Evaluation of the forecast skill of the North American Multi-Model Ensemble for monthly precipitation forecasts over Central America.

*G. Cristina Recalde-Coronel[1,2], Wassila M. Thiaw[1], Endalkachew Bekele[1,2], and Vadlamani Kumar[3]

1. Climate Prediction Center, National Centers for Environmental Prediction, National Oceanic and Atmospheric Administration, College Park, Maryland, United States

2. University Corporation for Atmospheric Research, Boulder, Colorado, United States

3. ERT, Inc.

***Contact information: cristina.recalde@noaa.gov**

Introduction

Central America's livelihood and socio-economic activities are affected by climate-related hazards. Guatemala, Honduras, and Nicaragua are among the ten countries most vulnerable to climate-based risks[3]. Therefore, a better understanding of the performance of the sub-seasonal-to-seasonal (S2S) meteorological predictions might help to improve climate forecast applications in climate-related sectors across Central America.

Fig.1. Region of Study

We present initial work on the NMME evaluation system. This study aims to quantify the precipitation monthly forecast skill using six NMME models and the multi-model ensemble mean across Central America.

Data and Methods

Data

- Observational data: CHIRPS[1] satellite dataset (1991-2023)
- NMME[2] models: CanCM4i, CFSv2, GEM5-NEMO, GFDL-SPEAR, NASA-GEOS5v2, and NCAR-CCSM4.
  Resolution: ~110 km
  33-year hindcast (1991–2023)
- SST indices: Niño 3.4 SST index(5°N–5S°, 120°W–170°W) (Huang et al. 2017)

Methods

- Verification results of the hindcast forecast initialized in May up to 6 lead months.
- We chose May as it is the start of the rainy season in most countries in Central America.
- We evaluated the accuracy of the ensemble mean using:
  - ✓ Deterministic methods: mean error, linear correlation, and root mean squared error maps.
  - ✓ Probabilistic methods: Brier Score and the Ranked Probability Score.
- We analyzed the impacts on precipitation hindcast performance for the six lead months associated with sea surface temperature (SST) anomalies in the Pacific Ocean.

