

ROSENSTIEL SCHOOL of MARINE & ATMOSPHERIC SCIENCE



Predicting Environmental Hazards: Where Data Science and Computing Meet

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- The Twilight Zone
- Basement Flooding
- Applied Mathematics: Trying to Do Something Good
- Predicting Hazards



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UC San Diego Mathematics

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Predicting Environmental Hazards: Where Data Science and Computing Meet

- The Challenge
- Predicting Across Time Scales
 - Wx Sub-seasonal Seasonal Multi-year Decadal
- Disruptors
 - Advances in Computing Power
 - Data Science Innovation





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U.S. 2020 Billion-Dollar Weather and Climate Disasters





1980-2020 Year-to-Date Billion Dollar Disaster Events



Prediction Across Time-Scales



ocean and evolving atmospheric composition (CO2)



Weather and Climate Model

Ex: Seasonal Forecasts

Sea Surface Temperature Anomaly



Sea Surface Temperature Anomaly





Near-term Climate Change: Projections and Predictability

Coordinating Lead Authors:

Ben Kirtman (USA), Scott B. Power (Australia)

Lead Authors:

Akintayo John Adedoyin (Botswana), George J. Boer (Canada), Roxana Bojariu (Romania), Ines Camilloni (Argentina), Francisco Doblas-Reyes (Spain), Arlene M. Fiore (USA), Masahide Kimoto (Japan), Gerald Meehl (USA), Michael Prather (USA), Abdoulaye Sarr (Senegal), Christoph Schär (Switzerland), Rowan Sutton (UK), Geert Jan van Oldenborgh (Netherlands), Gabriel Vecchi (USA), Hui-Jun Wang (China)

Contributing Authors:

Nathaniel L. Bindoff (Australia), Philip Cameron-Smith (USA/New Zealand), Yoshimitsu Chikamoto (USA/Japan), Olivia Clifton (USA), Susanna Corti (Italy), Paul J. Durack (USA/ Australia), Thierry Fichefet (Belgium), Javier García-Serrano (Spain), Paul Ginoux (USA), Lesley Gray (UK), Virginie Guemas (Spain/France), Ed Hawkins (UK), Marika Holland (USA), Christopher Holmes (USA), Johnna Infanti (USA), Masayoshi Ishii (Japan), Daniel Jacob (USA), Jasmin John (USA), Zbigniew Klimont (Austria/Poland), Thomas Knutson (USA), Gerhard Krinner (France), David Lawrence (USA), Jian Lu (USA/Canada), Daniel Murphy (USA), Vaishali Naik (USA/India), Alan Robock (USA), Luis Rodrigues (Spain/Brazil), Jan Sedláček (Switzerland), Andrew Slater (USA/Australia), Doug Smith (UK), David S. Stevenson (UK), Bart van den Hurk (Netherlands), Twan van Noije (Netherlands), Steve Vavrus (USA), Apostolos Voulgarakis (UK/Greece), Antje Weisheimer (UK/Germany), Oliver Wild (UK), Tim Woollings (UK), Paul Young (UK)



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Global mean temperature near-term projections relative to 1986-2005



Predicting Seasonal Environmental Hazards



UM Leads a Multi-Agency, Multi-Institutional Effort to Improve NOAA Seasonal Operational Forecasts (2015)





NOAA's Updated 2020 Atlantic Hurricane Season Outlook

Updated (Jutlook	Outlook Iss	ued 21 May	Y	
bove-Normal to Ext Probability of Sea	son Type	Above-Normal Ac Probability of S	tivity Most Likely Season Type	5	
		Above Neumat	Near Normal 30%		
Restaw Fear	10% mai		Normal 1095		
70% Probability Fo	Ton mal	70% Probability F	For Each Range		
70% Probability Fo	r Each Range	70% Probability F	For Each Range	1981-2010 Avera	ges
70% Probability Fo August U Named Storms	r Each Range Ipdate 19-25	70% Probability F	For Each Range May Outlook 13-19	1981-2010 Avera Named Storms	ges 12
70% Probability Fo August U Named Storms Hurricanes	r Each Range Ipdate 19-25 7-11	70% Probability F Named Storms Hurricanes	For Each Range May Outlook 13-19 6-10	1981-2010 Avera Named Storms Hurricanes	ges 12 6
70% Probability Fo August U Named Storms Hurricanes Major Hurricanes	r Each Range pdate 19-25 7-11 3-6	70% Probability F Named Storms Hurricanes Major Hurricanes	For Each Range May Outlook 13-19 6-10 3-6	1981-2010 Avera Named Storms Hurricanes Major Hurricanes	ges 12 6 3

(Left) An above-normal Atlantic hurricane season is now very likely (85% chance), and the potential for an extremely active season (ACE \geq 165% of median) has increased from the May outlook (Right)

NMME Operational Seasonal Forecasts





Montecito California: January 25th 2018

1/1 3

Improving Forecasts of Sub-Seasonal Flood Risk

Montecito California: January 8th 2018

Montecito California: January 25th 2018



UM-RSMAS Leads a Multi-Agency, Multi-Institutional Effort to Improve NOAA <u>Sub-</u> <u>Seasonal</u> Operational Forecasts

UNIVERSITY OF MIAMI COOPERATIVE INSTITUTE for MARINE & ATMOSPHERIC STUDIES CENTER for COMPUTATIONAL SCIENCE ~ Customized Subseasonal Weekly Forecasts ~

Very Important Disclaimer: These experimental anomaly forecasts are produced by the Subseasonal Experiment (SubX) Project for research purposes. They are not official forecasts and are not guaranteed to be timely or accurate. For official subseasonal climate outlooks, please visit the NOAA/NWS Climate Prediction Center.

Begin by selecting a SubX model, variable, and desired forecast period. Then specify the domain by choosing one of the preset options or manually editing the Longitude and Latitude ranges. Use the check boxes for additional customizations. Click the SUBMIT button to generate the plot.

SubX-RSMAS: Montecito 3-Week Lead Flood Forecast Valid Week Ending Jan. 12, 2018







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Standard climate simulation



University of Miami's climate simulation







Natural Decadal Variability



Kuroshio Extension and Western North American Rainfall



Predicting Coastal Flood Risk From Days to Decades



Traditional vs. Data Science Approach

Traditional models

• Models are implemented in complex "one-off" code.

Machine learning

• Machine learning software implemented in reusable code.

- Model algorithms are at odds with
 computer architectural trends.
- Data is a problem.

- Machine learning is well aligned with architectural trends.
- Data is still a problem, but with machine learning it is also an opportunity.

Random Forest and Neural Network Algorithms



Pure Data Science Approach: Atmospheric Rivers Example





Combining Data Science with Traditional Model: Harder but More Versatile





Is this a New Way of Doing and Teaching Science?



Emerging Data Science Academic Programs Based on Expertise Demand

SubX and NMME Real-Time Forecasts

