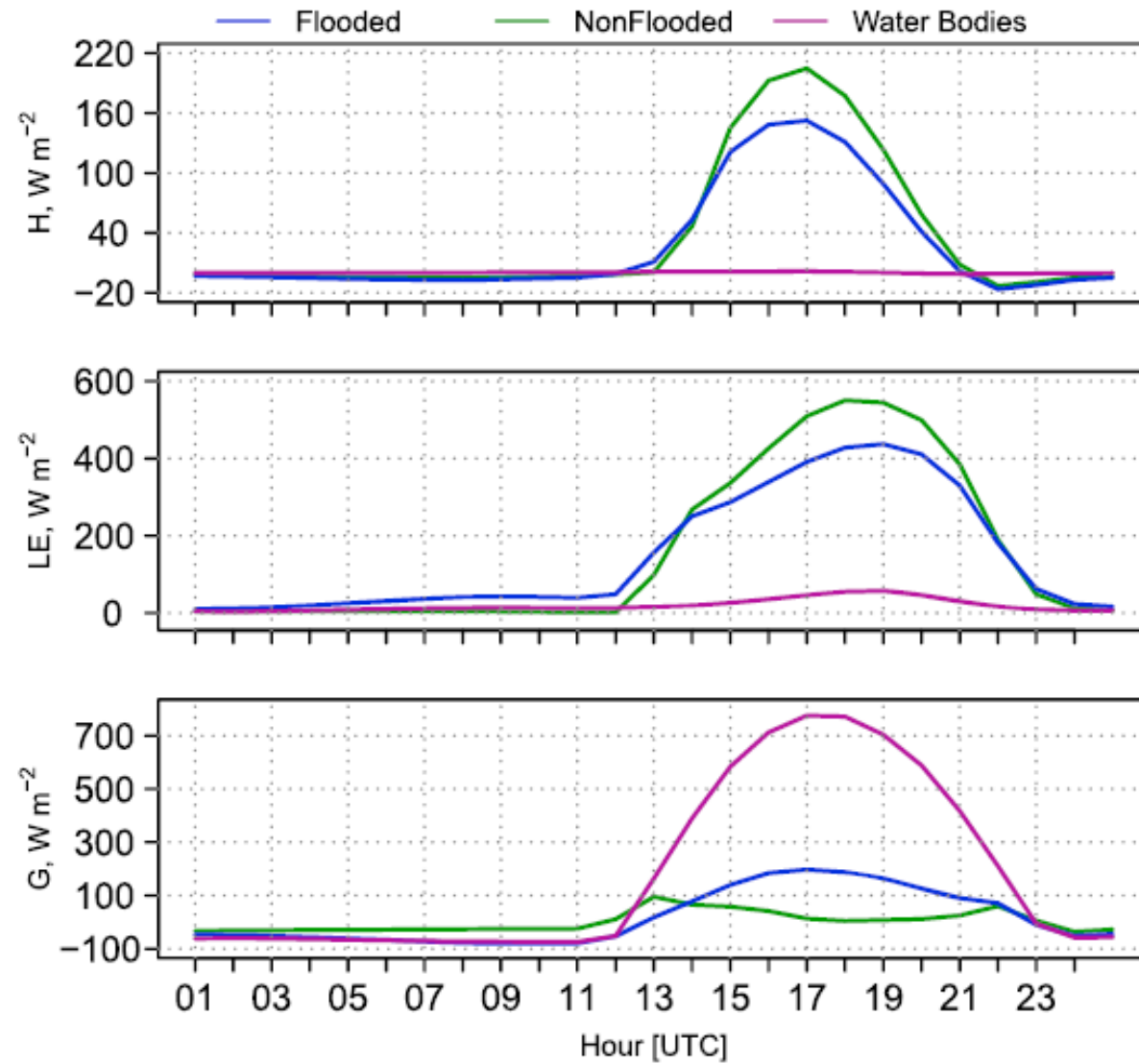


Figure 9. Surface fluxes simulated in the control experiment for 23 July 2011. H , LE , and G stand for sensible heat flux, latent heat flux, and ground heat flux, respectively. Positive values of H and LE indicate upward fluxes, while positive values of G are associated with downward flux.

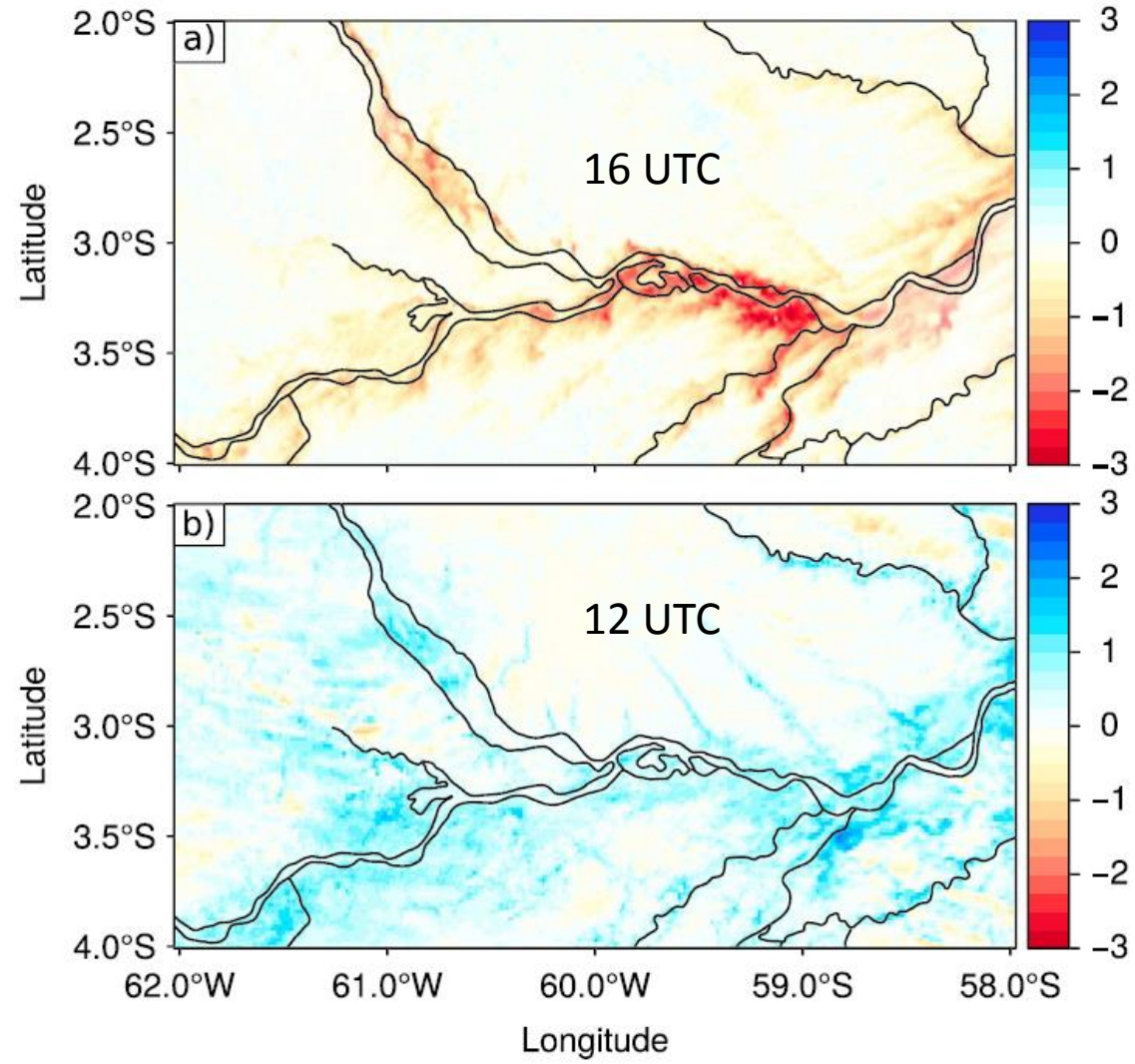


Figure 12. Difference between the near-surface temperature simulated in ExpFlood and ExpNonFlood (ExpFlood-ExpNonFlood). (a) 23 July 2011 at 16 UTC and (b) 24 July 2011 at 12 UTC.

Flood

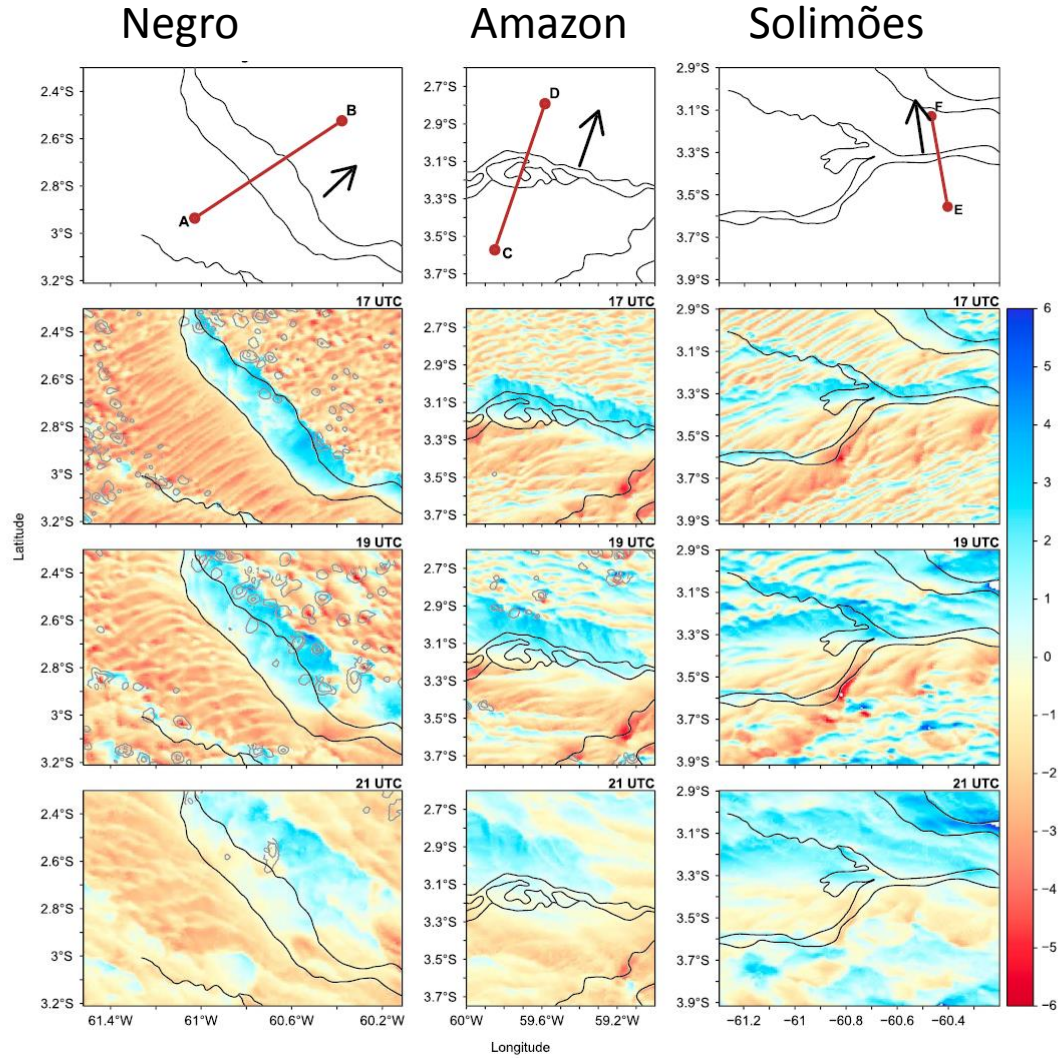


Figure 10. Wind perpendicular to the river margins (colors) and vertically integrated total condensate (q_{total} , contours) simulated in the control experiment. The black arrow is the wind across the reference. We considered only wind direction and orientation as reference.