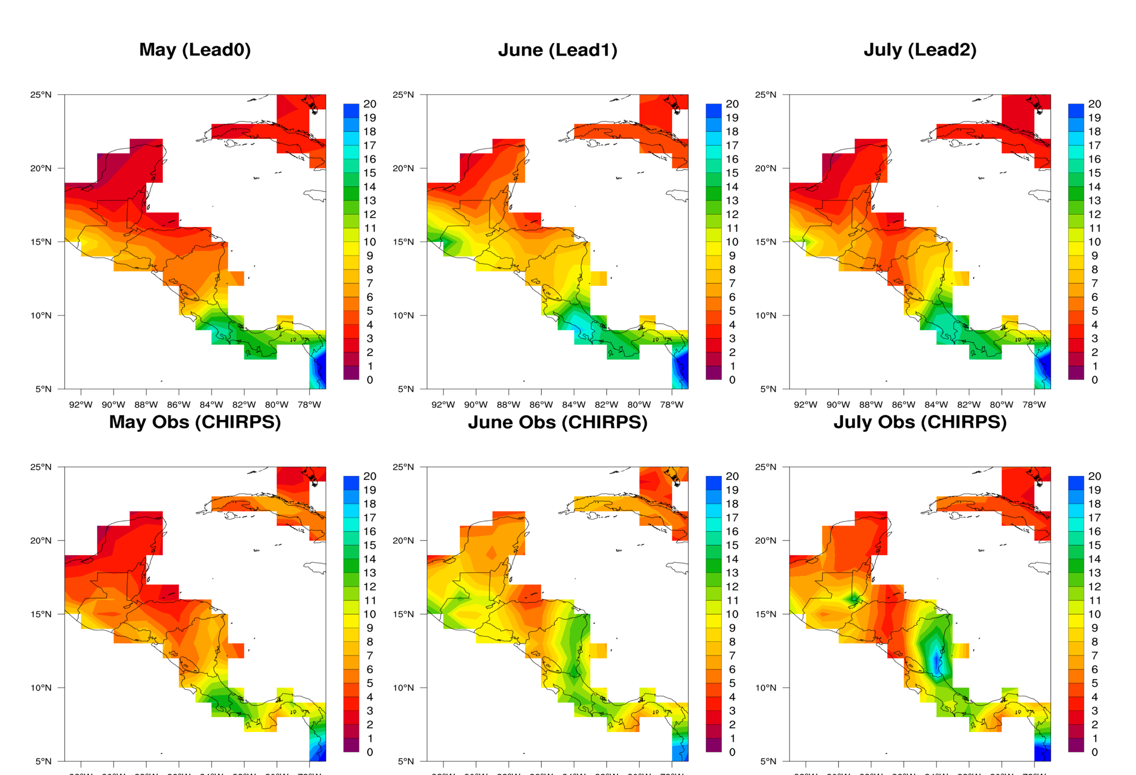

Fig.2. Spatial distribution of the long-term mean from 1991 to 2023 for rainfall (mm day^{-1}) during May, June, and July. Rainfall comes from the NMME multi-ensemble mean hindcast initialized in May (top panel), and from the observed CHIRPS data (lower panel).

Results

- **How well is precipitation forecasted by the multi-model NMME ensemble mean?**

