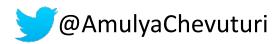
Forecasting annual maximum water level for Negro River at Manaus

Amulya Chevuturi a.chevuturi@reading.ac.uk

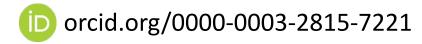
Nick Klingaman, Steve Woolnough Conrado Rudorff, Caio Coelho, Jochen Schöngart













Predicting the Evolution of the Amazon Catchment to Forecast the Level Of Water (PEACFLOW)

Determine the observed connection between antecedent rainfall in the Amazon catchment and the annual maximum water level in Manaus.

Determine the performance of seasonal forecast models, for predicting rainfall in the Amazon catchment.

03

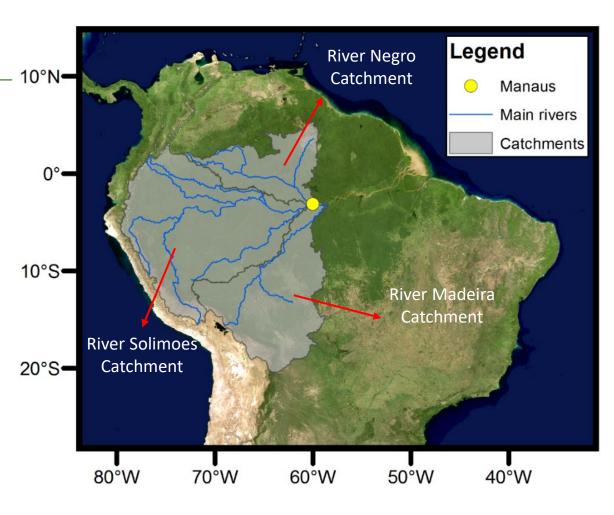
01

02

Develop a statistical model that links antecedent rainfall in the Amazon catchment to the annual maximum water level in Manaus.



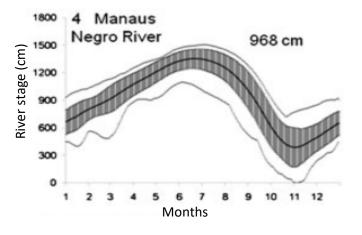
Validate the statistical model against the existing *CPRM and INPA models* for the annual maximum water level at Manaus.



Motivation

- Amazonian rivers present regular and predictable hydrological cycles
- High-water period followed by a low-water period during the annual cycle with large inter-annual variability
- Recent floods: 2009, 2012, 2013, 2014, 2015 and 2019
- Floods have affected hundreds of thousands of people living in the floodplains

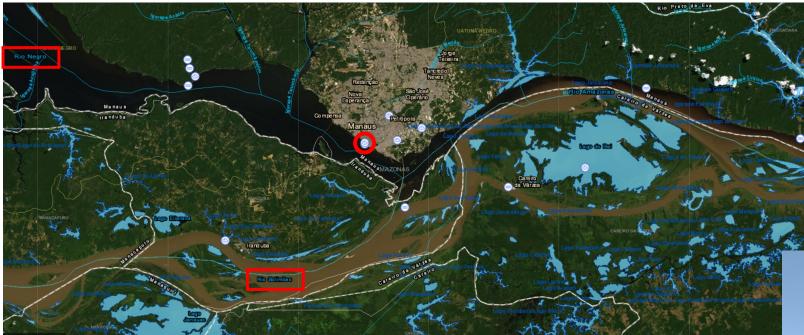




Station	Manaus		
River	Rio Negro		
Location	3.14° S; 60.03°W		
Data type	Daily river level		
Data length	Sep-1902 – Present		

Hydrograph for 1983 to 2005 (Junk et al. 2011)

