Identifying Forecast Errors in Atmospheric River Vapor Transport, Landfall Location and Precipitation through Traditional and Object-Based Verification

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Weather Forecasting of ARs

IARC 2018

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Sponsors: CA DWR, USACE

Outline

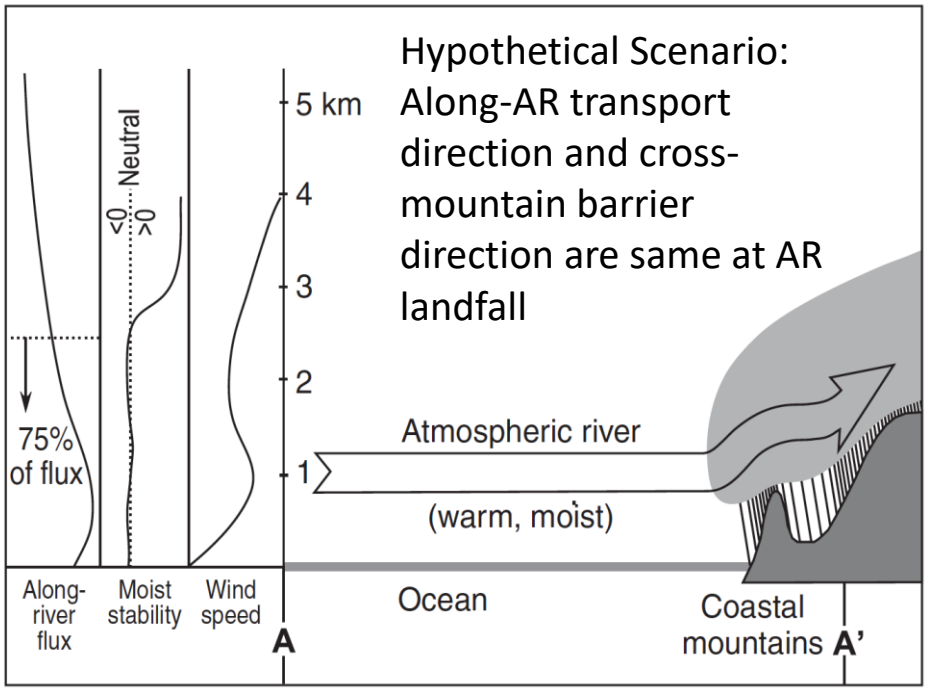
Part 1: Errors in forecasts of AR Orographic Precipitation

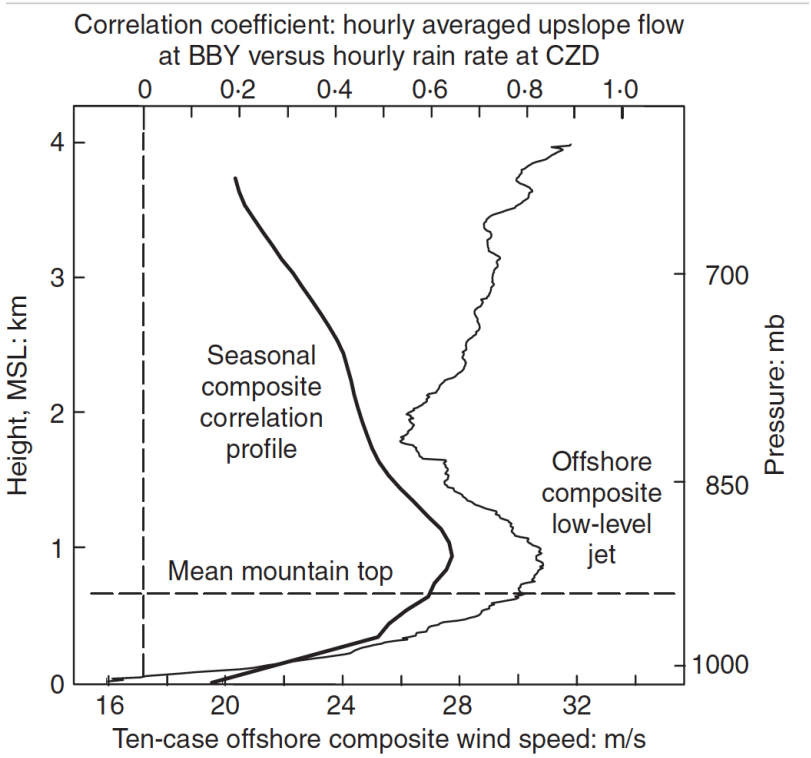
1. Background: How do we measure the orographic component of precipitation?
2. Multi-source error in West-WRF and GFS orographic precipitation during ARs
3. Apportioning errors in orographic precipitation

Part 2: Object-based verification of AR forecasts

1. What is object-based verification, how can we apply it to AR, and what can we measure with it?
2. Multi-model performance in forecasts of US West Coast ARs in WY 2017 and 2018
    - Intensity
    - Landfall Location