Non-flood

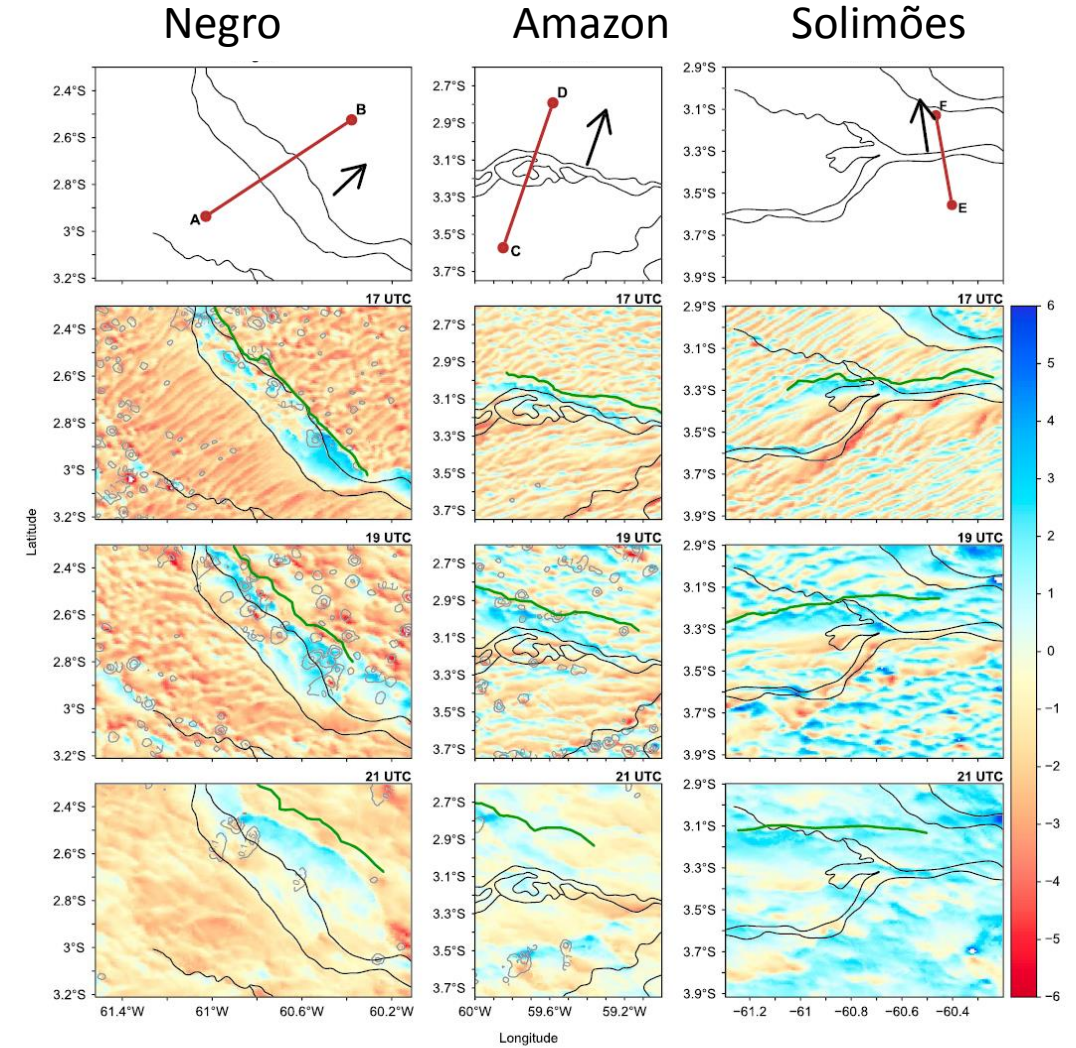
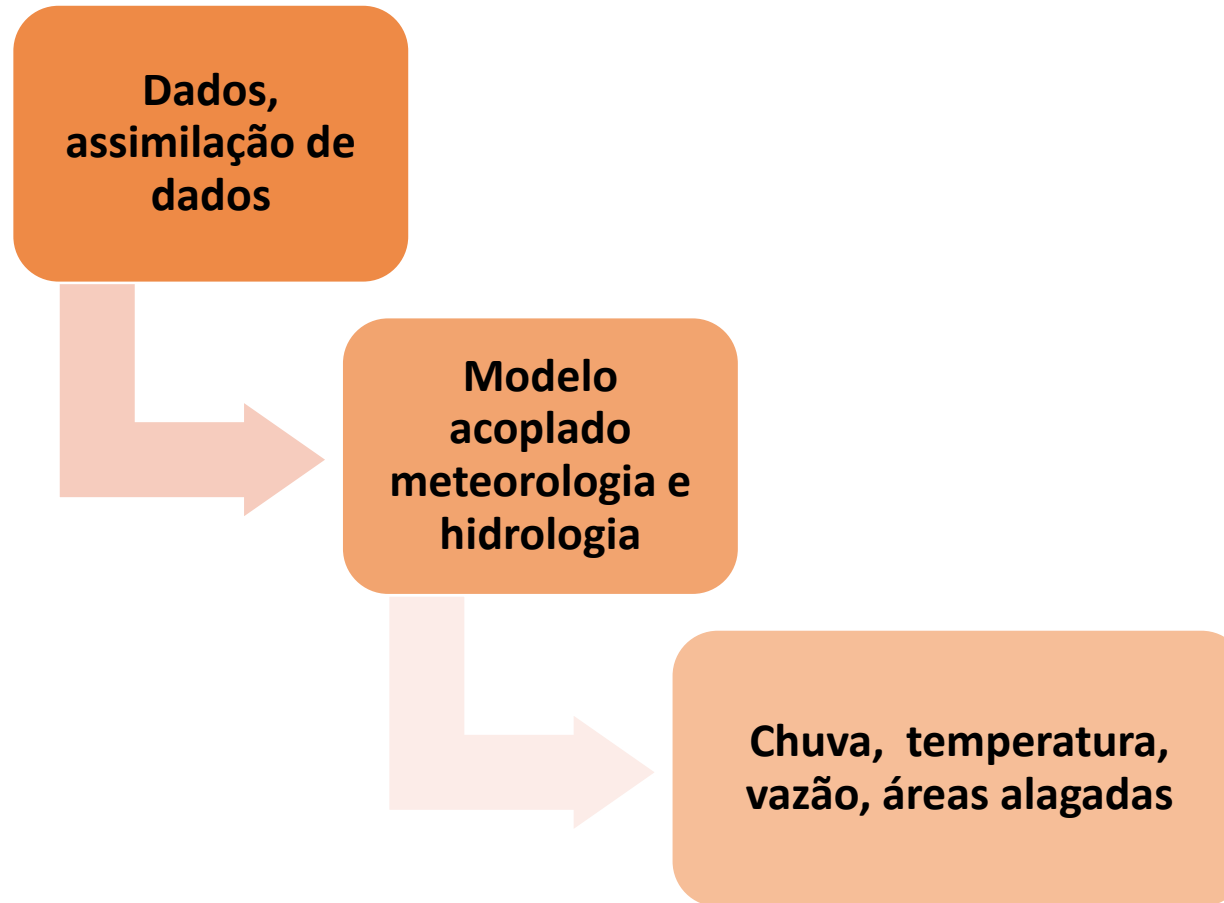


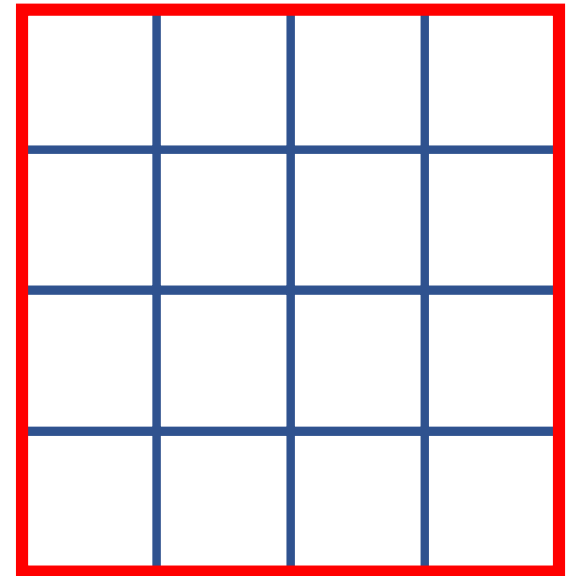
Figure 13. Wind perpendicular to the river margins (colors) and q_{total} (contours) simulated in the ExpNonFlood. The green lines highlight the river breeze front locations simulated in ExpFlood. The black arrow is the wind across the reference.

Processo acoplado de previsão



Incertezas (1)

- Os modelos meteorológico e hidrológico devem ser consistentes, na média espacial devem ter os mesmos fluxos de calor e de umidade
- Por exemplo:
 - Modelo meteorológico com 5 km de resolução
 - Modelo hidrológico com 1 km de resolução

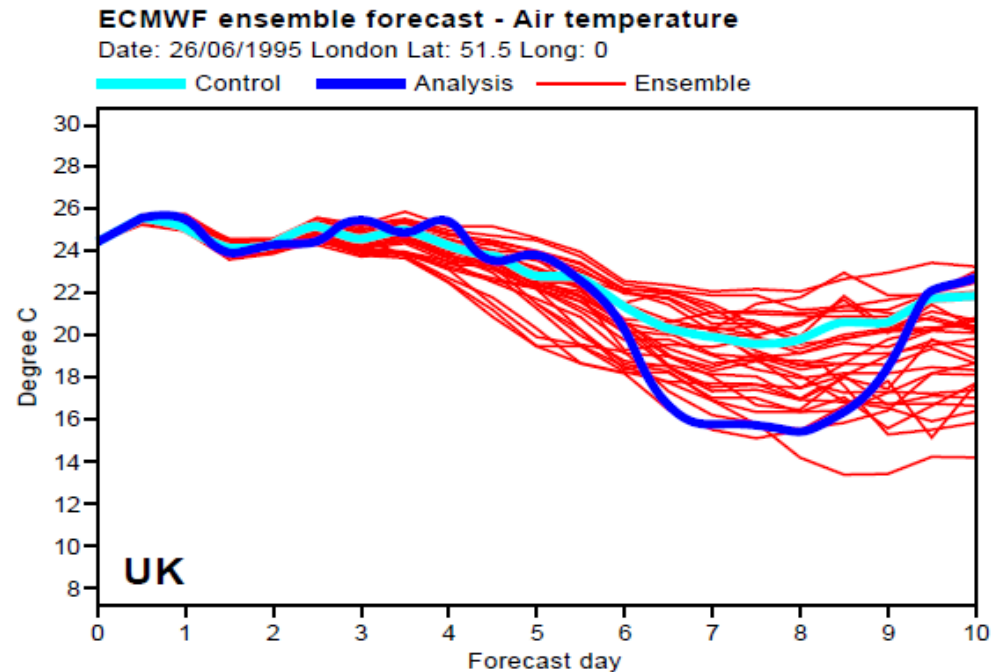


Incertezas (2)

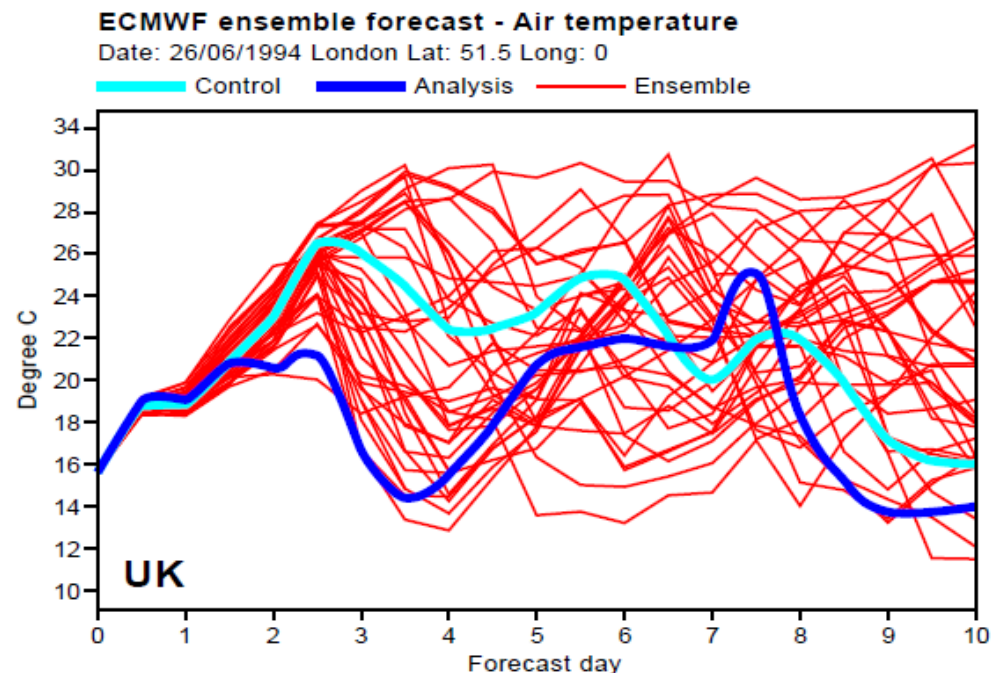
- A natureza caótica do sistema de equações não lineares

Lorenz: efeito borboleta

Pequenas perturbações nas condições iniciais – dados de entrada - podem levar a grandes diferenças na previsão.



