Seasonal Forecasts: A Shift Towards Probabilistic at the Weather Company, an IBM Business

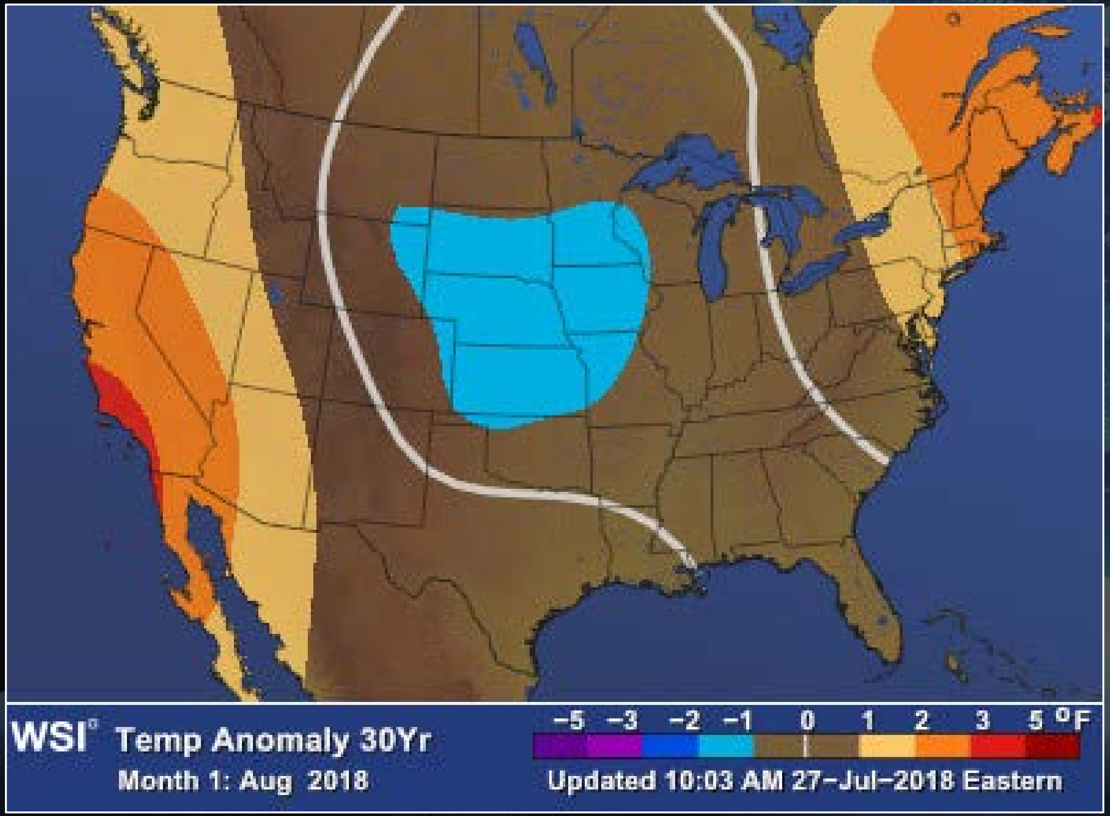
Author: Michael J. Ventrice

Co-Authors: James Belanger, Todd Crawford, John Williams

August 2019

IBM

Motivation: Quantify the Risk to Seasonal Forecasts



Example "Old" Deterministic Forecast provided to Energy clients of U.S. Sector

- Seasonal Forecasts (Forecast Months 1-6+) are known to have little to no skill, yet these forecasts are demanded across many facets of business and consumers.
  - B2B: Energy, Agriculture, Retail, Travel
  - Consumer: Weddings, Travel, Outdoor Event Planning
- For decades, most B2B users only wanted a deterministic outlook.
  - Example Energy Forecast Map
- We are beginning to see a subset of companies request information on quantifying risk in a deterministic seasonal forecast, globally.
  - **Opportunity for Probabilistic Forecasts**