Manaus and meeting of the rivers

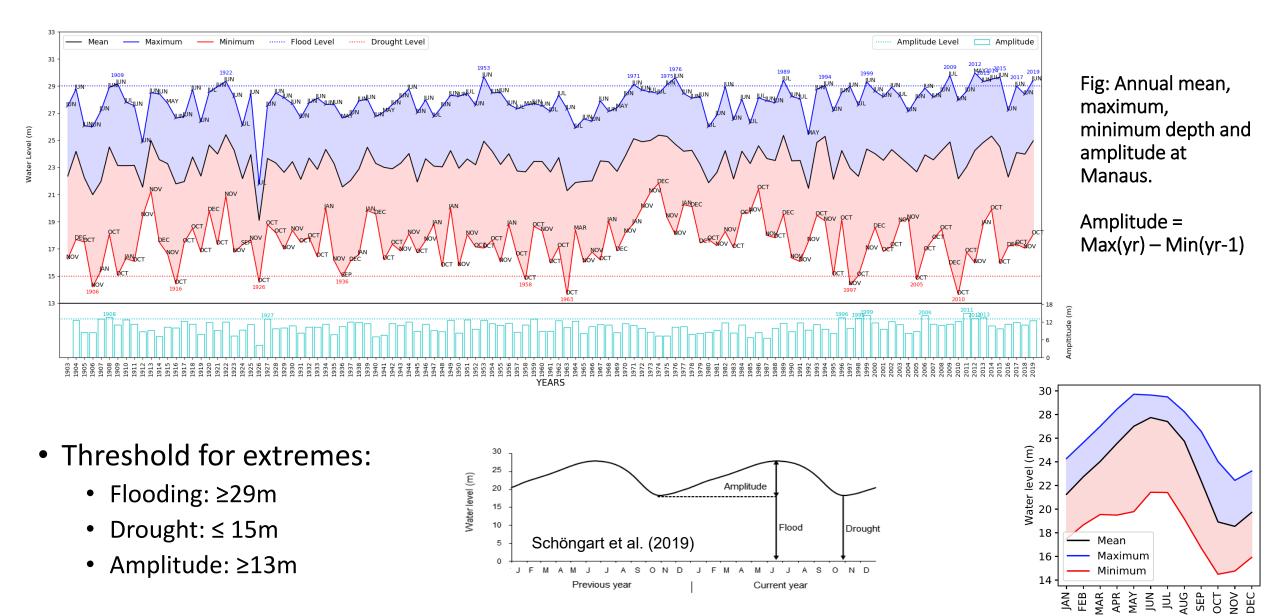


- Meeting of Rivers Negro and Solimoes at Manaus
- Measurement station at Manaus, is for River Negro
- River levels influenced by backwater effect