Part 1: Background

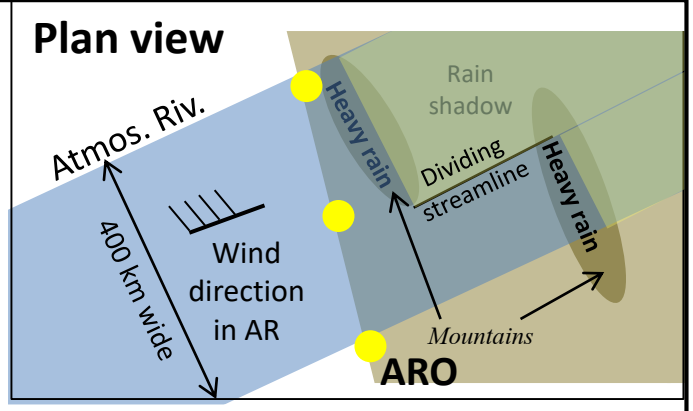


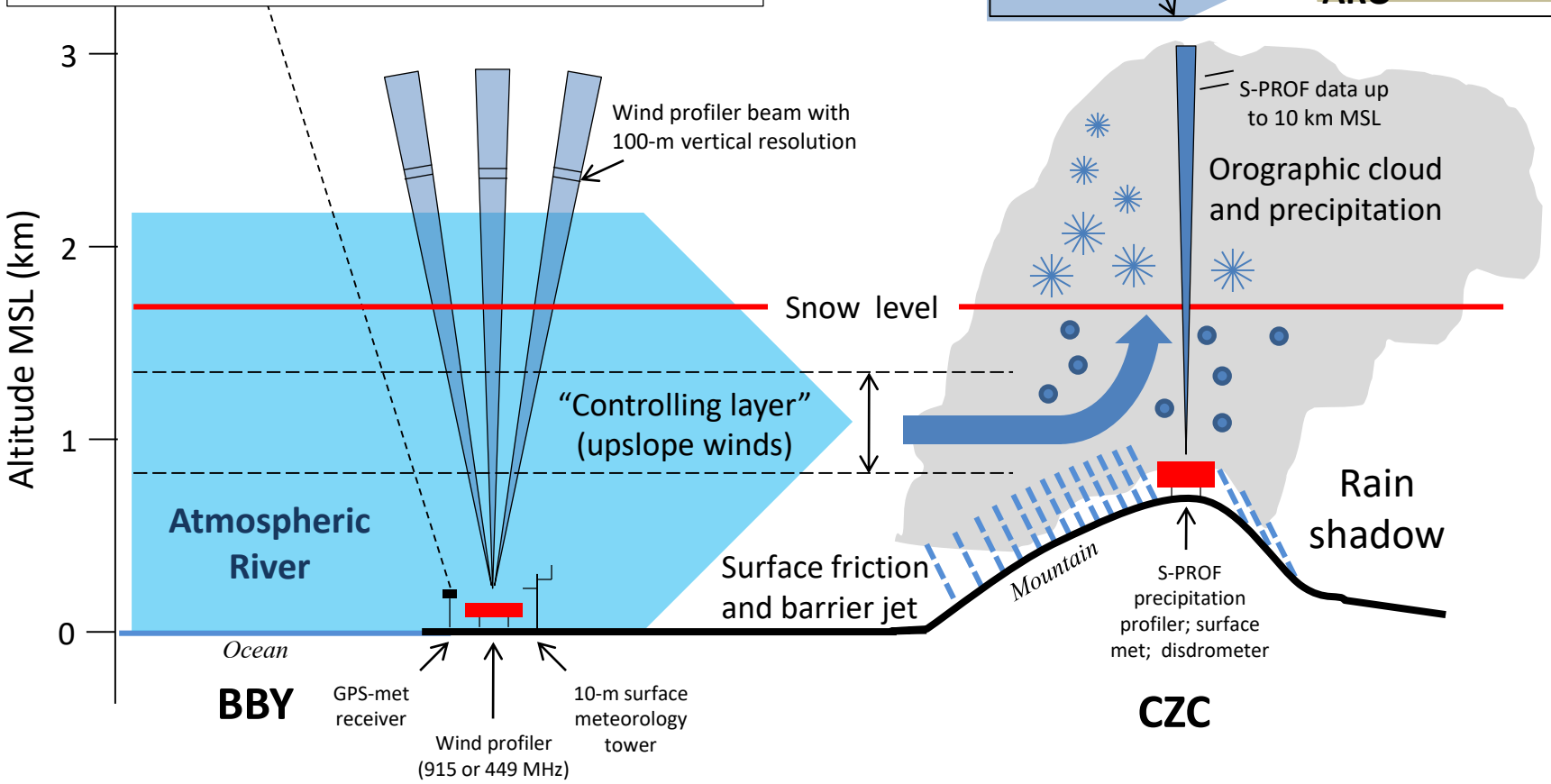


Neiman et al. (2009) *Water Management*

Concept: The coastal measurement "bulk upslope flux" (BUF) can be related to the precipitation and cloud measurements at mountaintop.