Start date
26 June 1995



Start date
26 June 1994

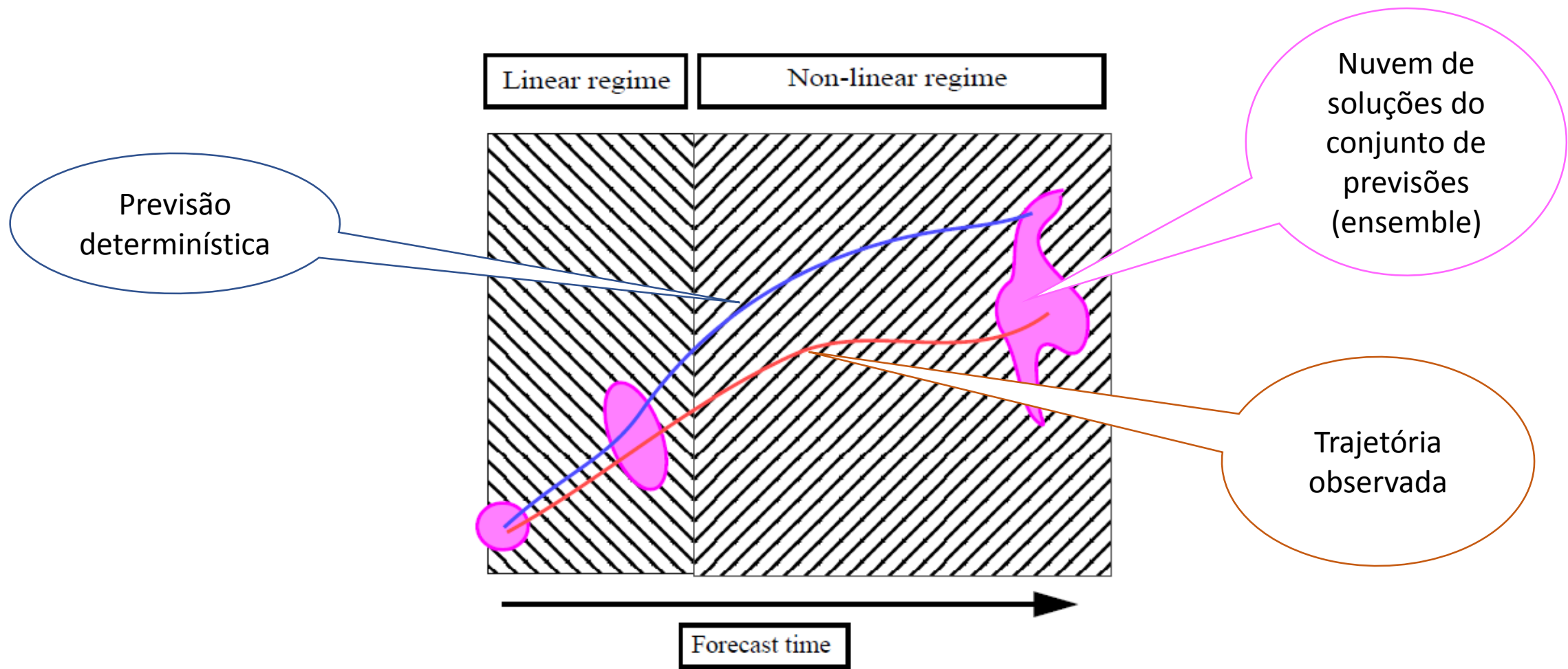
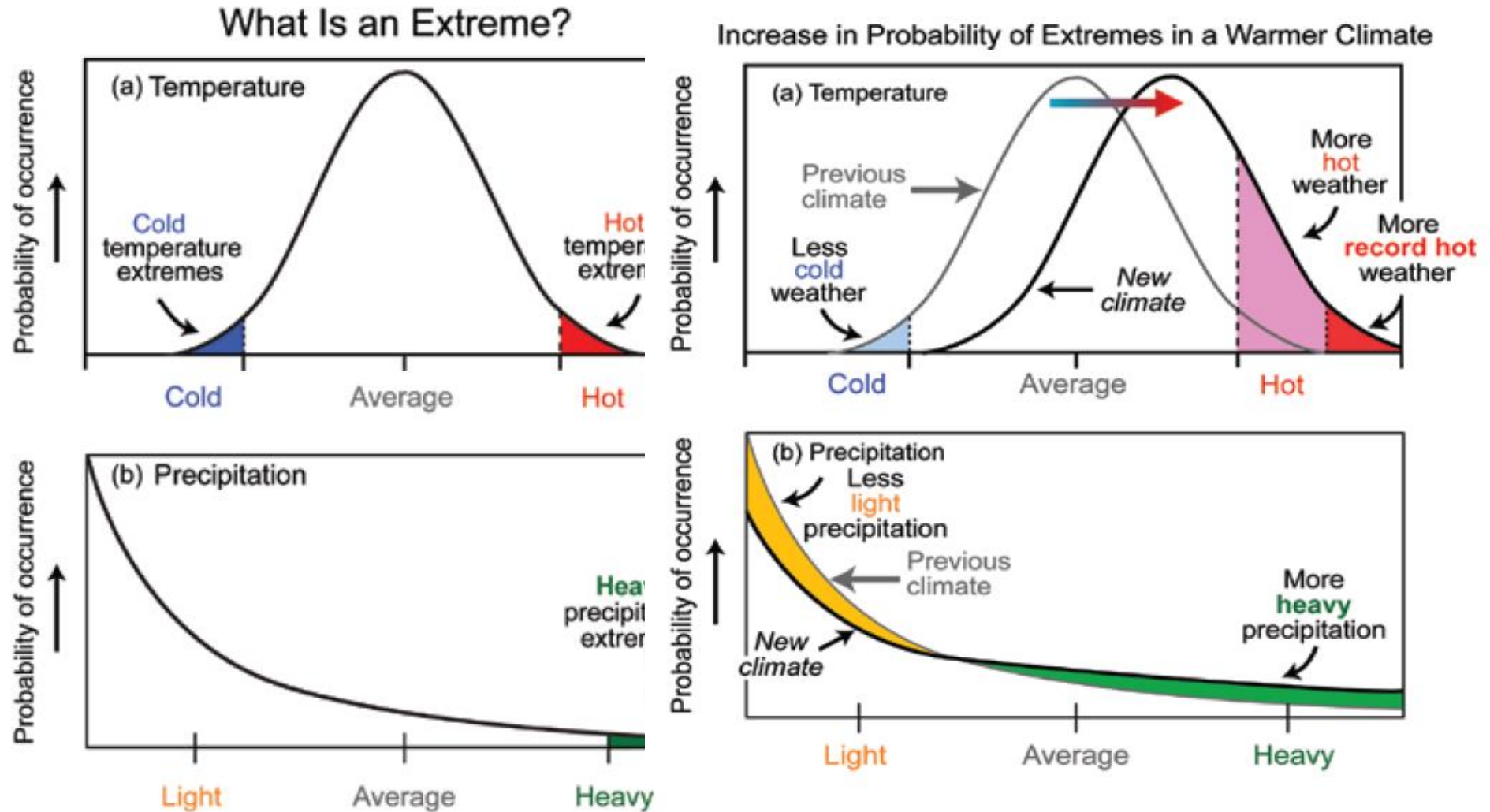


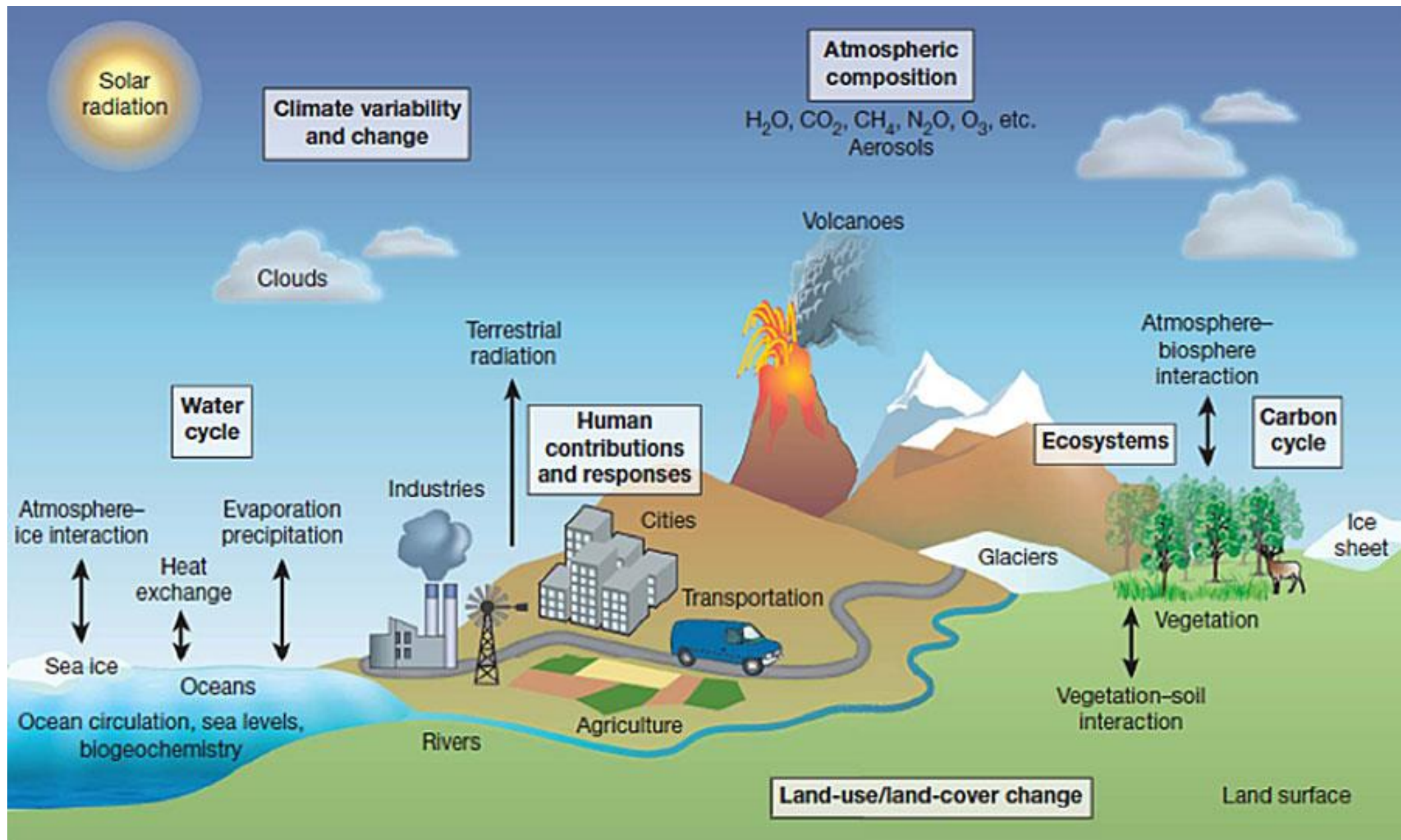
Figure 2. The deterministic approach to numerical weather prediction provides one single forecast (blue line) for the “true” time evolution of the system (red line). The ensemble approach to numerical weather prediction tries to estimate the probability density function of forecast states (magenta shapes). Ideally, the ensemble probability density function estimate includes the true state of the system as a possible solution.