Data Source

ECMWF

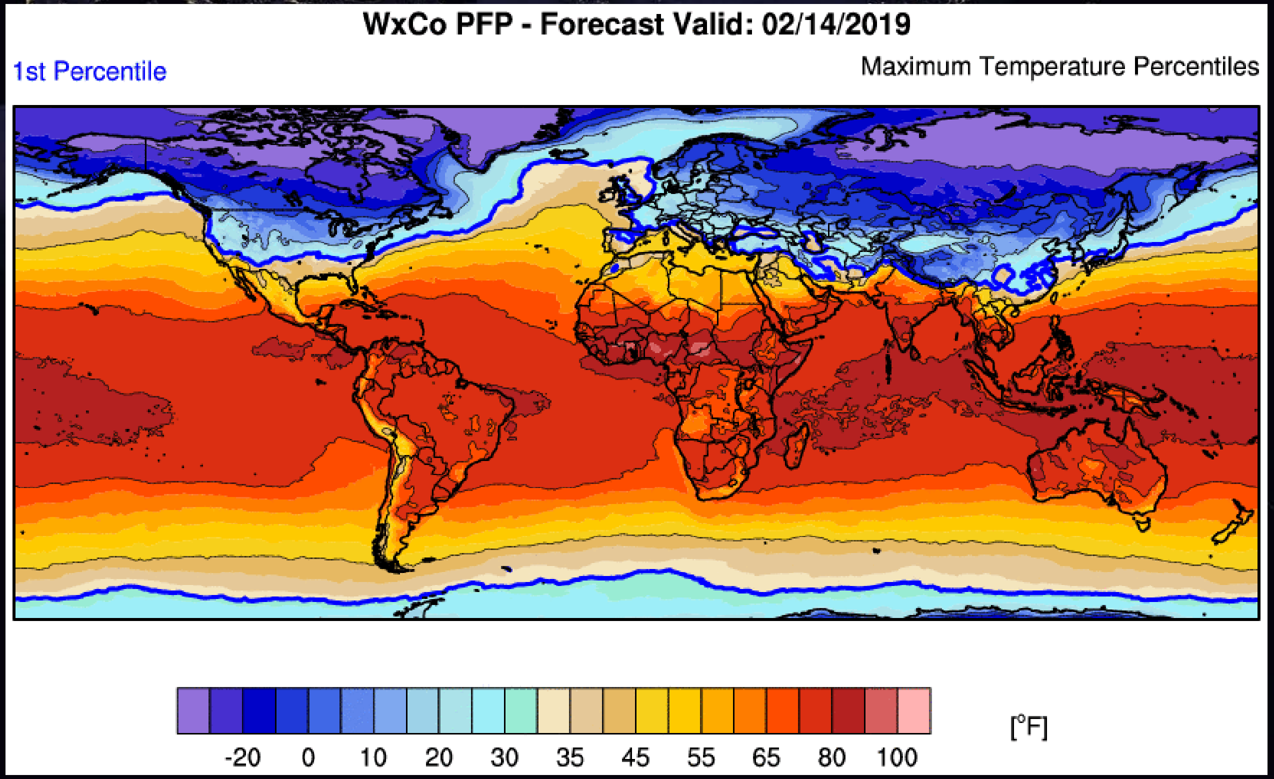
- Leverages the ECMWF System-5 Climate Model
- Historical Hindcast Reforecast (1981-2016 – 25 members)
- 0.4 degree resolution
- Daily Resolution
- 51 members in Live run
- Global
- Updates on the 5th of the Month

IBM

Calibrated Seasonal Forecasts (Global)

1. 11-Percentiles & 50-Prototypes
   - 0.4 degree grid
   - Daily Resolution
   - Max Temperature
   - Min Temperature
   - Average Temperature
   - Daily Precipitation

2. Data Format
   - ❖ NetCDF Grids
   - ❖ Point Request System



This Talk…

1. Reforecast Hindcast Prerequisites
2. Temperature Bias Correction
3. Calibration Technique used in Prototype/Percentile Computations
4. Calibration Results
5. User Case Examples (if time)

Hindcast Reforecasts

- ➢ Download & Store all ECMWF-S5 Hindcast Reforecasts (1981-2016) from MARS.
  - Extensive dataset, >1T of data
  - Took over 3 months to download off MARS!
  - Max, Min Temperature, Precipitation