$$BUF = IWV(\vec{u}_{CTL} \cdot \hat{u}_{upslope})$$

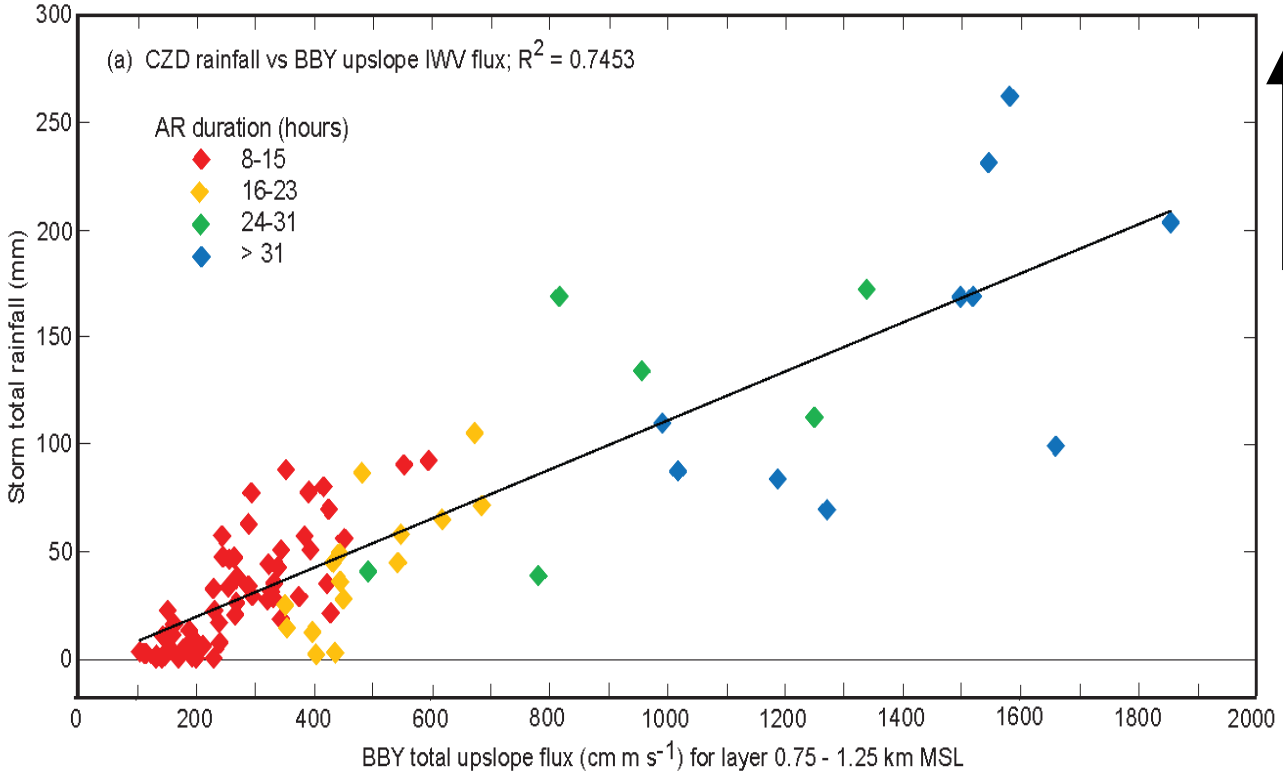




Schematic Courtesy F. M. Ralph

Motivating Result

Measurements in N. CA Show a Quasi-Linear Relationship Between Cross-Mountain AR Moisture Flux (x-axis) and Mountaintop Precipitation (y-axis)



The greater the AR strength and duration →

The regression line is the first-order precipitation caused by horizontal flux of vapor being forced up the mountain.

Other factors:
- buoyancy
- large-scale lift
- variations in low-level jet
- latitude

contribute to the deviations from the line.

The greater the precipitation

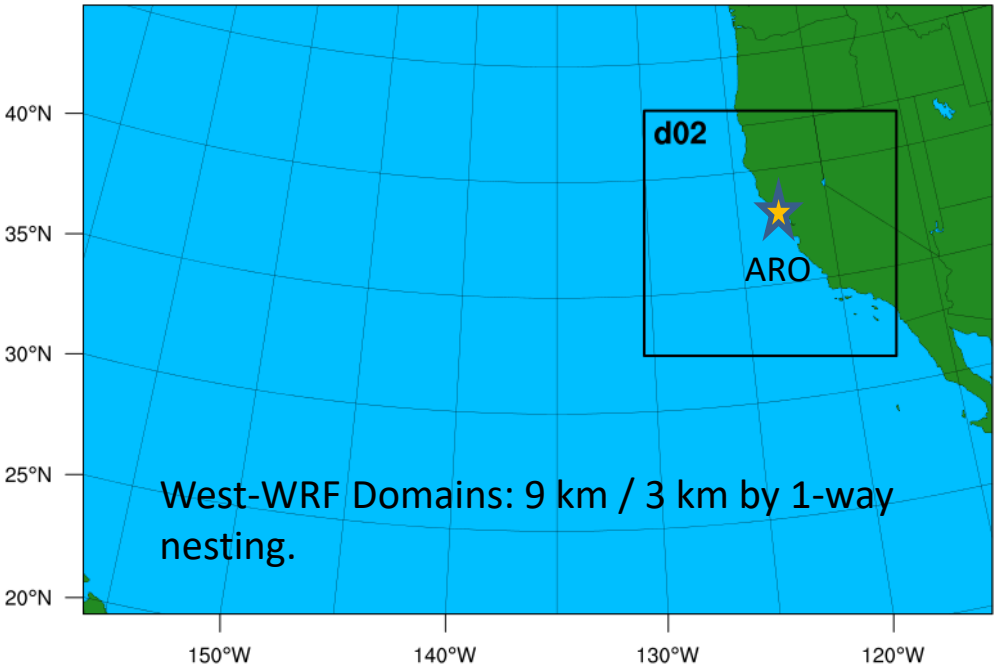
Figure Courtesy F. M. Ralph

Ralph et al., 2013 *JHM*

What is West-WRF?

West-WRF is a configuration of WRF-ARW v3.9.1.1

With domain, dynamics and physics options tailored to AR prediction.



Unique Forecast Challenges Posed by Western US Extreme Events

Challenge	Primary NWP Shortcoming	References
AR Landfall Characteristics	Location and strength of water vapor flux	Wick et al. (2013) Ralph et al. (2017)
Extreme Precipitation Skill	Overprediction of light rain, Underprediction of extreme amounts	Ralph et al. (2010) Ralph and Dettinger (2012) Sukovich et al. (2014)
Snow level	Low precision, Biases near terrain	White et al., (2010) Neiman et al. (2014) Minder and Kingsmill (2013)