Como prever os extremos? Usar as propriedades do ensemble...



Incertezas na previsão das chuvas, e dos extremos das chuvas, como reduzir?

- Dados: aumentar a densidade dos dados e o uso de métodos de recuperação de informações a partir de dados de satélites
- Assimilação de dados em 4-D
- Melhoria dos modelos, maior realismo nas parametrizações dos processos sub-grade, melhor representação dos processos físicos na presença de topografia
- Uso operacional de modelos acoplados contendo todas as componentes do sistema: oceano-atmosfera- terra-hidrologia-química os chamados Modelos do Sistema Terra
- Melhoria da comunicação das incertezas para o usuário





The quiet revolution of numerical weather prediction

Peter Bauer , Alan Thorpe & Gilbert Brunet

Nature **525**, 47–55(2015) | [Cite this article](#)

4918 Accesses | **339** Citations | **533** Altmetric | [Metrics](#)

Abstract

Advances in numerical weather prediction represent a quiet revolution because they have resulted from a steady accumulation of scientific knowledge and technological advances over many years that, with only a few exceptions, have not been associated with the aura of fundamental physics breakthroughs. Nonetheless, the impact of numerical weather prediction is among the greatest of any area of physical science. As a computational problem, global weather prediction is comparable to the simulation of the human brain and of the evolution of the early Universe, and it is performed every day at major operational centres across the world.

The **first** successful **numerical** prediction was performed using the ENIAC digital computer in **1950** by a team composed of American meteorologists Jule Charney, Philip Thompson, Larry Gates, and Norwegian meteorologist Ragnar Fjørtoft, applied mathematician John von Neumann, and computer programmer Klara Dan von Neumann.

Comunicação da previsão em termos de probabilidades

- Baseada em **previsões por conjuntos**: quantificação da incerteza
- Previsão em termos de probabilidades tem vantagens sobre as previsões determinísticas :
 - reflete a incerteza e permite ao usuário levar em conta essa incerteza em face das demais em seu negócio.
 - Permite quantificar os custos de **tomar uma decisão** versus **fazer nada**.
 - Permite um trabalho conjunto do tomador de decisão e do previsor de forma a utilizar
 - O conhecimento do previsor quanto às limitações da previsão
 - O conhecimento do tomador de decisão sobre a natureza específica da decisão a ser tomada.

Meteorologia – Hidrologia

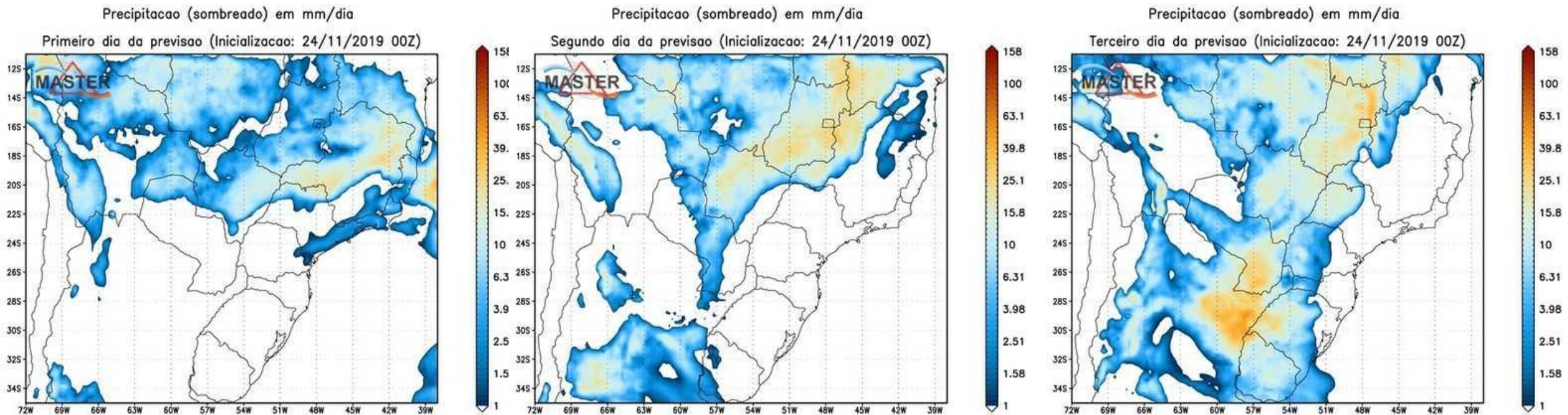
Escala temporal das aplicações da previsão acoplada

Previsão imediata	Curto prazo	Médio prazo	Sub-sazonal	Sazonal
0 – 6 horas	1-3 dias	4-15 dias	15 a 60 dias	3-6 meses

Segurança pública: chuvas, áreas alagadas
Geração de energia hidrelétrica : vazões (impacto no preço de energia)
Uso da água (urbano, agricultura, indústria)

Previsão de chuva de curto prazo

Previsão de chuva de curto prazo 0 – 3 dias



www.master.iag.usp.br



Comparação entre modelos

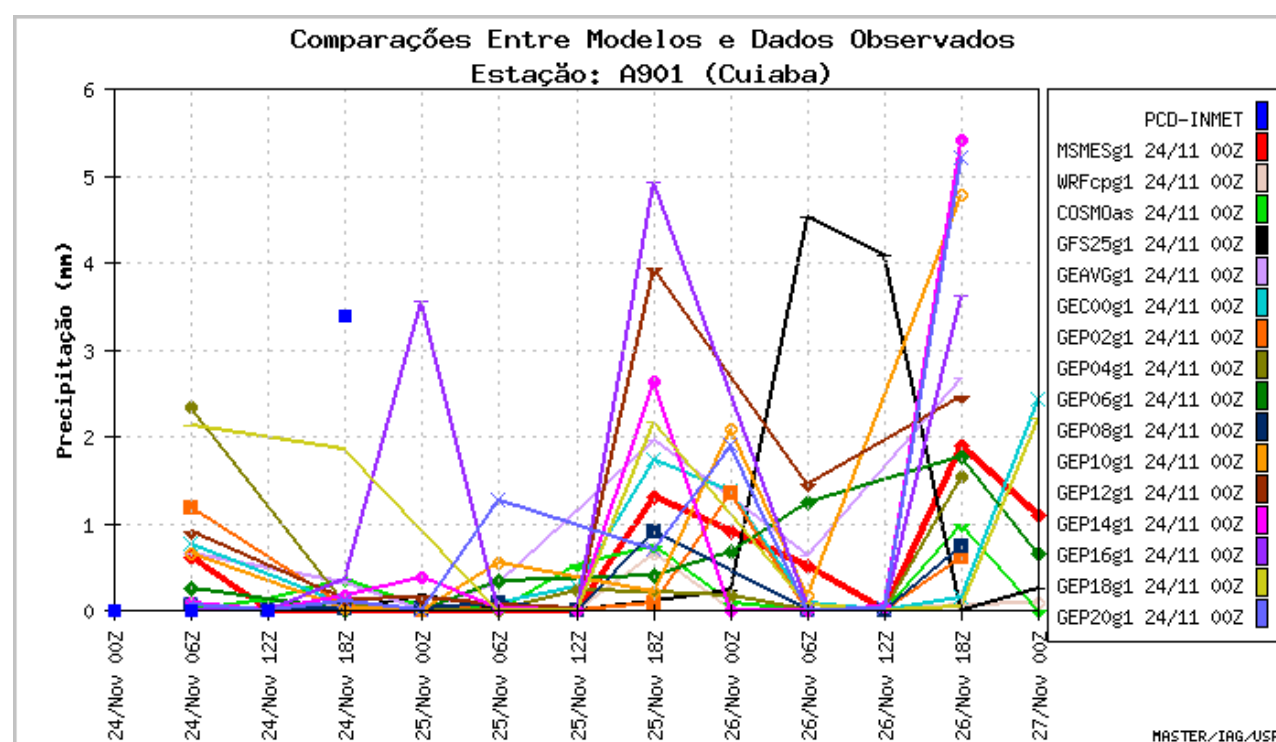


[INÍCIO](#) / [PRODUTOS NUMÉRICOS](#) / [COMPARAÇÃO ENTRE MODELOS](#)