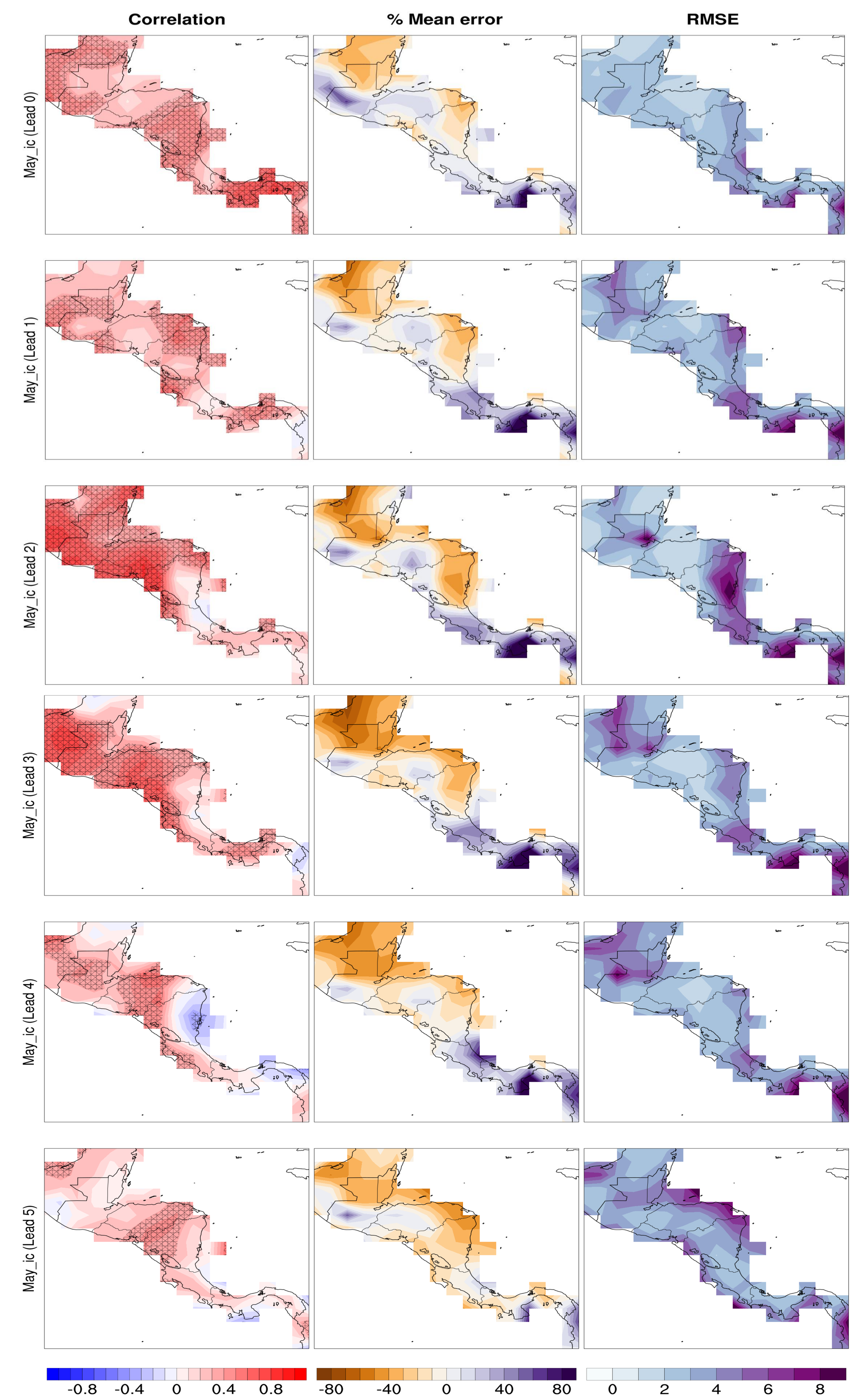

Fig. 3. Rainfall spatial distribution maps of correlation, percentage mean error (bias), and the root-mean-square Error (RMSE; unit: mm) between hindcast and CHIRPS data for 0-month lead (May), 1-month lead (June), 2-month lead (July), 3-month lead (Aug), 4-month lead (Sep), and 5-month lead (Oct). Statistical significance for the correlation maps were assessed with a t-test: stippling indicates significance at 90% confidence.

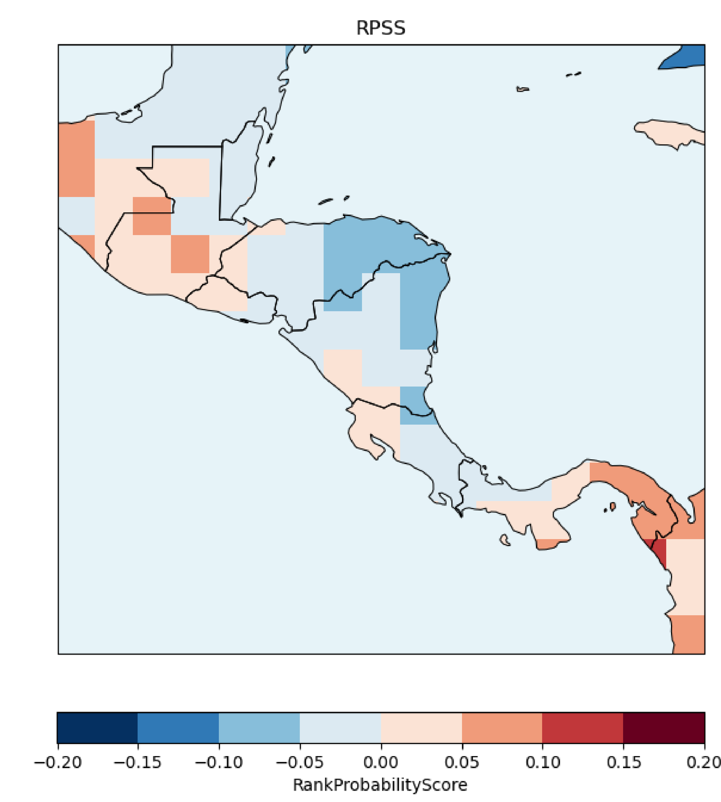

Fig.4. Rank Probability Skill Score (RPSS) map for the multi-model ensemble of the cross-validated probabilistic hindcast dataset relative to the climatological probability for May. The figure was obtained using the XCast[4] toolkit.