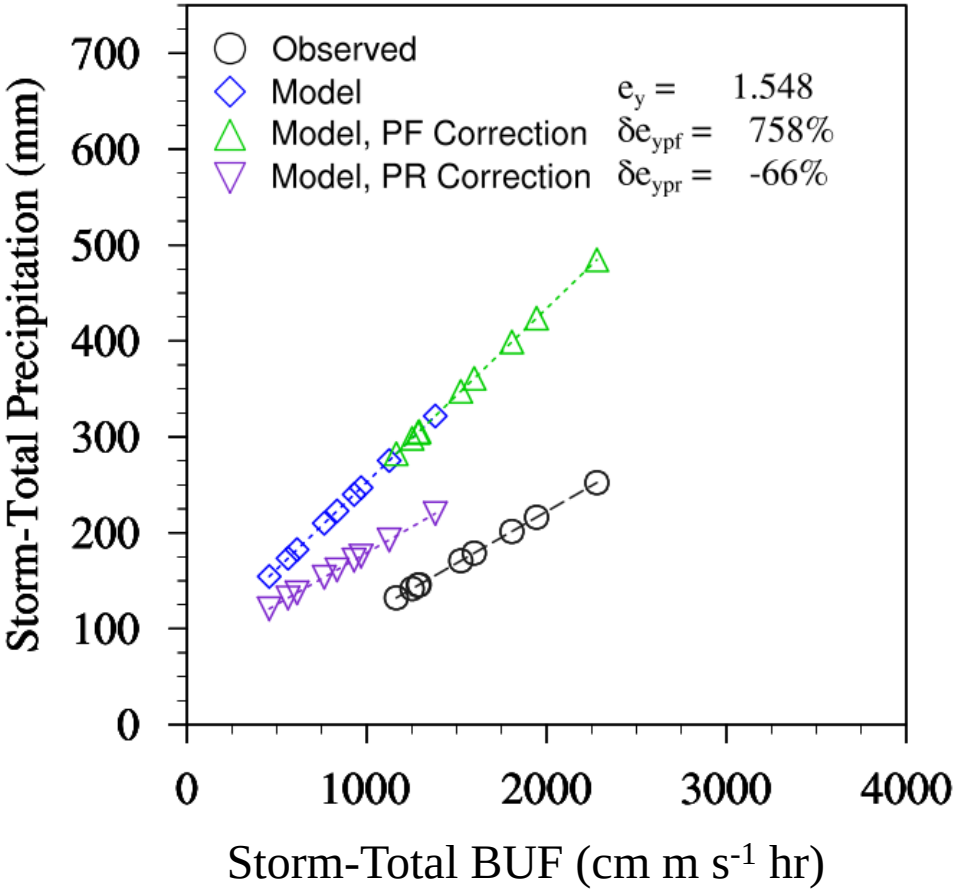
Multi-factor orographic precipitation error in NWP

e_{xy} for:
West-WRF and GFS reforecasts of 10 ARs with IVT ≥ 500 kg m^{-1} s^{-1}

Lead Time (days)	West-WRF	GFS reforecast
1 - 2	0.82	4.29
3 - 4	2.25	4.53
5 - 6	4.65	7.37

Martin et al., 2018 *JHM*

Diagnosing Model Flaws Using the Multi-Factor Relationship



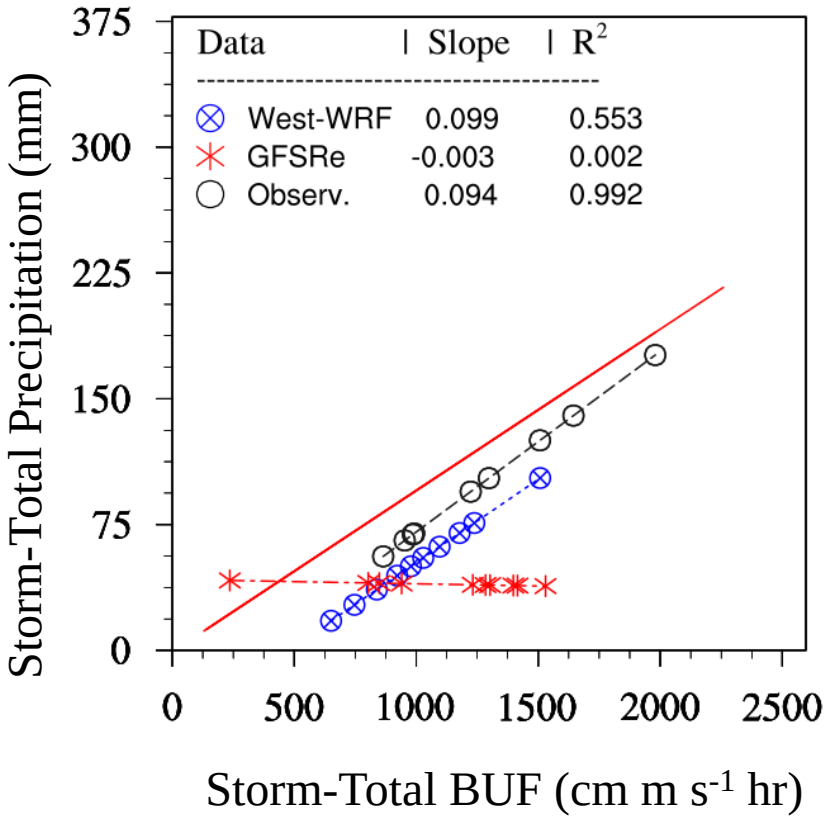
For a set of observed storms (black), we can evaluate the error in y for a hypothetical model (in blue).

We could also use the least-squared relationship to ask how much is the error improved or worsened (δe_{ypf}) if the observed forcing is substituted in the linear formula.

We could do the same by substituting the observed response relationship and measuring the fractional change in error (δe_{ypr}).

Martin et al., 2018 *JHM*

Contribution of Simulated Forcing and Response to NWP Errors



Lead Time (hr)		$12 \leq t_i \leq 59$	$60 \leq t_i \leq 107$	$108 \leq t_i \leq 155$
e_y	**GFSRe**	1.544	2.072	2.568
	West-WRF	0.470	1.295	2.109
δe_{ypf}	**GFSRe**	18.1%	14.2%	0.0%
	West-WRF	10.7%	-57.6%	-78.1%
δe_{ypr}	**GFSRe**	18.9%	-35.0%	-19.3%
	West-WRF	20.4	-47.2%	-51.9%

Except at short forecast lead times, West-WRF forecasts of precipitation could become more accurate by improving either forcing or response.