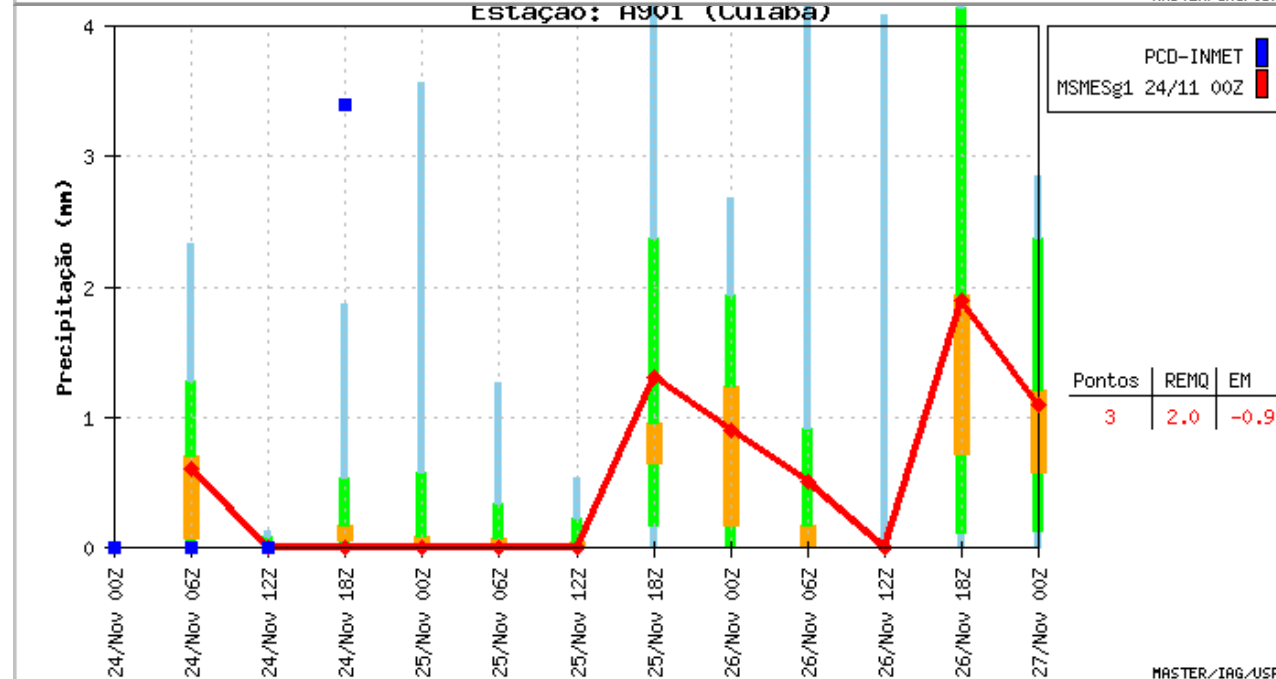


Master - IAG/USP

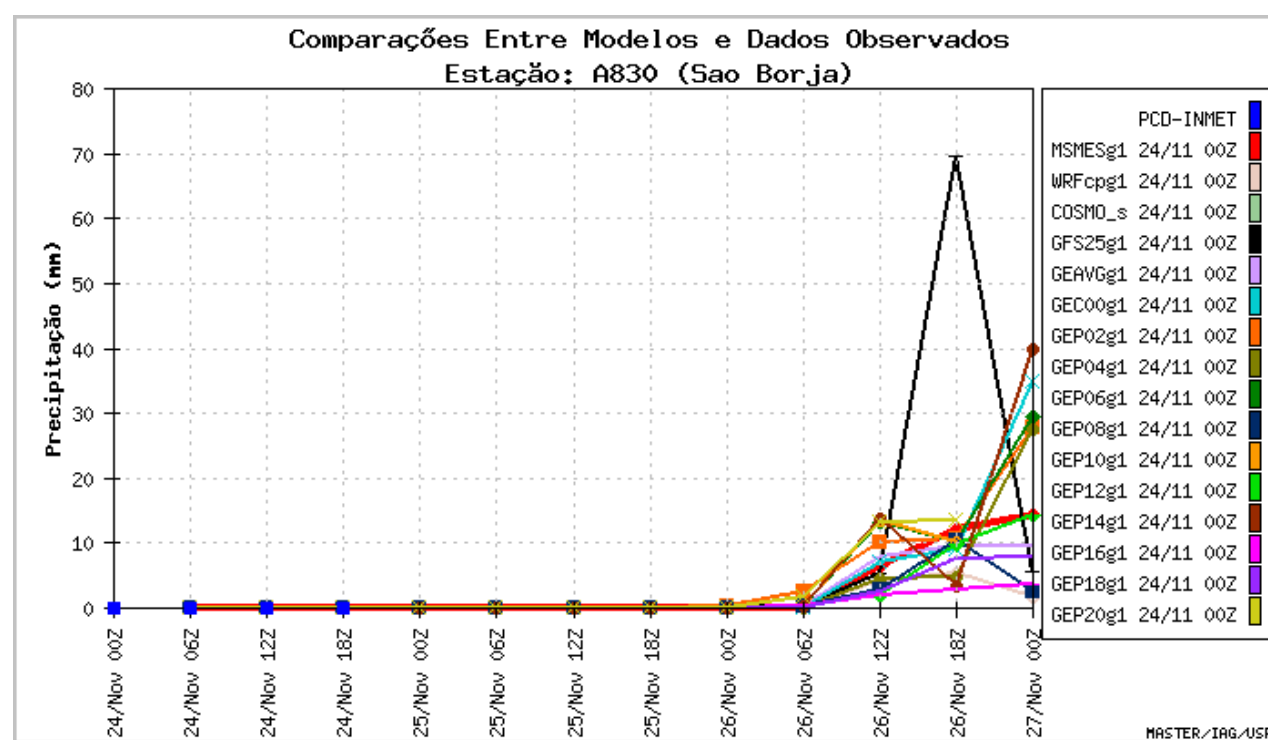
Previsão de chuva a cada 6 horas por um conjunto de modelos



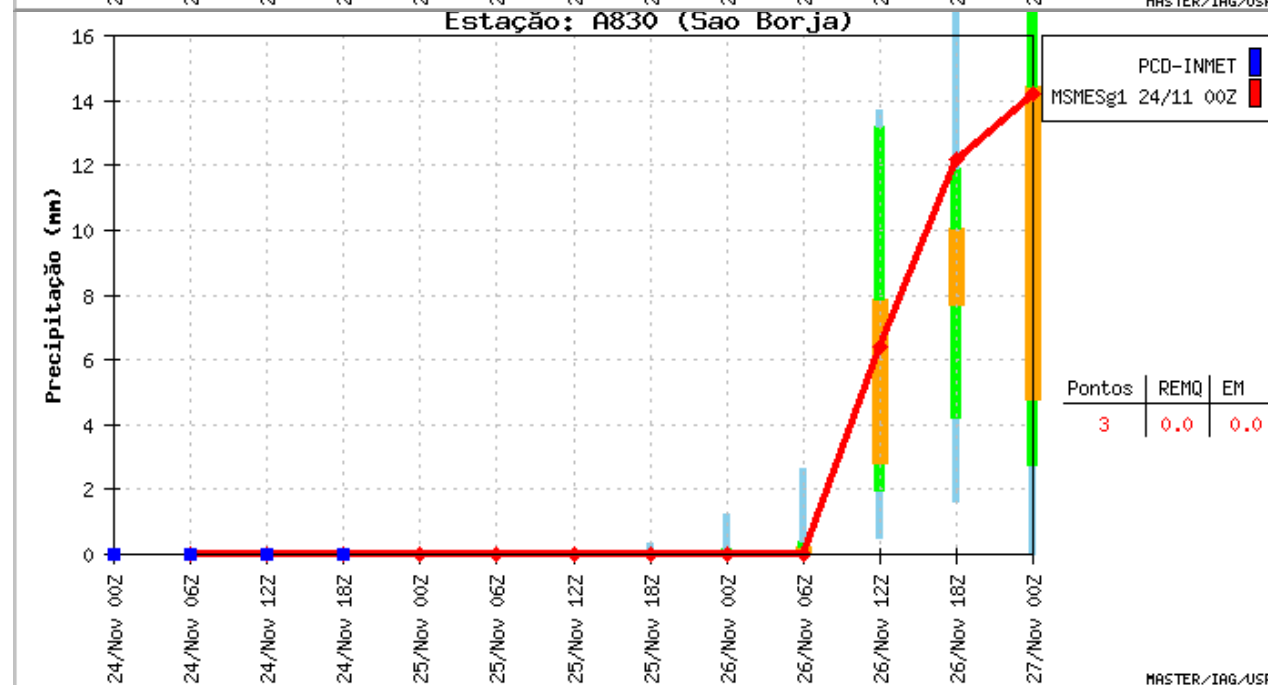
Previsão estatística e quintis da previsão por conjuntos



Previsão de chuva a cada 6 horas por um conjunto de modelos



Previsão estatística e quintis da previsão por conjuntos



O papel das técnicas de inteligência artificial

Perez, 2018 Improving the quantitative precipitation forecast: a deep learning approach

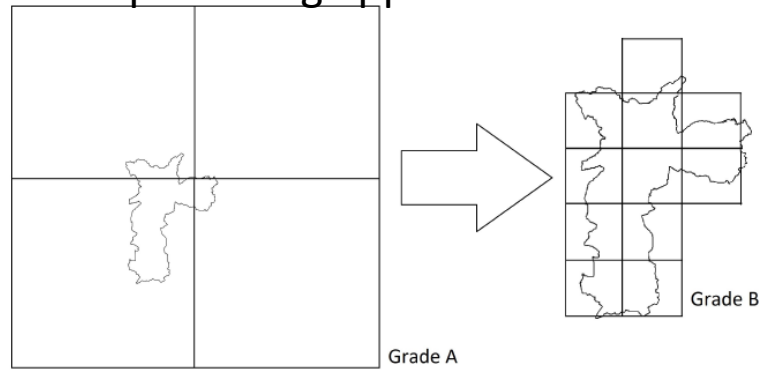


Figura 1 – Grade A, correspondente ao GFS e grade B, criada para dividir o domínio de cada rede neural.

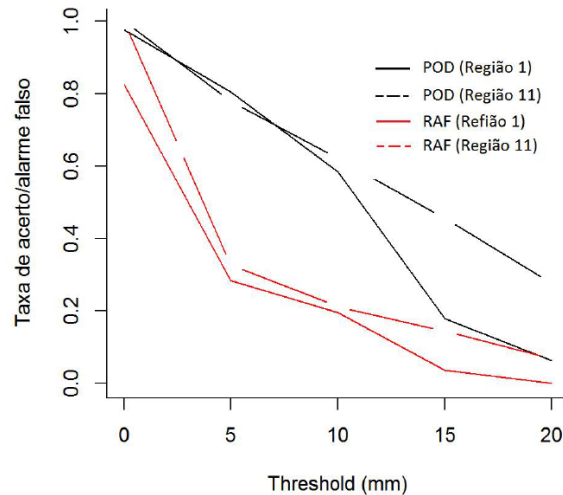
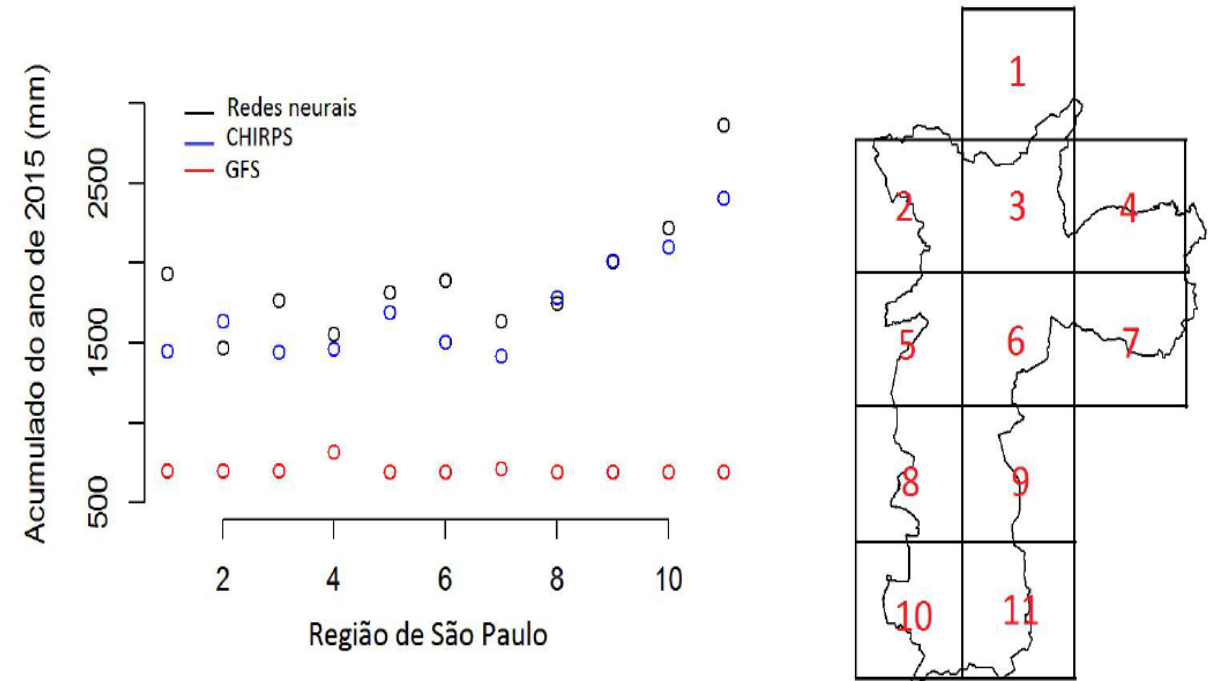


Figura 4 – Probabilidade de detecção e taxa de alarme falso da previsão das redes neurais na regiões 1 e 11 da grade B para o ano de 2015.