- **How well is precipitation forecasted by NMME models?**

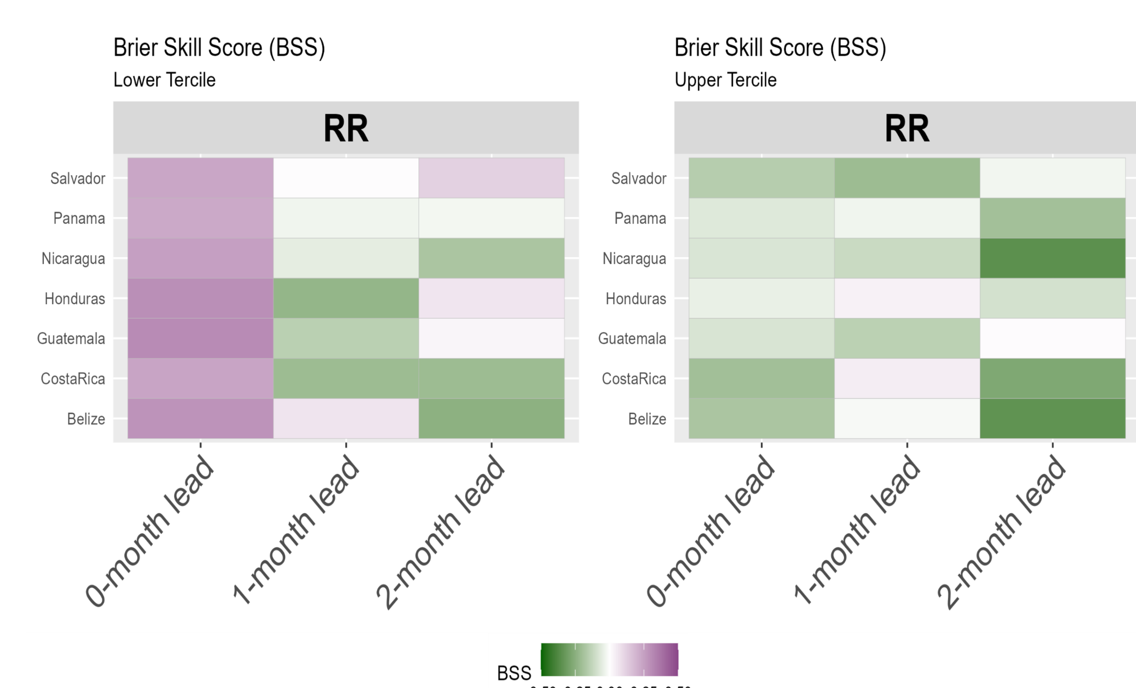

Fig.5. Rainfall heatmap of BSS for below-average and above-average for 0-month lead (May), 1-month lead (June), and 2-month lead (July) hindcast. BSS measures the relative skill of the hindcast compared to the climatology reference from CHIRPS data for a specific category. A score above 0 indicates that the hindcast benefits with respect to the reference.

- **How sensitive is precipitation to El Niño Southern Oscillation (ENSO) variability?**