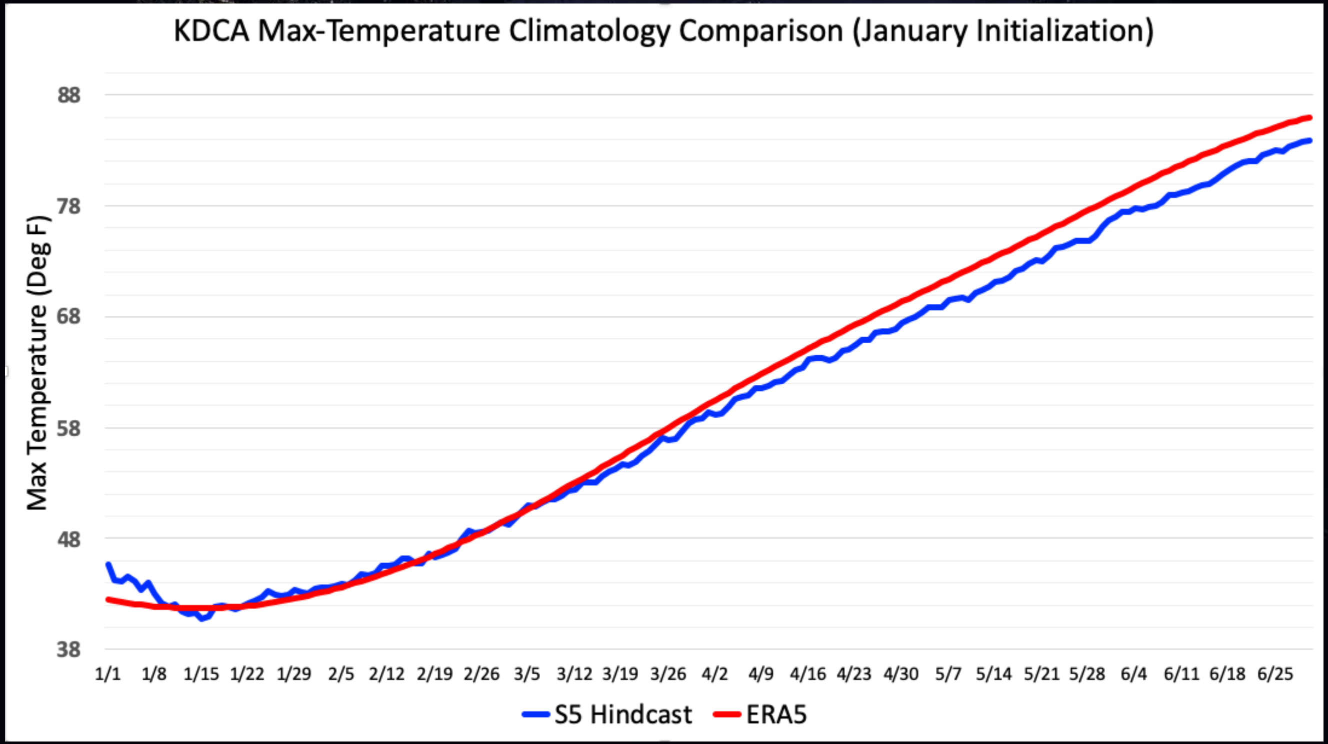
Hindcast Reforecasts

- ECMWF-S5 Hindcast Reforecast offering is of critical importance for two reasons:
  1. Compute a global Hindcast Reforecast Climatology for each forecast lead used in Temperature bias correction step.
  2. Develop a historical reforecast probabilistic dataset for model training and verification (B2B).

Temperature Bias Correction Step

- Long-range forecasts of temperature can drift towards a model-climatology, not necessarily representative of a “true” climatology.

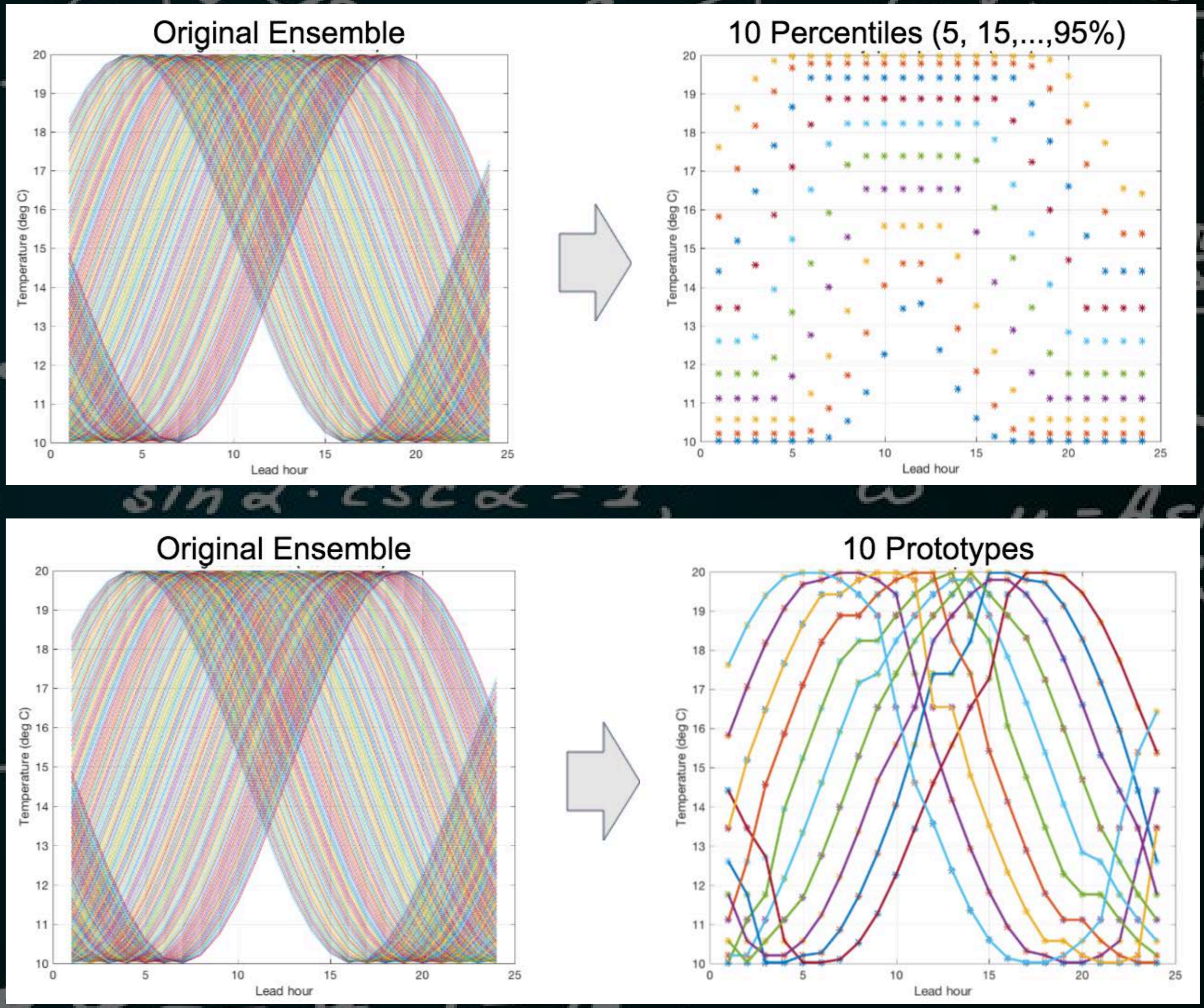
- Biases are a function of forecast initialization and location. Thus, there is a need to correct biases for all points around the globe for each initialization.