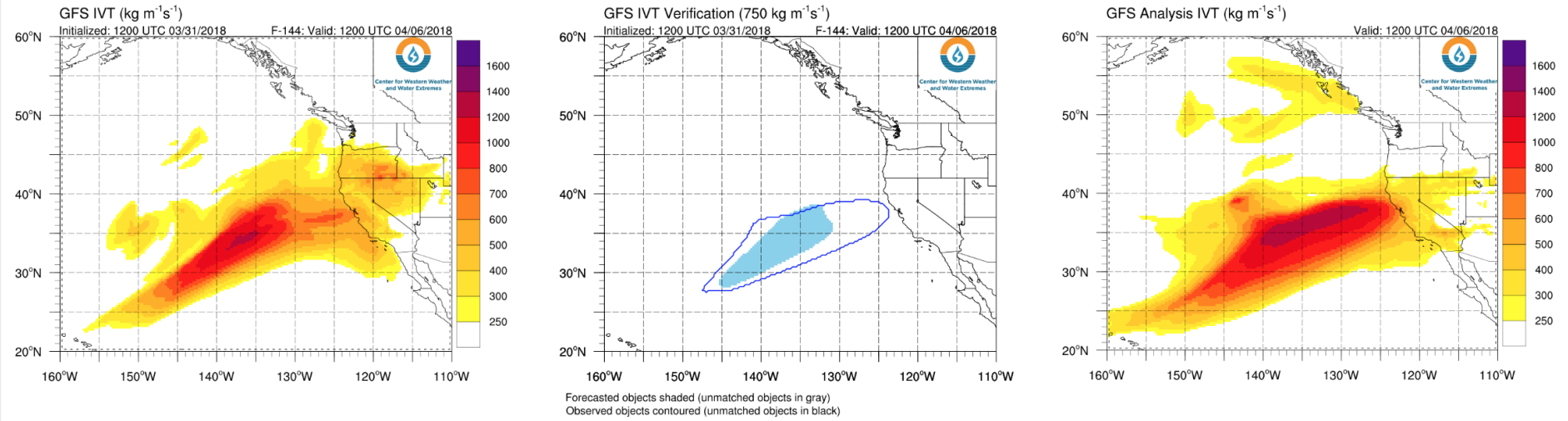
The lower resolution GFSRe forecasts start with such a poor response function that they can cannot expect to improve through more accurate forcing.

Martin et al., 2018 *JHM*

Part 2: CW3E AR Landfall Verification Tool

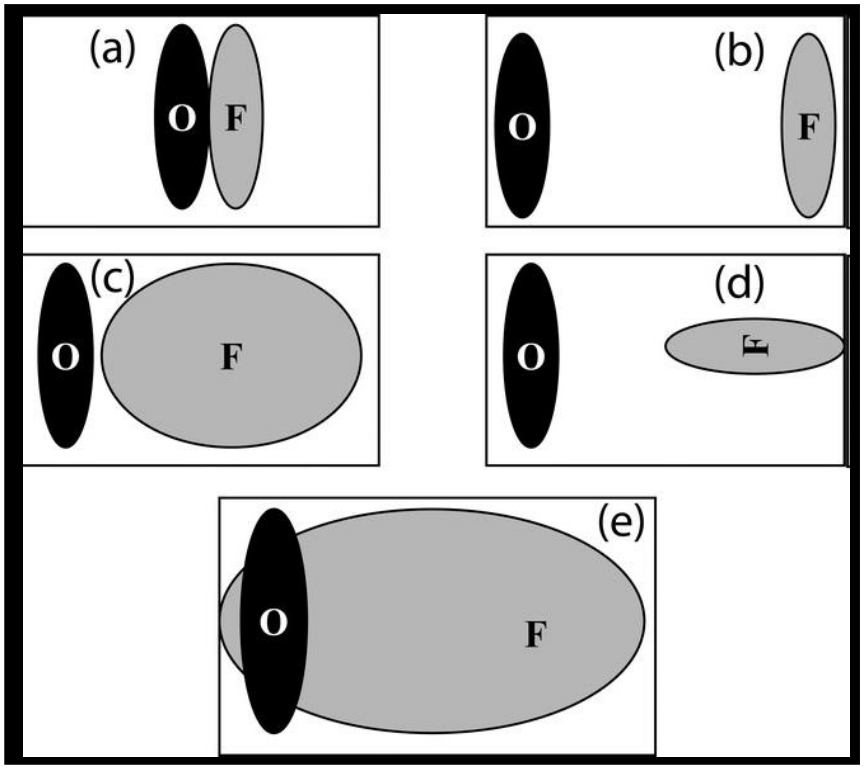
GFS 6 day forecast for 04/06/2018, 750 kg m^{-1} s^{-1} threshold

Forecasted | **Object Verification** | **Model Analysis**



-use MODE (**M**ethod for **O**bject-Based **D**iagnostic **E**valuation) to find objects based on IVT
-consider both observed (model analysis) and forecast for 5 models
-Object detection based on threshold and aspect ratio
-AR detection additionally considers geographic location, angle and size
-compute stats for each AR: Landfall Position, Spatial Overlap, Intensity, and Angle

Motivation & Benefits of Object-Based Verification



	a-d	e
Correlation Coefficient	0.0	0.2
Probability of Detection	0.0	0.9
False Alarm Ratio	1.0	0.9
Gilbert Skill Score	0.0	0.1