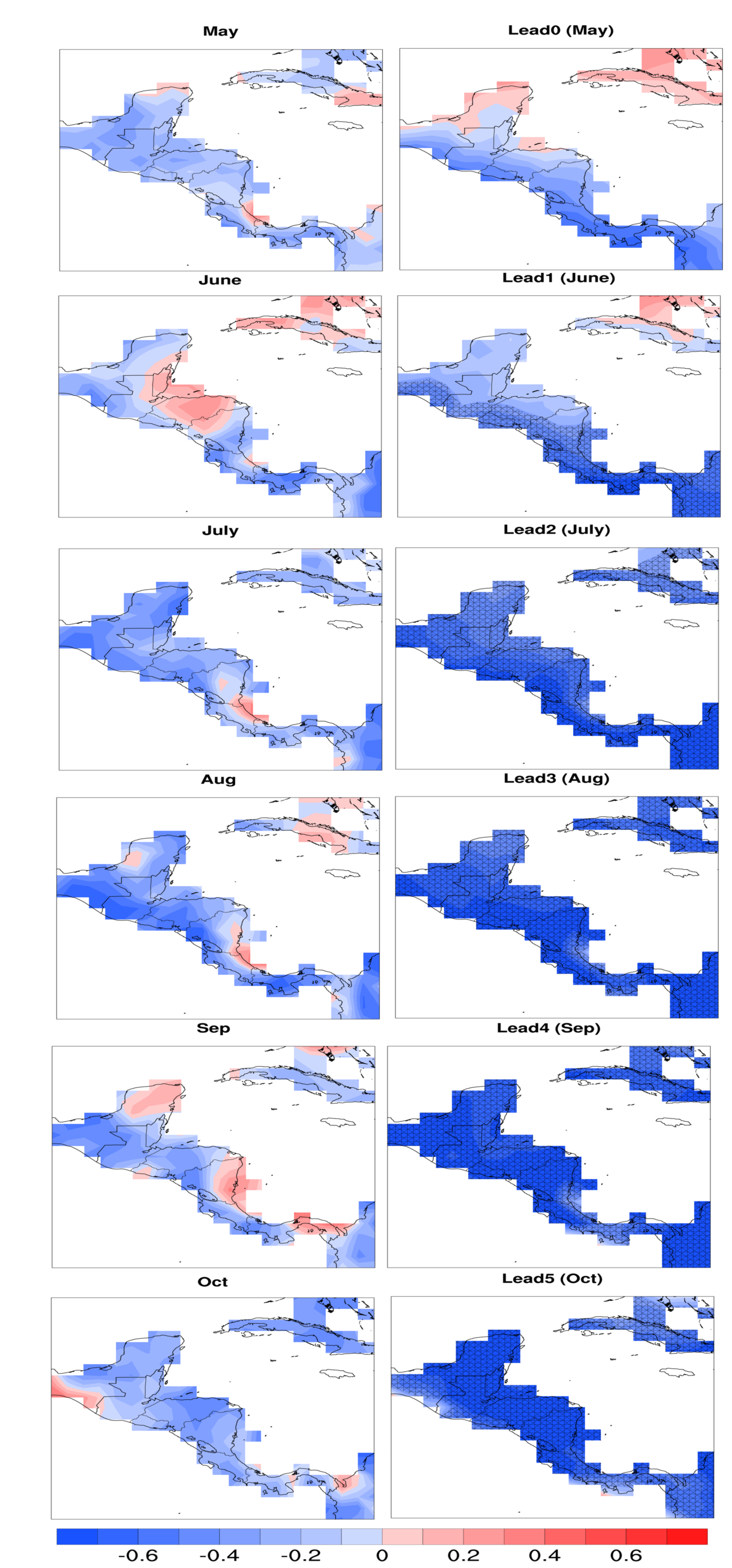

Fig.6. Monthly correlation maps between ENSO 3.4 index and CHIRPS data (left panel) and rainfall anomalies of the hindcast (right panel). Statistical significance for the correlation maps was assessed with a t-test: stippling indicates significance at 90% confidence.

Conclusions

- ✓ Positive rainfall correlations are stronger in northern Central America during all the lead months.
- ✓ For all the lead times, the percentage mean error maps show a dry bias in northern Guatemala, El Salvador, eastern Honduras, and eastern Nicaragua. Meanwhile, there is a wet bias in southern Guatemala, Costa Rica, and most of Panama.
- ✓ RMSE maps illustrate better hindcast skills during the 0-month lead time. As the lead forecast increases, the RMSE tends to become larger, particularly over northern Guatemala, coastal areas facing the Caribbean Sea, and central and southern Panama.
- ✓ For May, the RPPS map shows that the hindcast benefits with respect to the reference across some areas in Guatemala, western El Salvador, southwestern Nicaragua, northwestern Costa Rica, and most of Panama.
- ✓ The BSS score shows that the hindcast benefits with respect to the reference across Central America for the 0-month lead-time, over Belize for the 1-month lead-time, and over El Salvador, Honduras, and Guatemala for the 3-month lead-time. In the case of the upper tercile, Honduras and Costa Rica showed better skills than climatology in the 1-month lead-time.
- ✓ Comparing the correlation maps of CHIRPS precipitation and Niño 3.4 to the correlation maps of the hindcast precipitation and Niño 3.4, we see that the hindcast generally agrees with the observation data. However, in June and September, we can see disagreements over Guatemala, Belize, Honduras, and Nicaragua.

References

1. CHIRPS Global Daily Precipitation data used in this study are available from NOAA at [https://data.chc.ucsb.edu/products/CHIRPS-2.0/]
2. Kirtman, B. P., and Coauthors, 2014: The North American Multi-Model Ensemble (NMME): Phase-1 seasonal to interannual prediction; phase-2 toward developing intra-seasonal prediction. Bull. Amer. Meteor. Soc., 95, 585–601, https://doi.org/10.1175/BAMS-D-12-00050.1.
3. Kreft, S., Eckstein D and Mechioor I, 2017: Global Cliamte Risk Index 2017Who Suffers Most From Extreme Weather Events?
4. K. J. C. Hall and N. Acharya, 'XCast: A python climate forecasting toolkit', Frontiers in Climate, vol. 4, 2022.

Acknowledgements

This research is supported by the NOAA - Climate Adaptation and Mitigation Program and administered by UCAR's Cooperative Programs for the Advancement of Earth System Science (CPAESS) under contract NA21OAR4310473 and NA23OAR4310473B.