Acumulado de chuva anual previsto pela técnica de IA, pelo GFS e o total anual do CHIRPS, para 11 sub-regiões da RMSP

Previsão de chuva de médio
prazo

Previsão de chuva média por bacia em acumulado de 5 dias

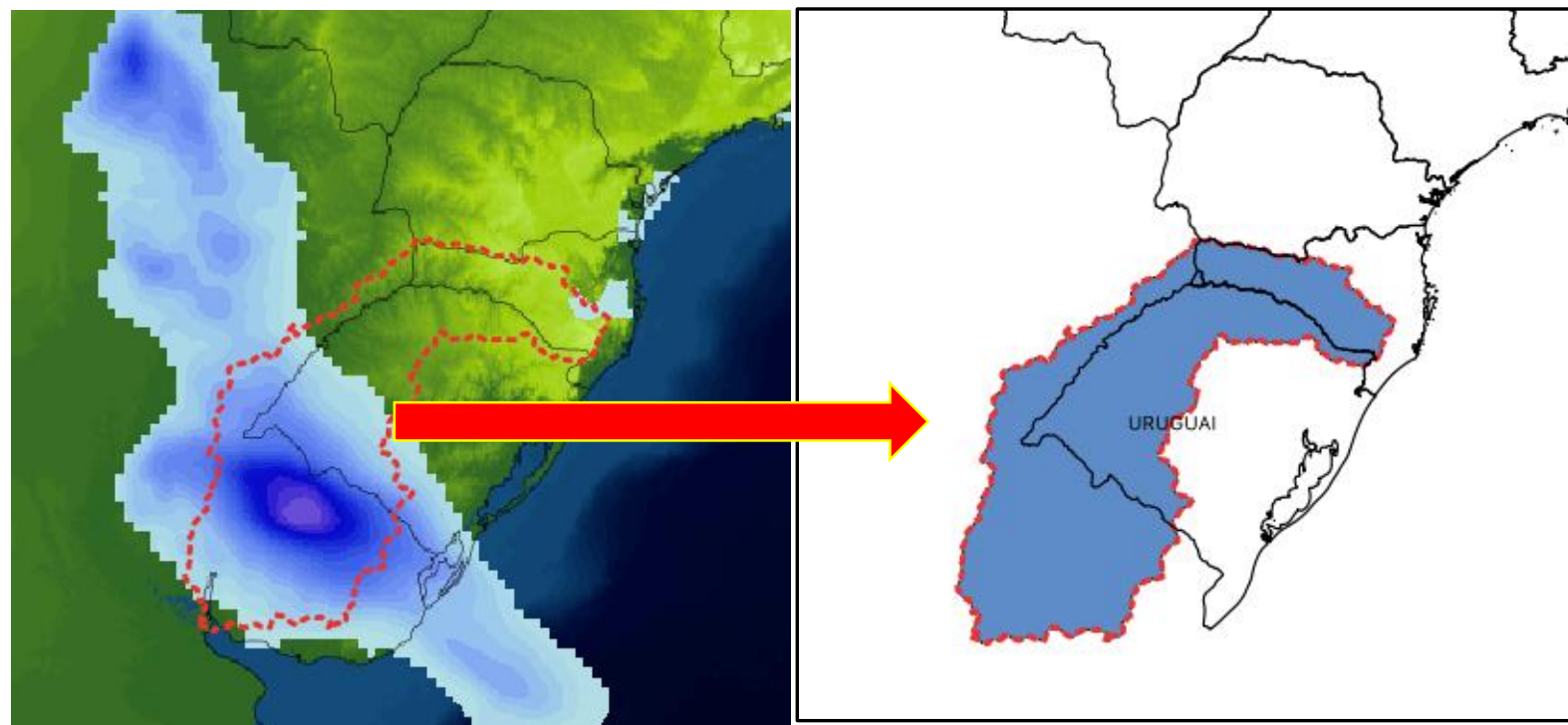


Figura 1. (a) Previsão de chuva acumulada para um dia qualquer e (b) a representação dessa chuva em média na bacia (b) direita.

Retirada do viés dos últimos 30 dias

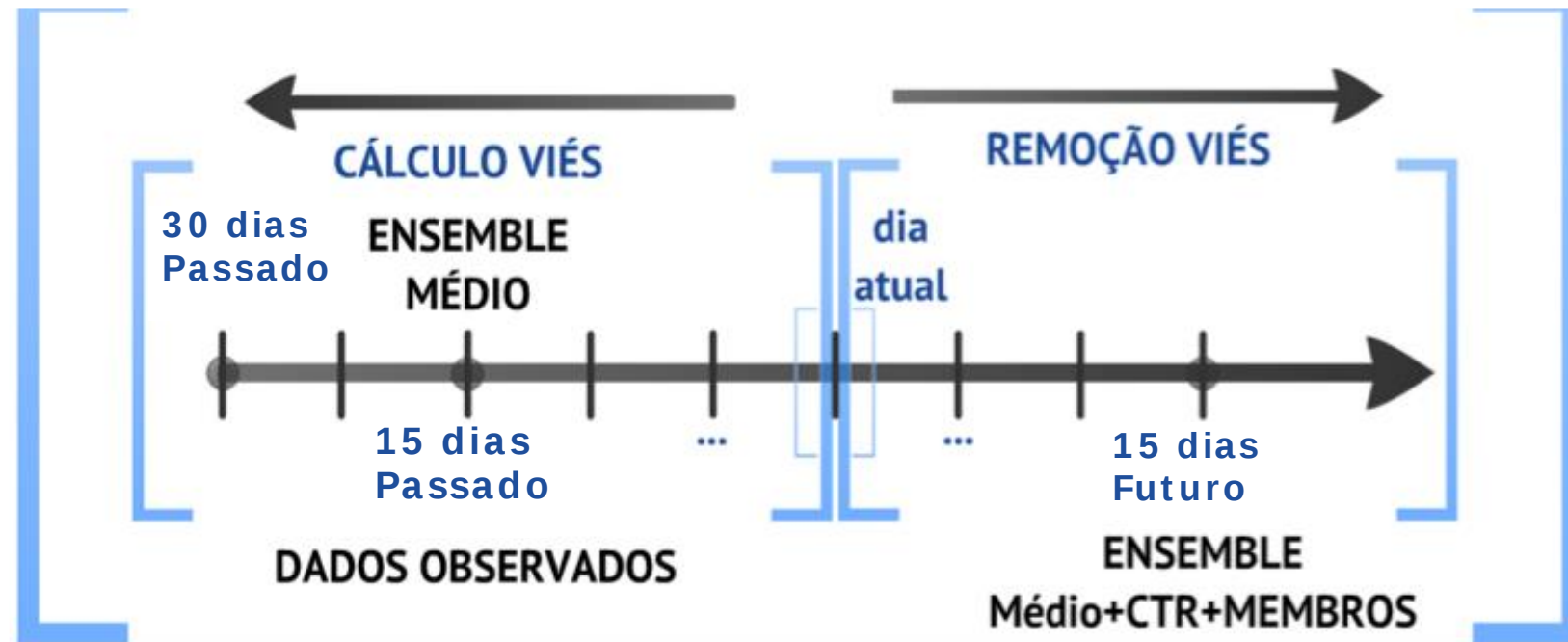


Figura 1. Ilustração esquemática para o cálculo do viés. O dia atual aparece ao centro, os 30 dias passados à esquerda e os 15 dias futuros à direita. P1, P2 e P3 correspondem às 3 pênadas de previsão.

A previsão probabilística da chuva para os primeiros 15 dias

- Cálculo do RMS (erro médio quadráticos - *root mean square error*): utilizando o membro médio do *ensemble* é calculado o RMS de cada conjunto, e para cada pêntrada de previsão. O RMS é a raiz quadrada do valor médio do viés ao quadrado das últimas previsões, para cada pêntrada de previsão;
- Probabilidade de ocorrência de precipitação no conjunto: sendo n o número de membros que apresentam ocorrência de chuva, a probabilidade desse evento será n dividido pelo número de membros do *ensemble*;
- A probabilidade de ocorrência de precipitação é igual ao somatório das probabilidades dos conjuntos, utilizando o inverso do seu RMS como peso. Desta forma, é penalizado o conjunto que estiver apresentado maior erro nos últimos 15 dias.
- O valor médio da chuva é obtido através do somatório do valor médio de cada conjunto também utilizando o RMS como peso.

Previsão por intervalos baseados em percentis do ensemble (21 membros do GFS/NCEP)
(chuva média na bacia, acumulada em pântadas)

			Intervalo de previsão	
data início pântada	Probabilidade de ocorrência de chuva (%)	Valor médio previsto (mm)	30% (mm)	70% (mm)
20/10/2018	95	14	11	18
25/10/2018	68	11	4	20
30/10/2018	66	18	4	38

Previsão de longo prazo: sazonal

Previsão Sazonal de Vazão na Bacia do Rio Uruguai 2: Previsão Climática-Hidrológica

Walter Collischonn, Carlos Eduardo Morelli Tucci, Robin T. Clarke
Instituto de Pesquisas Hidráulicas - UFRGS
collischonn@iph.ufrgs.br

Pedro L. S. Dias

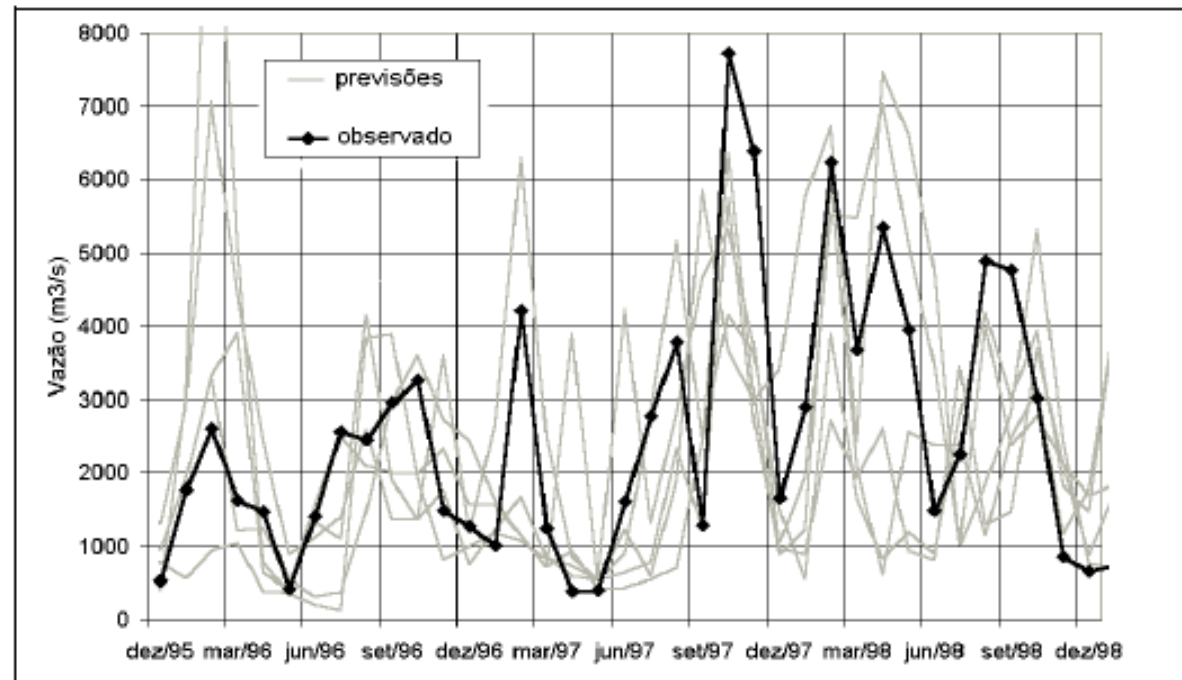


Figura 10 - Previsões de vazão no rio Uruguai com base nas previsões climáticas com correção (as 5 linhas cinzas correspondem às 5 realizações).