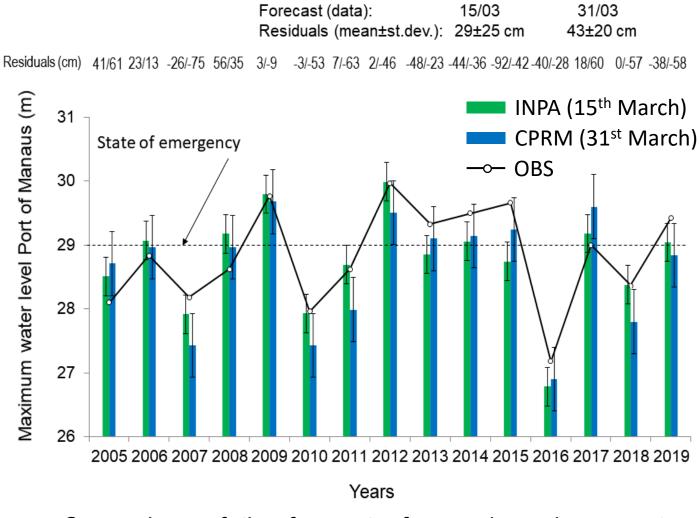


Annual levels

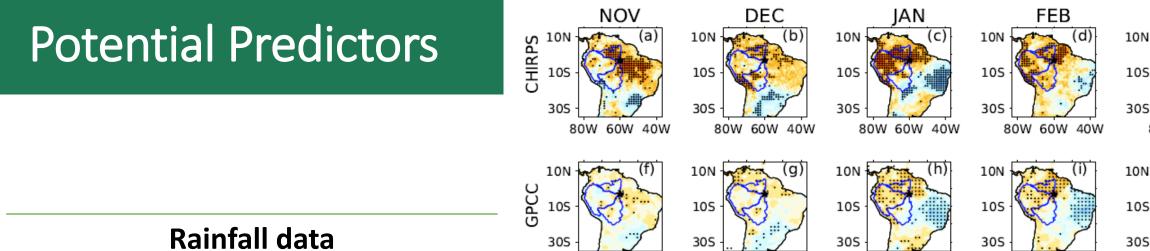


Existing Models

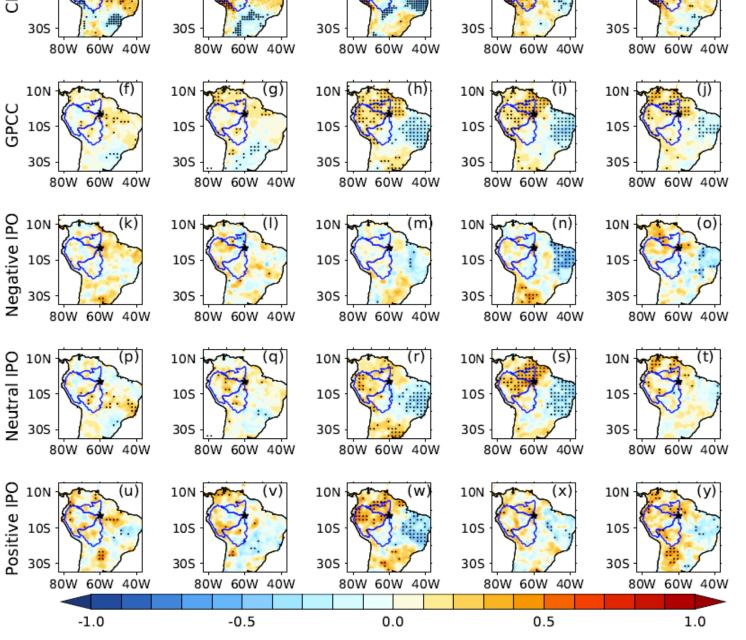
- Operational forecasts by the Brazilian Geological Survey (CPRM):
 - March: March water levels
 - April: April water levels
 - May: May water levels
- Improved forecasts by National Institute of Amazonian Research (INPA):
 - Schöngart & Junk (2007): Level_Feb, SOI_Feb
 - Schöngart & Junk (2020): Niño3.4_DJF, SOI_NDJ, PDO_Feb, Pmin, Level_7Mar



Comparison of the forecast of annual maximum water levels for the period 2005-2019 between models (Schöngart & Junk 2020)



Data	CHIRPS	GPCC
Version	2.0	2018
Spatial Resolution	0.05°	1.0°
Temporal Extent	1981 – Present	1891 – Present
Reference	Funk et al. (2015)	Schneider et al. (2013)

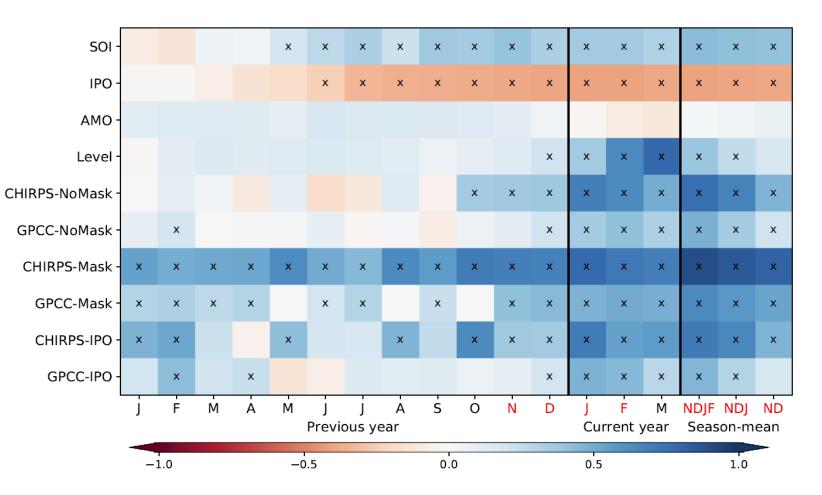


MAR

(e)