-Allows for comparison of models on different grids

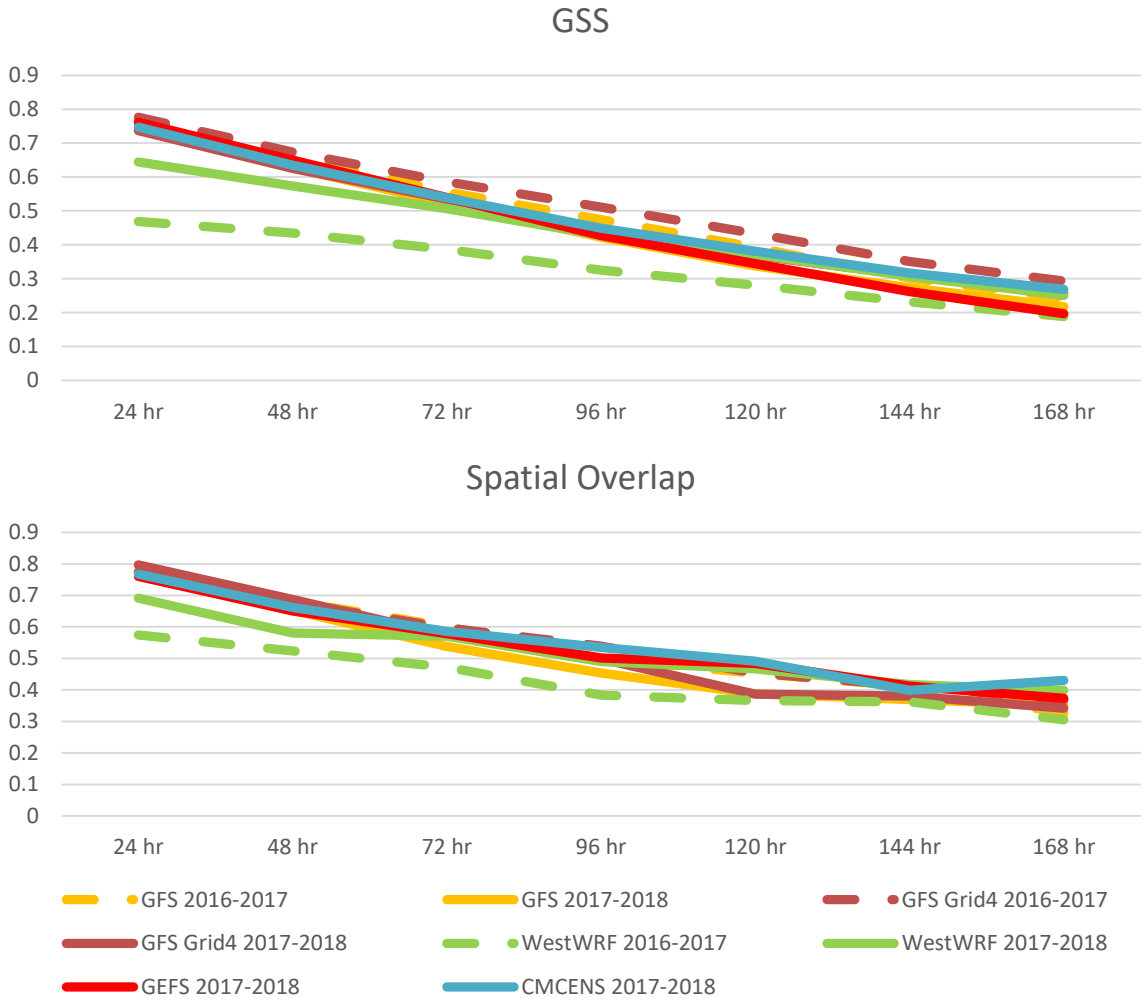
-Criteria tunable to users needs

-Errors from storm motion and storm attributes can be separated.

Models Evaluated

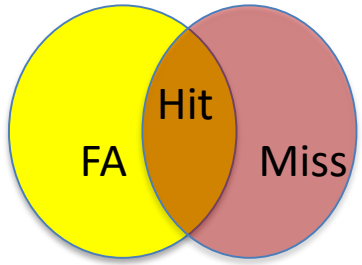
	2016-2017	2017-2018	Resolution
GFS	X	X	¼ degree
GFS grid4	X	X	½ degree
West WRF	X	X	9 km
GEFS (mean)		X	1 degree
CMCENS (mean)		X	1 degree

Gilbert Skill Score & Spatial Overlap



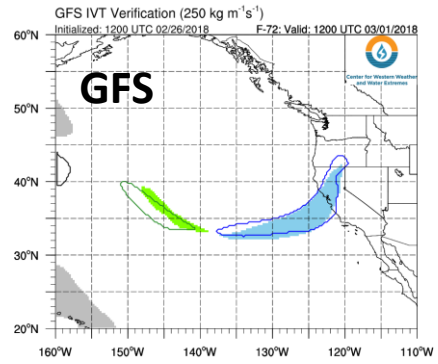
Spatial Overlap is the ratio of Intersection / total area:

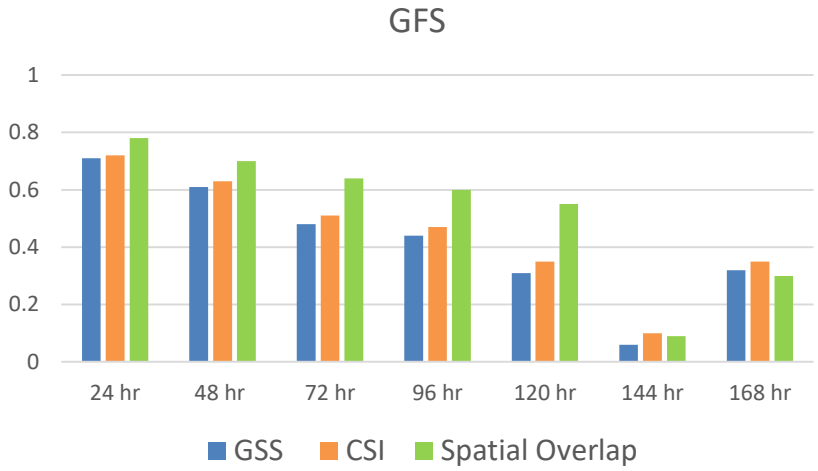
Hit / Hit + Miss + FA



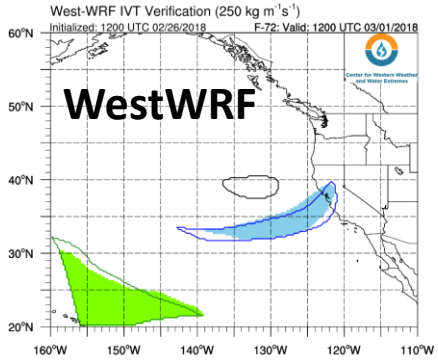
Seasonal Averages
IVT threshold of 250 kg m^{-1} s^{-1}