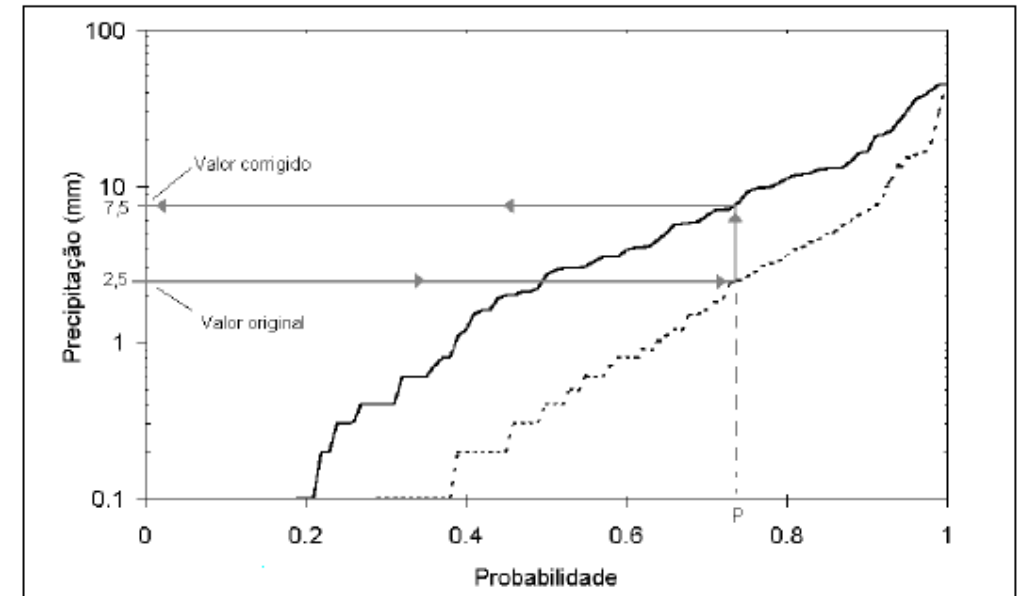


Figura 6 - Curvas empíricas de distribuição de probabilidade acumulada de precipitações diárias no ponto 9, válidas para o mês de janeiro, no período de dezembro de 1995 a dezembro de 1998 (probabilidade de que a precipitação em um dia qualquer seja inferior ao valor indicado na curva – a linha contínua corresponde aos dados observados e a linha pontilhada aos dados previstos).

Previsão de chuva de longo
prazo: subsazonal a sazonal (S2S)

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

(November 2018–December 2023)

WEATHER CLIMATE WATER



“The World Weather Research Programme (WWRP) and the World Climate Research Programme (WCRP) Sub-seasonal to Seasonal Prediction Project (S2S) was launched in November 2013, with the primary goals of improving forecast skill and understanding the dynamics and climate drivers on the sub-seasonal to seasonal timescale (from 2 weeks to a season).

The S2S project has a special emphasis on high-impact weather events, developing coordination among operational centres, and on promoting uptake of S2S information by the applications communities.”

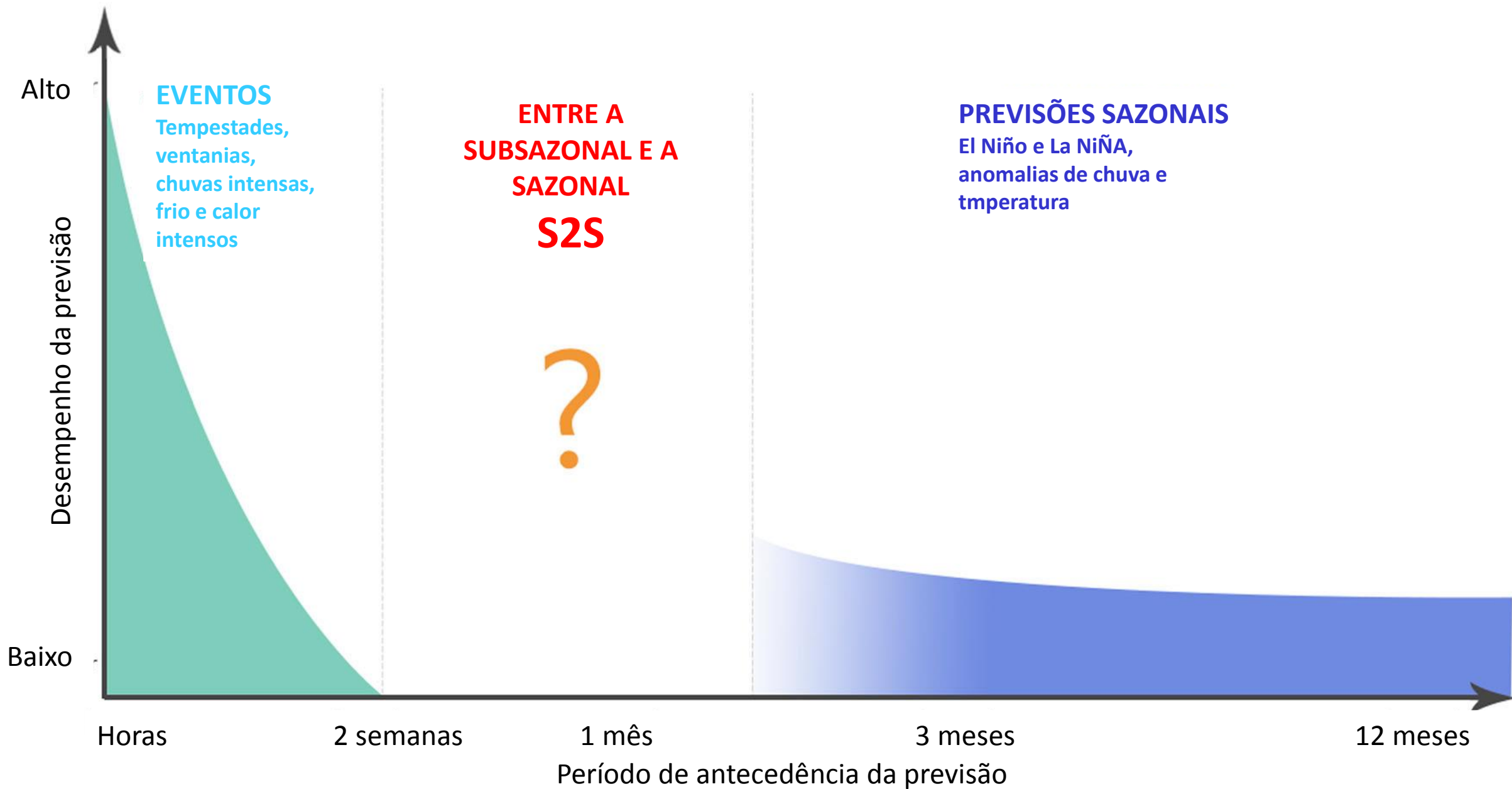
nature > npj climate and atmospheric science > perspectives > article

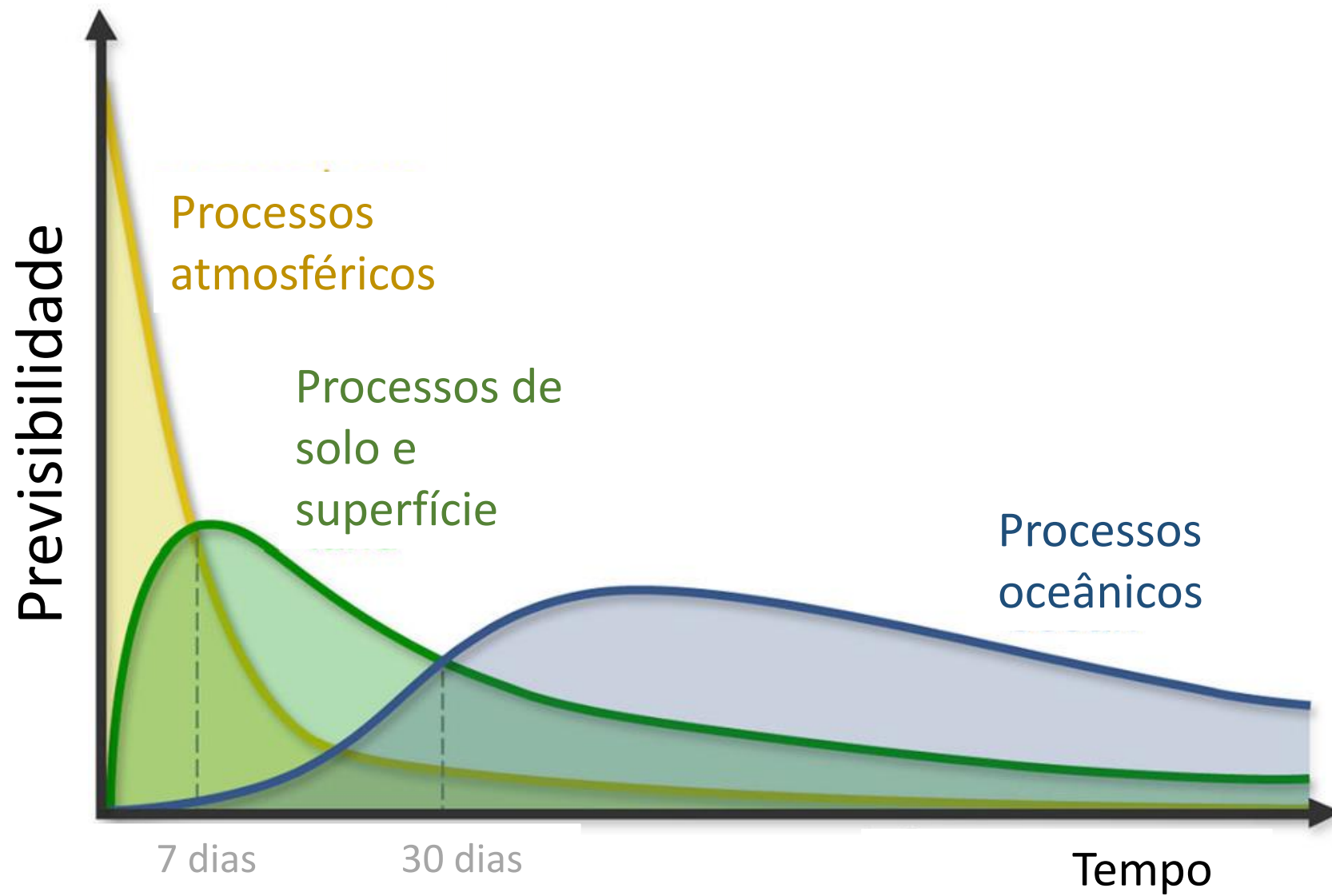
npj | Climate and Atmospheric Science

Perspective | [Open Access](#) | Published: 26 March 2018

Progress in subseasonal to seasonal prediction through a joint weather and climate community effort

Annarita Mariotti , Paolo M. Ruti & Michel Rixen





[< Previous Article](#)

[Next Article >](#)

Collaboration of the Weather and Climate Communities to Advance Subseasonal-to-Seasonal Prediction

Gilbert Brunet, Melvyn Shapiro, Brian Hoskins, Mitch Moncrieff, Randall Dole, George N. Kiladis, Ben Kirtman, Andrew Lorenc, Brian Mills, Rebecca Morss, Saroja Polavarapu, David Rogers, John Schaake, *and* Jagadish Shukla

<https://doi.org/10.1175/2010BAMS3013.1>

Received: 11 March 2010

Published Online: 1 October 2010

Scientific priorities to accelerate advances in analysis and prediction at subseasonal-to-seasonal time scales, which include

- i) advancing knowledge of mesoscale–planetary-scale interactions and their prediction;
- ii) developing high-resolution global–regional climate simulations, with advanced representation of physical processes, to improve the predictive skill of subseasonal and seasonal variability of high-impact events, such as seasonal droughts and floods, blocking, and tropical and extratropical cyclones;
- iii) contributing to the improvement of data assimilation methods for monitoring and predicting used in coupled ocean–atmosphere–land and Earth system models; and
- iv) developing and transferring diagnostic and prognostic information tailored to socioeconomic decision making.

8 The Subseasonal to Seasonal (S2S) Prediction Project Database

F. Vitart
ECMWF, Reading, United Kingdom

[See all authors & affiliations](#) ▾

<https://doi.org/10.1175/BAMS-D-16-0017.1>

Final Form: 10 June 2016

Published Online: 23 January 2017

A main deliverable of this project is the establishment of an extensive database containing subseasonal (up to 60 days) forecasts, 3 weeks behind real time, and reforecasts from 11 operational centers

By the end of 2015, about 300 users from 42 countries had registered and had already executed over 200,000 requests to extract about 30 TB of data from ECMWF. ECMWF and CMA are working together closely to ensure the timely synchronization of the two databases.

The S2S database at ECMWF can be accessed online (at <http://apps.ecmwf.int/datasets/data/s2s>; <http://s2s.ecmwf.int>) for the reforecasts.

The S2S database at CMA can be accessed at <http://s2s.cma.cn/>.