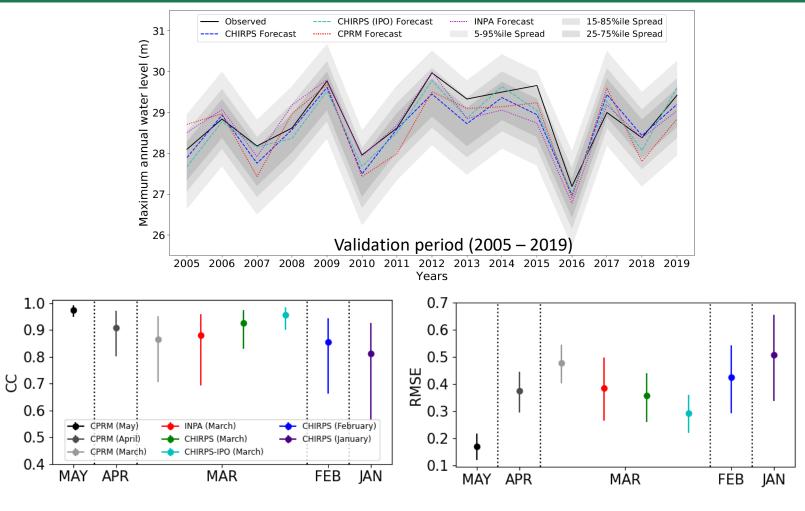
Potential Predictors

- Antecedent masked rainfall
- Preceding water levels
- Large-scale modes of climate variabilities:
 - Atlantic SSTs
 - Pacific SSTs
- Previous minimum (r = 0.13)
- Linear trend (Time; r = 0.33*)



Forecast Models and Validation

- Multiple linear regression used to find the best fit during the training period (1904—2004)
- Screening regression approaches:
 - Forward selection
 - Backward elimination
- Forecast uncertainty is based on the empirical distribution of residuals in the training period
- Operational forecast date:
 - CHIRPS models: 15th March
 - INPA: 15th March
 - CPRM: 31st March



2020	CPRM (MAY)	CPRM (APR)	CPRM (MAR)	INPA (MAR)	CHIRPS (MAR)	CHIRPS (IPO)	CHIRPS (FEB)	CHIRPS (JAN)
Forecast	28.60	28.25	28.30	28.48	28.44	28.52	28.84	29.37
Bias	+0.08	-0.27	-0.22	-0.04	-0.08	0.00	+0.32	+0.85

Sensitivity tests

Model based on unconditional masks

Spatial extent: Different basins | Box region

Masks: No mask | CHIRPS | GPCC

Predictors: Monthly | Seasonal

Model based on conditional masks

Indices: SOI | AMO | IPO

Significance level: 0.1 | 0.05

Categories of phases: Tercile | Quartiles

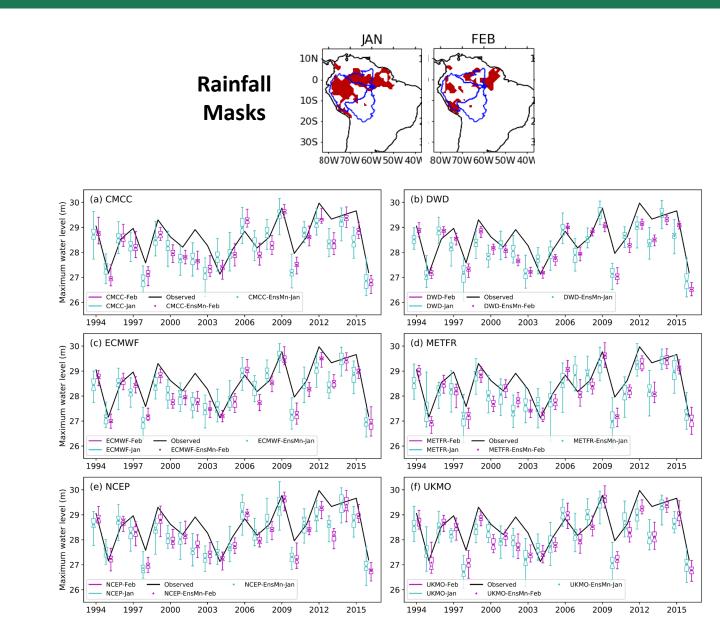
Masks: Monthly | Seasonal masks

Seasonal Hindcasts

System	Model	Ensemble	Time Extent
СМСС	SPSv3	40	1993-2016
DWD	GCFS2.0	30	1993-2016
ECMWF	SEAS5	25	1981-2016
METFR	Météo- France	25	1993-2016
NCEP	System 7 CFSv2	28 (Jan); 24 (Feb)	1993-2016
UKMO	GloSea5	28	1994-2016