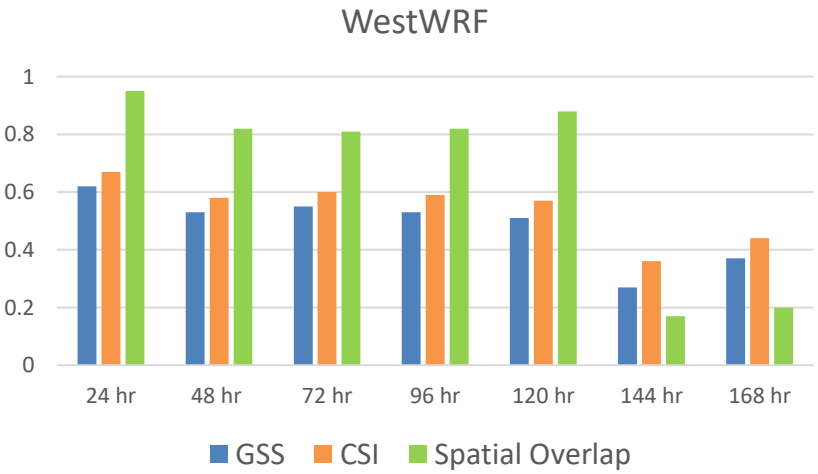
Example AR Object from 03/01/2018



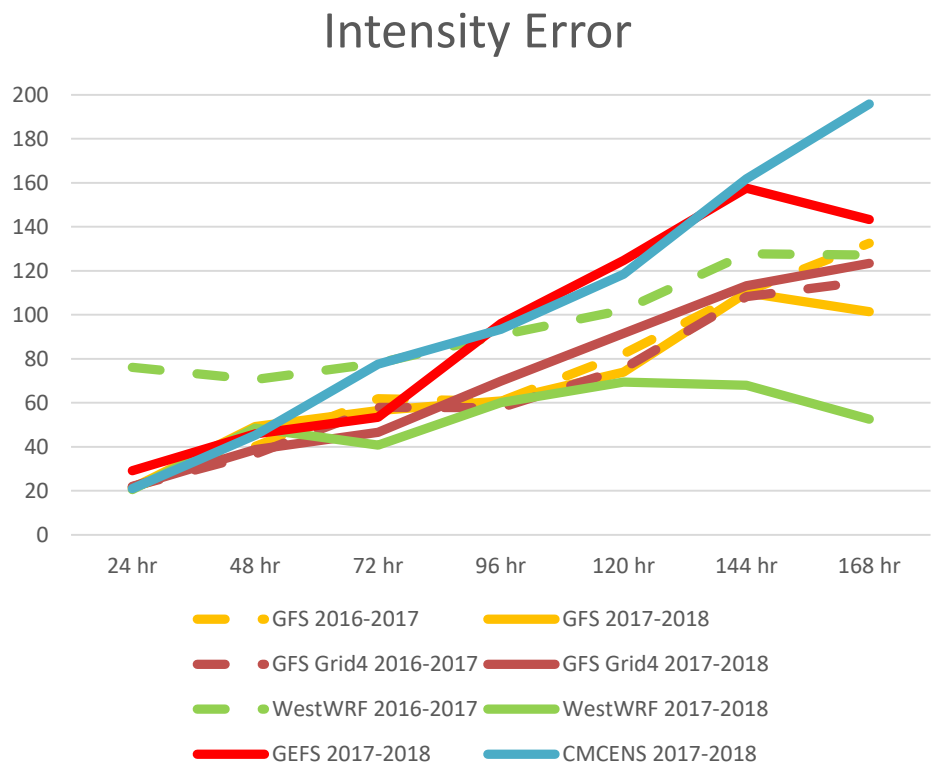


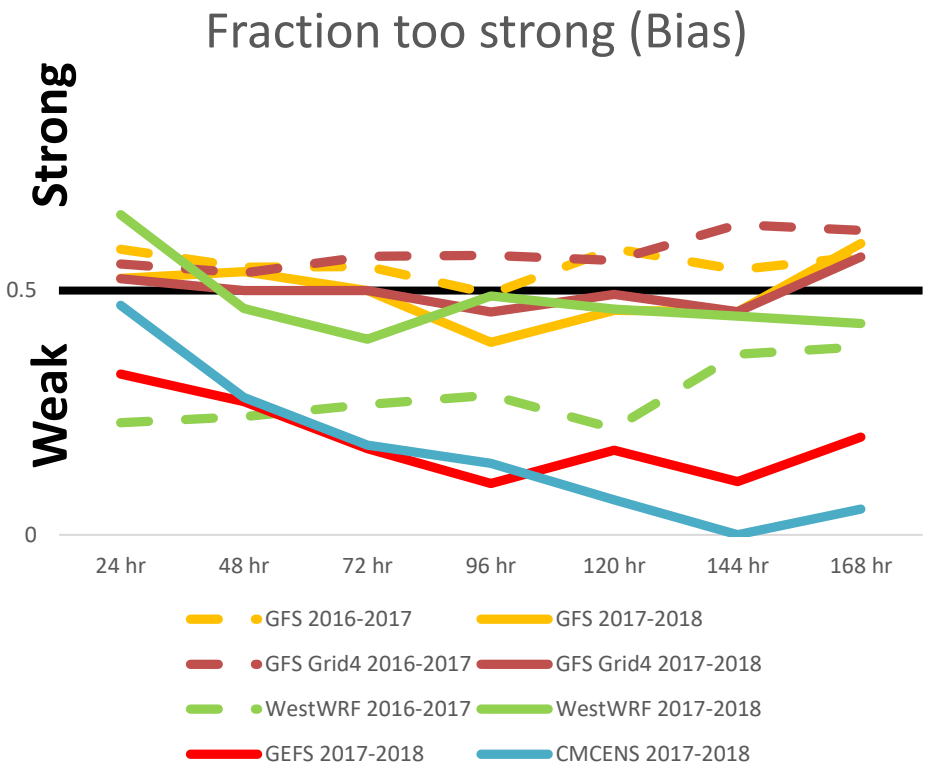
Threshold 250 kg m^{-1} s^{-1}
72 hour Forecast