ERA5 vs. ECMWF-S5 Reforecast climatology analysis (Jan. initialization) for KDCA.

What is a "Prototype"?

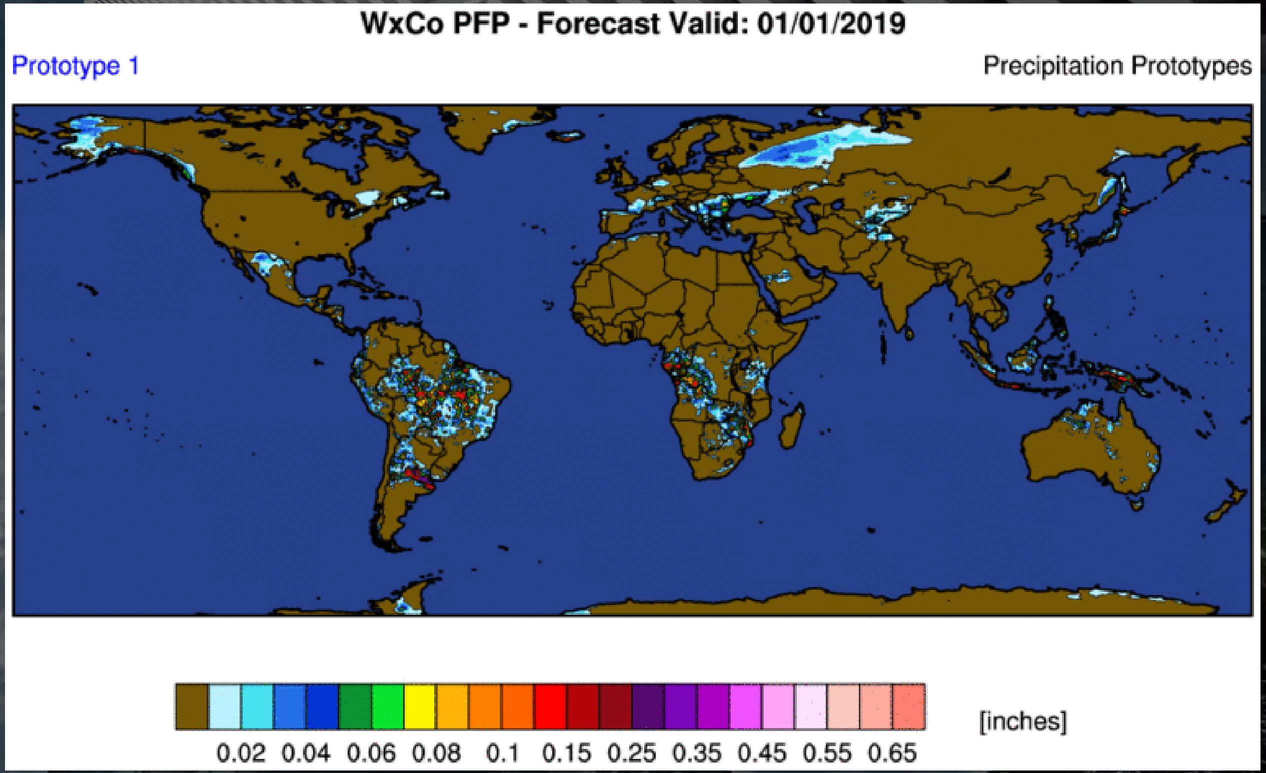
A Prototype is a "Calibrated" Ensemble Member that is equally likely to verify.