A verification framework for South American sub-seasonal precipitation predictions

CAIO A.S. COELHO*, MÁRI A.F. FIRPO and FELIPE M. DE ANDRADE

Centro de Previsão de Tempo e Estudos Climáticos (CPTEC), Instituto Nacional de Pesquisas Espaciais (INPE)

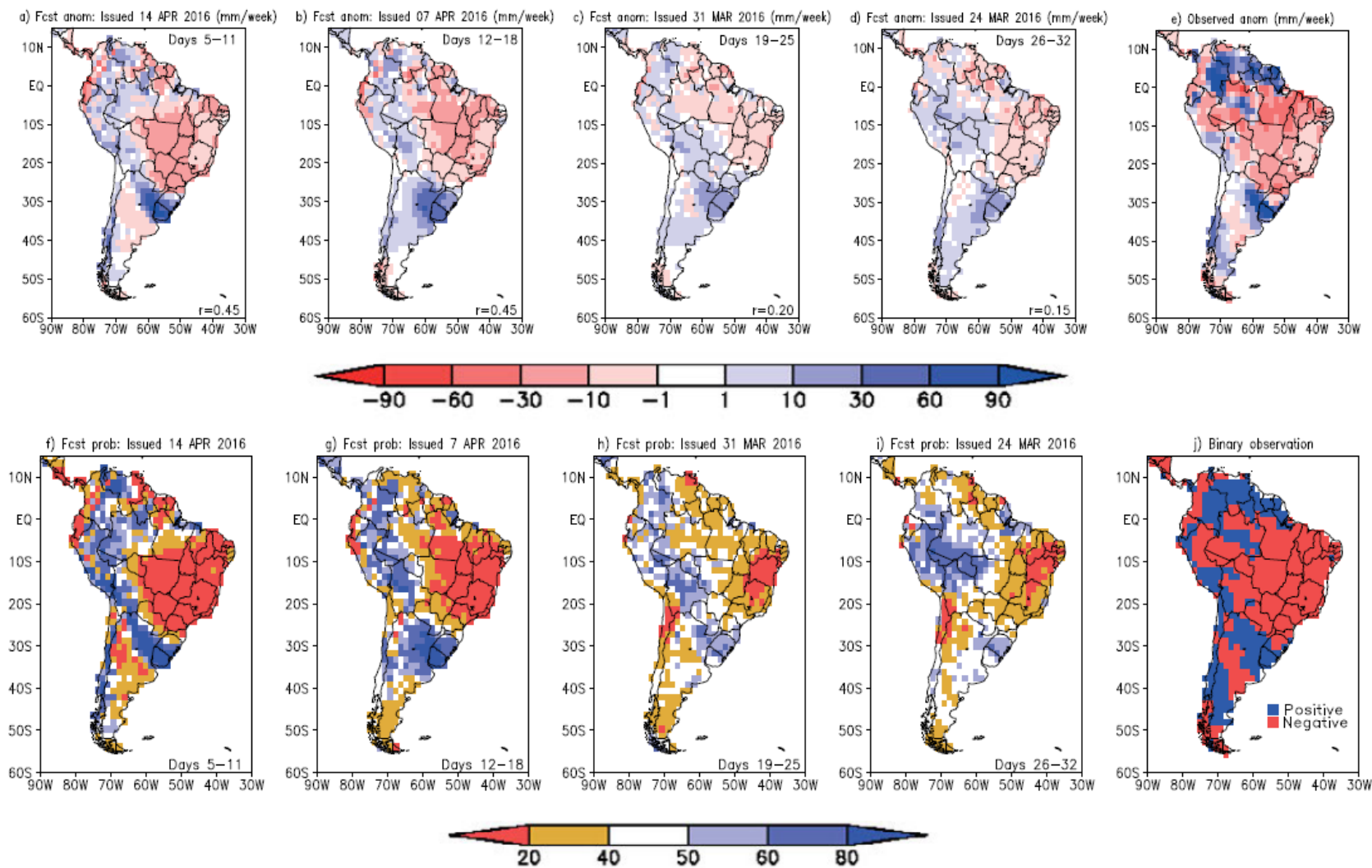


Figure 1: ECMWF ensemble mean forecast accumulated precipitation anomalies for the target week of interest (18–24 April 2016) initialized on the a) 14 April 2016, b) 7 April 2016, c) 31 March 2016 and d) 24 March 2016, representing forecasts valid for weeks 1 to 4 as described in Section 2.1. A total of 51 ensemble members were used for computing the ensemble mean forecast, and anomalies were calculated with respect to the 1996–2015 hindcast period (20 years) for which an ensemble of 11 members was available for each of these 20 years. e) Observed accumulated precipitation anomalies for the week 18–24 April 2016 with respect to the 1996–2015 period

Heavy Rainfall in Paraguay during the 2015/16 Austral Summer: Causes and Subseasonal-to-Seasonal Predictive Skill

JAMES DOSS-GOLLIN

*Columbia Water Center, and Department of Earth and Environmental Engineering, Columbia University,
New York, New York*

ÁNGEL G. MUÑOZ

*Atmospheric and Oceanic Sciences, Princeton University, Princeton, New Jersey, and International Research
Institute for Climate and Society, The Earth Institute, Columbia University, Palisades, New York*

SIMON J. MASON

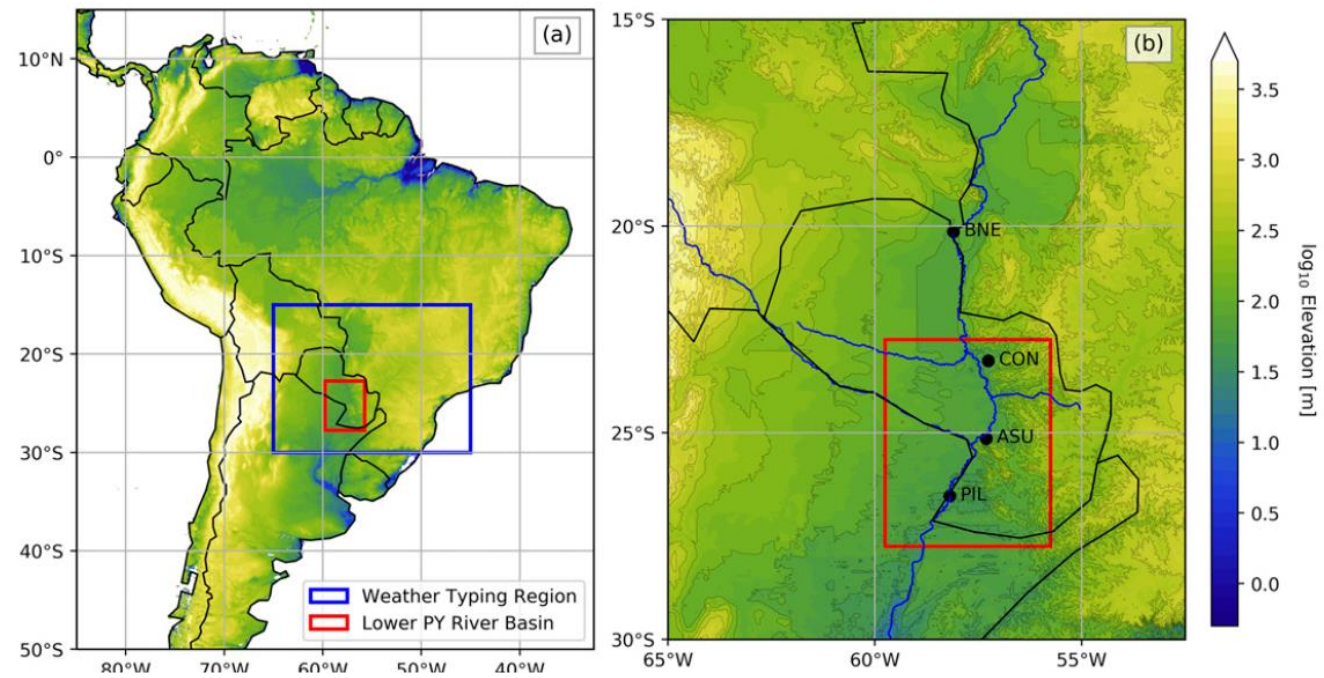
International Research Institute for Climate and Society, The Earth Institute, Columbia University, Palisades, New York

MAX PASTÉN

*Dirección de Meteorología e Hidrología, Asunción, and Facultad Politécnica, Universidad Nacional de Asunción,
San Lorenzo, Paraguay*

Raw subseasonal forecasts of heavy rainfall exhibited limited skill at lead times beyond the first two predicted weeks, but a **model output statistics** approach involving principal component regression substantially improved the spatial distribution of skill for **week 3** relative to other methods tested, including extended logistic regressions.

A continuous monitoring of climate drivers impacting rainfall in the region, and **the use of statistically corrected heavy precipitation seasonal and subseasonal forecasts**, may help improve flood preparedness in this and other regions.



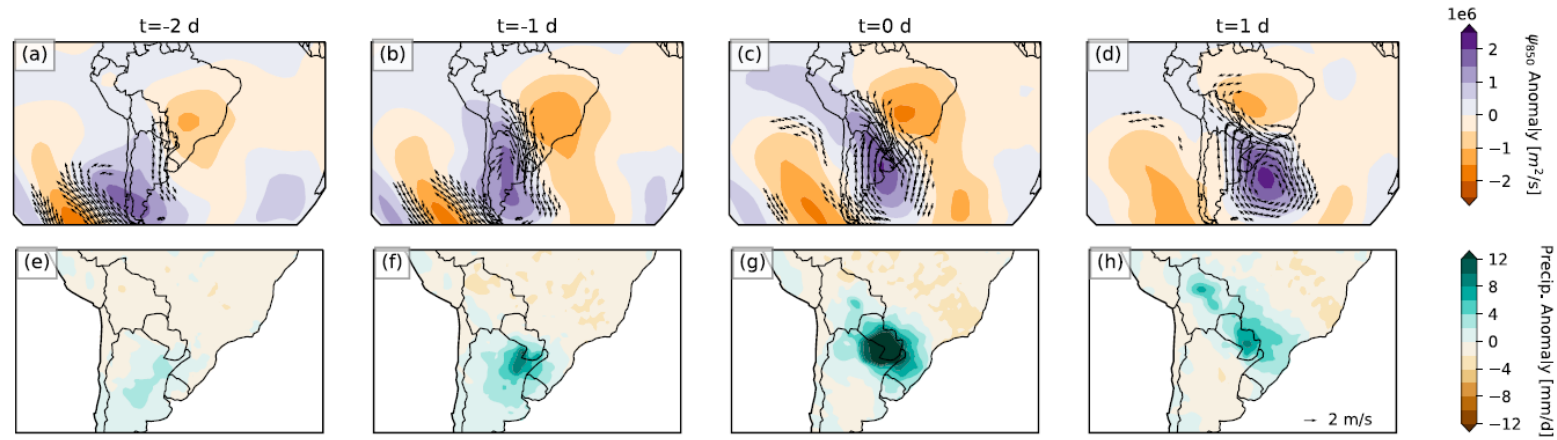


FIG. 4. Composite anomalies associated with heavy rainfall (90th percentile exceedance of area-averaged rainfall in the LPRB). Lagged composites are shown, for $t =$ (a),(e) -2 , (b),(f) -1 , (c),(g) 0 , and (d),(h) 1 day relative to the date of heavy rainfall. (top) Composite ψ_{850} (shading) and wind anomalies at 850 hPa (vectors), with the strongest 5% of wind anomaly vectors between 60°S and 10°N (all longitudes) are also shown, and (bottom) composite rainfall anomalies (mm day^{-1}).

Conclusão

- Pesquisas são necessárias em áreas fundamentais
 - Acoplamento de modelos
 - Melhoria da representação dos processos de escala sub-grade
 - Aumento de disponibilidade de dados e assimilação de dados em 4-D
 - Uso de técnicas de Inteligência Artificial para melhorar as previsões estendidas – em todas as escalas
 - Melhorias na comunicação da incerteza e interação com o usuário

Obrigada pela atenção!