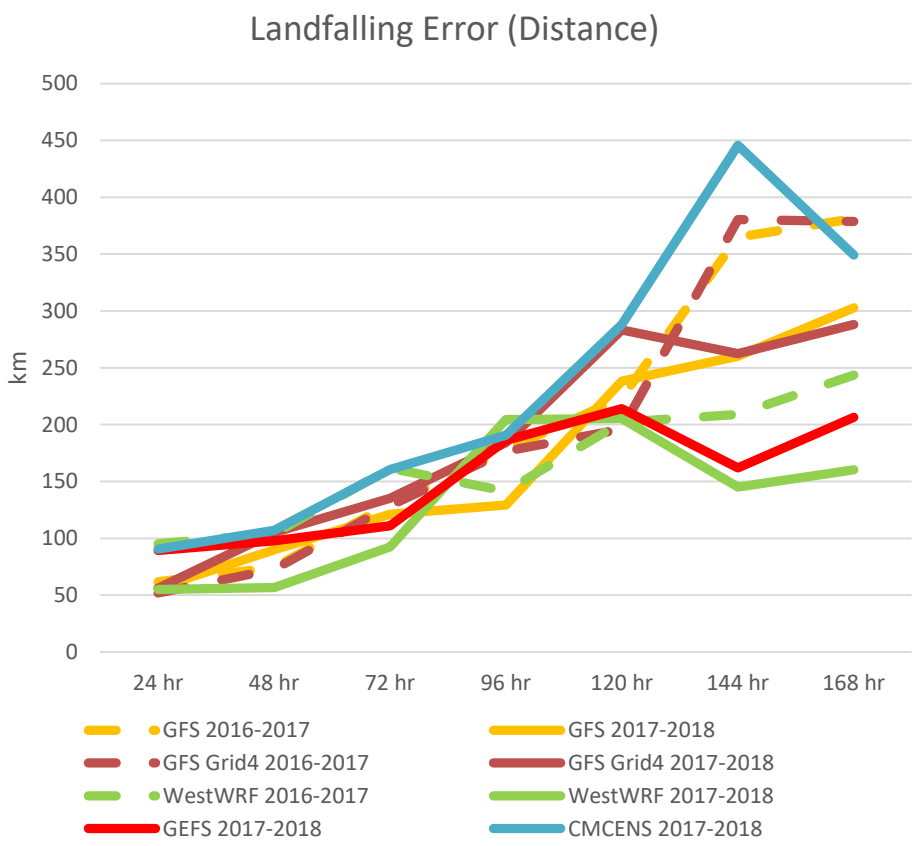
Intensity Error



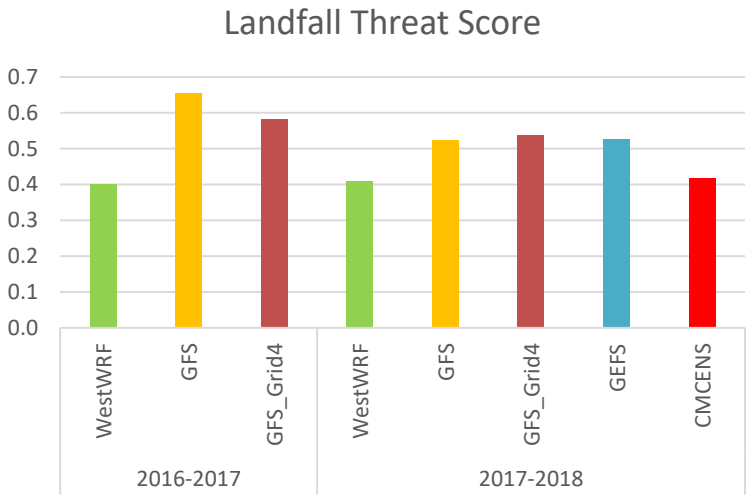


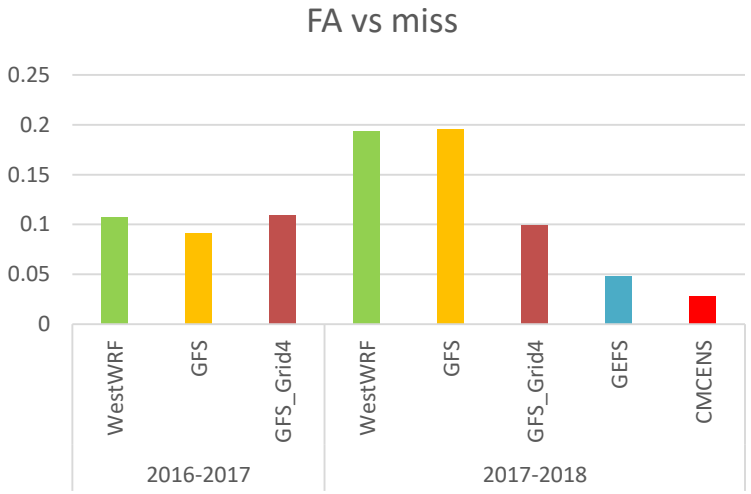
Threshold: 250 kg m^{-1} s^{-1}

Landfall Statistics



Threshold 250 kg m^{-1} s^{-1}





Ongoing Work in Object-Based Verification

-Add more years and models to the seasonal analysis

-Provide useful statistics on the duration and speed of ARs:

-Compare AR detection results with AR tracking (time-dependent) method

CW3E Atmospheric River Verification Tool Website:
http://cw3e.ucsd.edu/cw3e-atmospheric-river-landfall-met-mode-verification-tool/