Construction of Prototype + Percentile Grids

- Global Grid Prototype & Percentile Forecasts
  - Utilizes current month initialization + 1 month (previous initialization) lag for ensemble members.
    - ¾ weight given to most recent initialization
    - Limits forecasts to 6-months from initialization date.

  - Calibration is applied to all forecast variables.



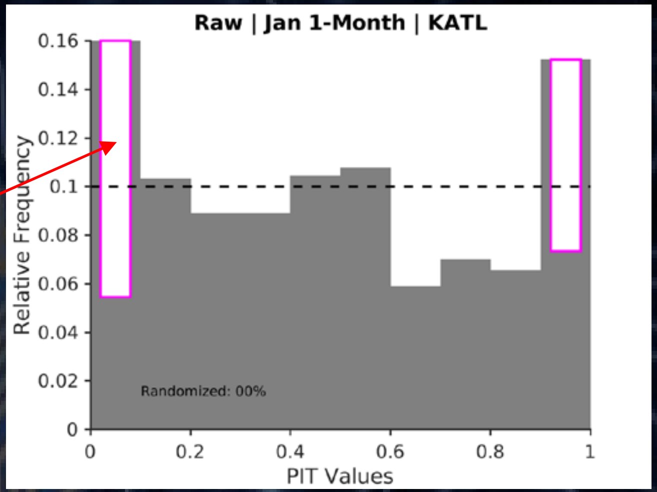
Precipitation Prototypes for January 1, 2019 from November 2018 initialization

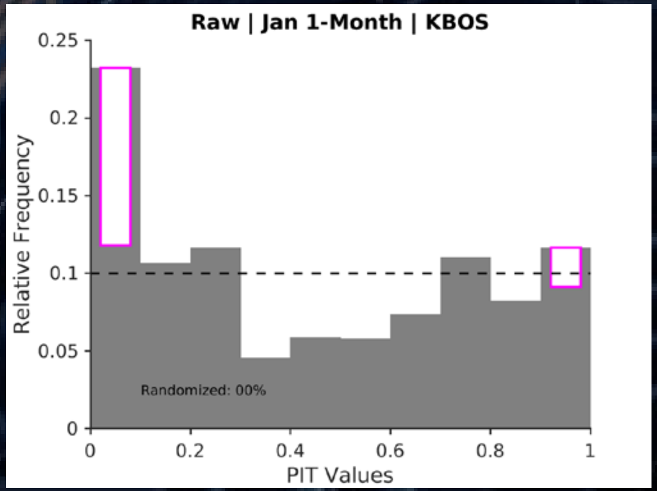
Calibration: The Key to this offering

- The ECMWF-S5 forecasts exhibit bias and are under-dispersive for the set of forecast variables delivered in Seasonal PFP.
- Classic ”U” shape in PIT diagram, indicative of an under-dispersive distribution.
  - Observations are frequently falling outside the predicted distribution.
- There is a need to calibrate these forecasts.