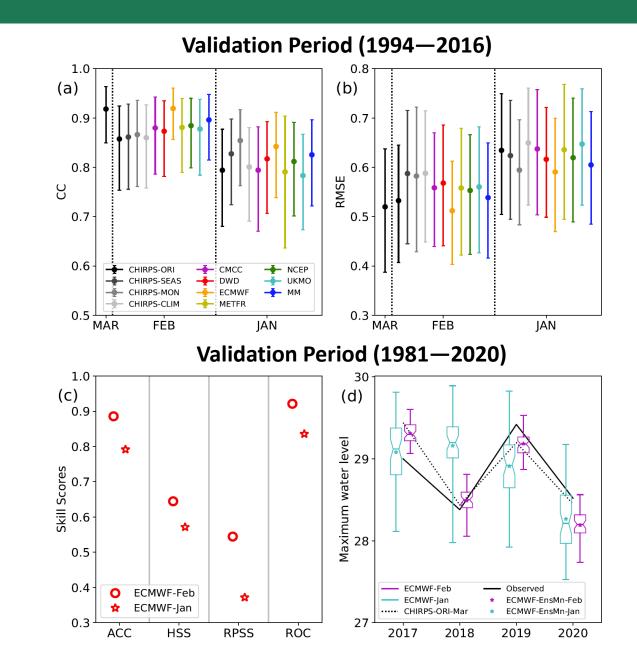
Forecast Models

- Rainfall masks for the seasonal hindcasts are adapted from the original CHIRPS rainfall masks
- Forecasts using hindcast with lead time of:
 - February = observed NDJ + F seasonal hindcast
 - January = observed ND + JF seasonal hindcast
- Compared against:
 - Original rainfall models
 - Forecasts using climatology
 - Forecasts using persistence



Model Validation

- ECMWF (February lead time) forecasts outperform all the other models as well as forecasts with climatology and persistence
- ECMWF (Feb) forecasts for February have same skill as original March forecasts using observed data
- ECMWF (Jan) forecasts are not significantly better than the observed monthly persistence (Jan) forecasts
- Lower and upper terciles show higher skill than the middle tercile category
- ECMWF seasonal forecast can be used for real-time operational forecasting and has been tested for the hindcast years 2017— 2020

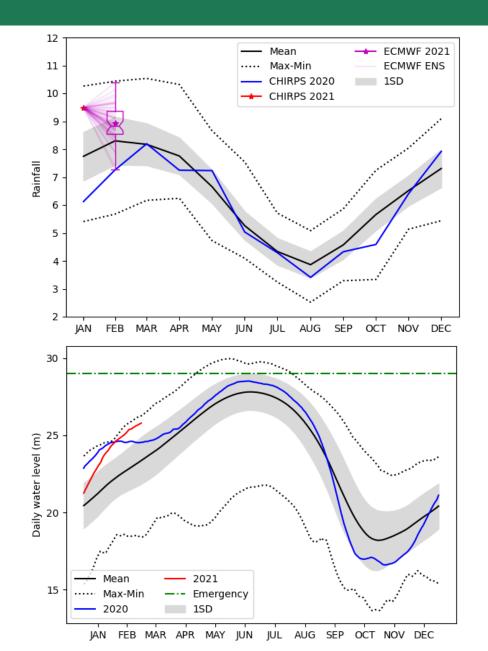


Operational Forecasting

- These statistical models can be implemented for operational forecasting for Manaus and have been tested for 2020 hindcast and 2021 forecast
- Forecasts for 2021 >29m, with all models, forecasting an extreme flood event in Manaus
- GitHub open-source models
 <u>https://github.com/achevuturi/PEACFLOW_Manaus-flood-forecasting</u>

Mod	el	2020 Forecast	2021 Forecast	
Input	Lead-time	(Bias)		
Observations	March	28.44 (-0.08)	29.38	
	February	28.84 (+0.32)	29.45	
	January	29.37 (+0.85)	29.06	
Observations +	February	28.19 (-0.33)	29.20	
ECMWF Forecasts	January	28.27 (-0.27)	29.26	

Observed annual maximum water level at Manaus for 2020 was 28.52m



Conclusions and future work

- Rainfall-based models provide an additional one-month lead time compared to existing models
- Using ECMWF seasonal reforecasts increases lead-time by another one month
- Models implemented for operational use and forecast an extreme flood for 2021
- GitHub open-source models
 <u>https://github.com/achevuturi/P</u>
 <u>EACFLOW Manaus-flood-</u>
 <u>forecasting</u>
- Same method can be used to develop models for:
 - minimum water level
 - other regions of Amazon