Pink-white bar represents frequency of outlier observations

Uncalibrated

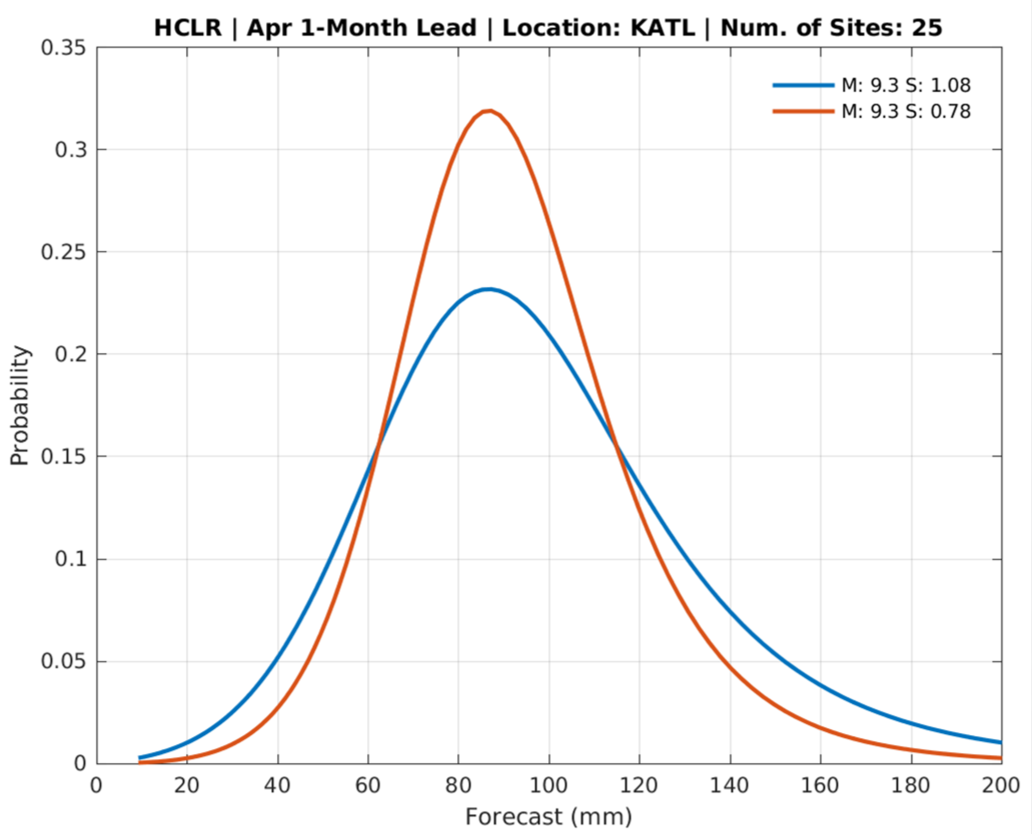




TMAX PIT Diagrams

Calibration: The Key to this offering

- Heteroscedastic (censored) Logistic Regression technique used for calibration
- Applied separately to monthly averaged 2m max, min temperatures and monthly total precipitation.
- For Precipitation, the point-mass at 0 was represented via a separate logistic regression and the continuous portion of the density was represented using a logistic distribution after performing a sqrt(x) transformation.



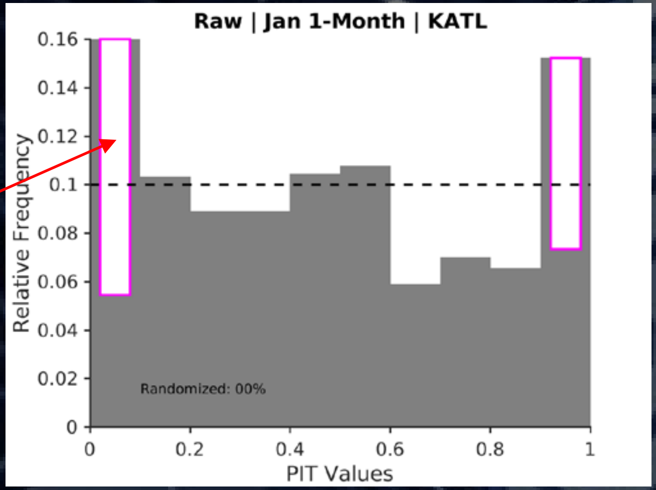
Monthly Total Precipitation

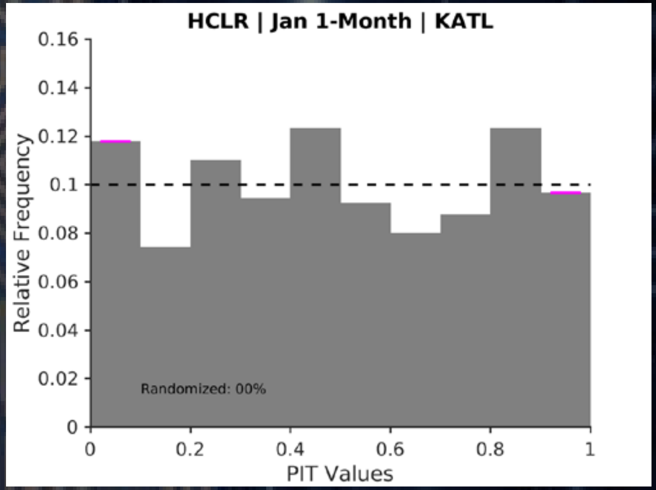
Calibration Results: Max Temperature

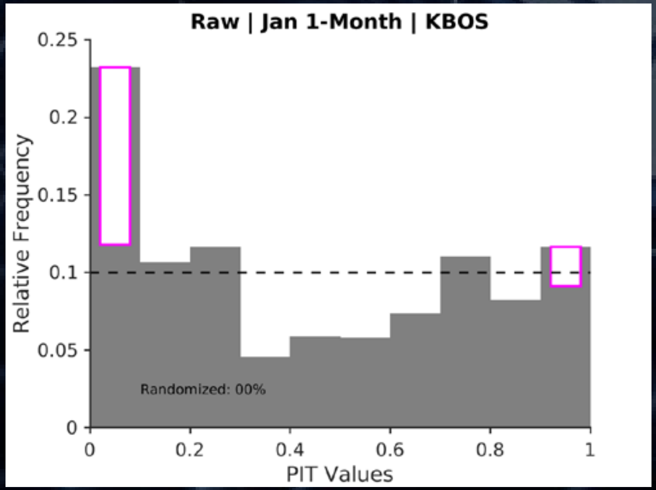
Uncalibrated

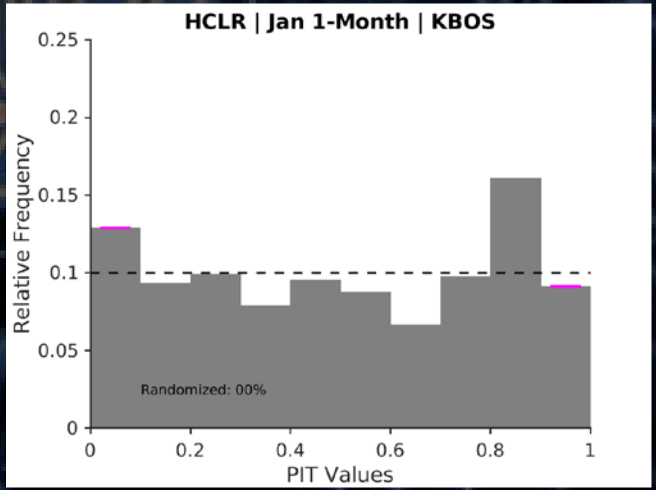
Calibrated

Pink-white bar represents frequency of outlier observations



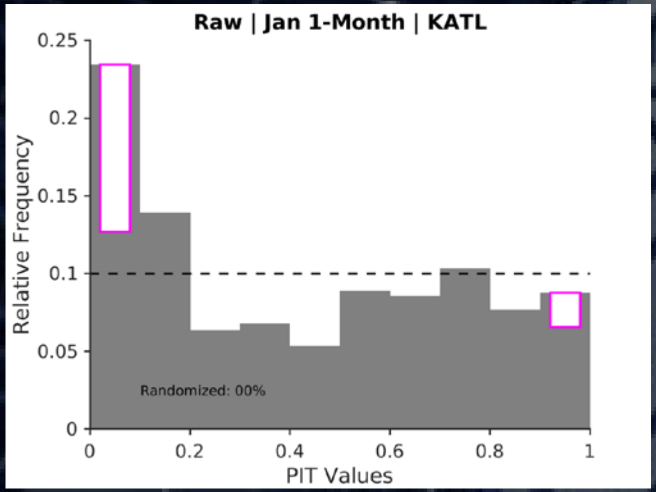


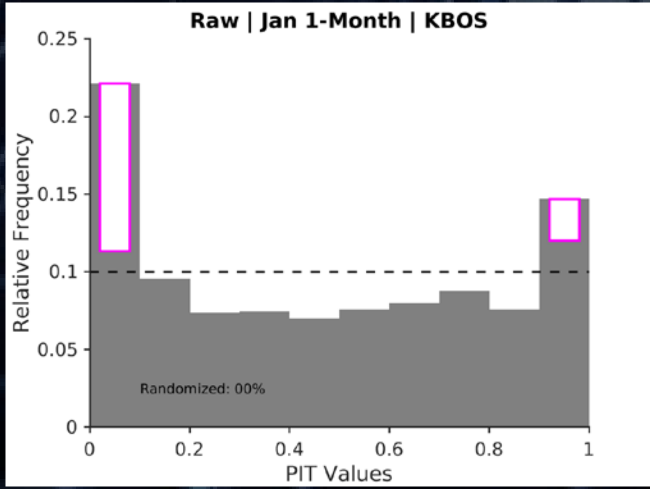




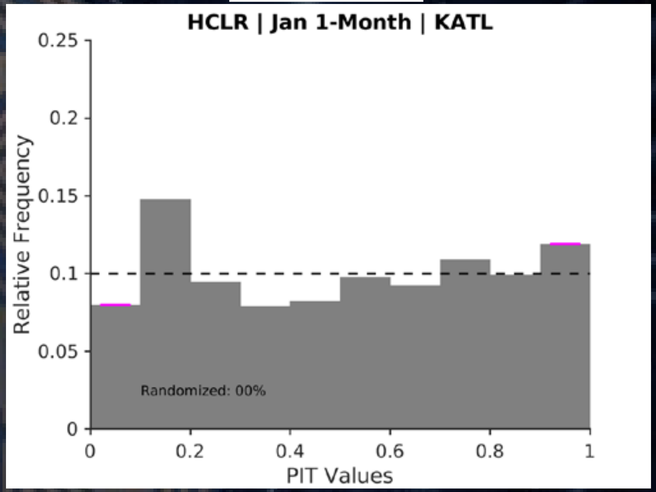
Calibration Results: Precipitation

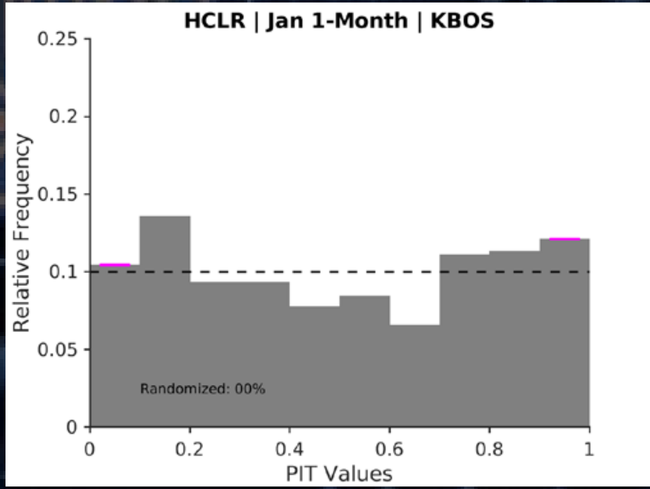
Uncalibrated





Calibrated



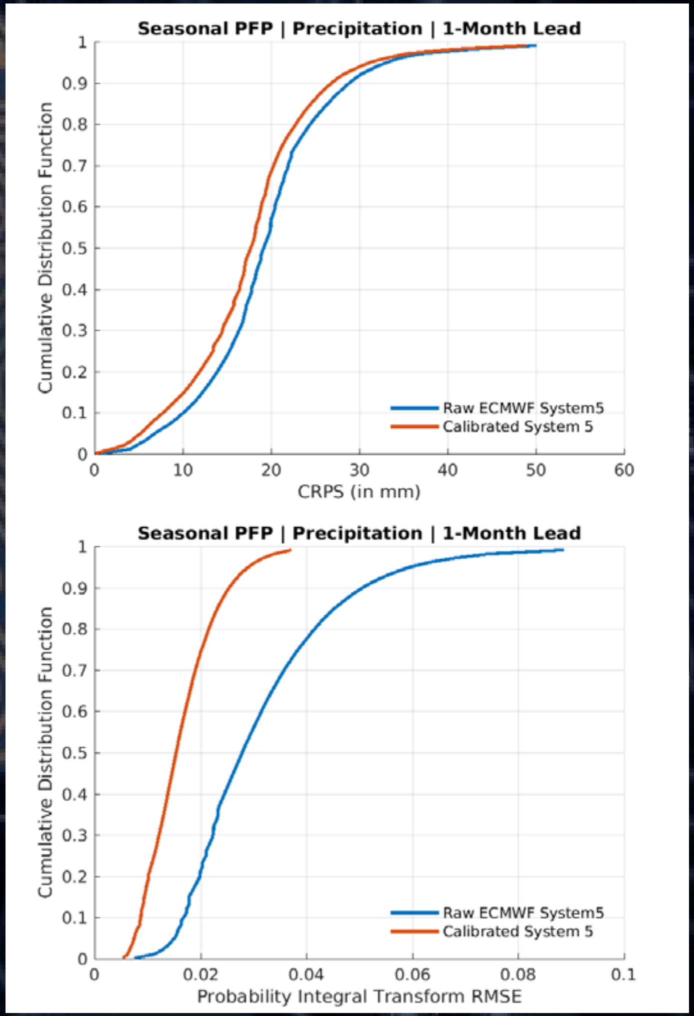


Calibration Results: Summary

- Diagrams show the CDF of cross-validated CRPS (i.e. error) and PIT RMSE (i.e. calibration/reliability) for 1-month lead precipitation, max/min temperature

- Calibrated forecasts are materially more reliable (~large reduction in PIT RMSE) with a significant reduction in CRPS error for all variables

- Calibrated forecasts are sharper than using historical observations (industry standard for B2B avenues such as Agriculture).



Challenges Faced

1. Prospective Client Verification Analyses
   - Companies often ask for a single forecast initialization to explore an extreme weather event that impacted their business to assess the skill in our system.
     - Use the Prototype Mean to assess the skill of our “Probabilistic” system.
     - Verify SPFP forecasts against reanalysis (i.e., CFSR) as “Truth” in data-sparse regions.

2. Calibration Implementation
   - Not calibrating against station observations.
     - Can result in colder distributions compared to station climatology.

3. Seasonal PFP, alone, is of lesser value to most companies.
   - Need to convert to a decision based platform.
     - Example: There’s a 50% chance for crop failure in your region based on the predicted weather criteria. If you change your crop from “corn” to “soybeans”, the risk for crop failure drops to 5%.

IBM

Future Work + Data Requests

1. Add Sub-Seasonal Model Forecasts into Seasonal Probabilistic Forecasts
   - Increase the frequency of updates (once-a-month is too infrequent for some clients).
   - Better resolution on some of those extreme weather events that climate models cannot resolve at seasonal timescales.
   - Some companies only care about sub-seasonal space. Using 1-month old forecasts for Weeks 3-6 is not ideal.

2. Convert Seasonal PFP + short-term forecasts into a meaningful, decision-based platform.
   - Forecast Data alone will not impact the decision makers but converting it to a decision will.

3. Add in additional robust, NOAA-supported, operational Climate Models into system.
   - “New” GEFS is a candidate when it becomes unified.
     - Daily Resolution
     - Out at least 7 months
     - Full Hindcast Available
     - Relevant Parameter Offerings (i.e., Snowfall)

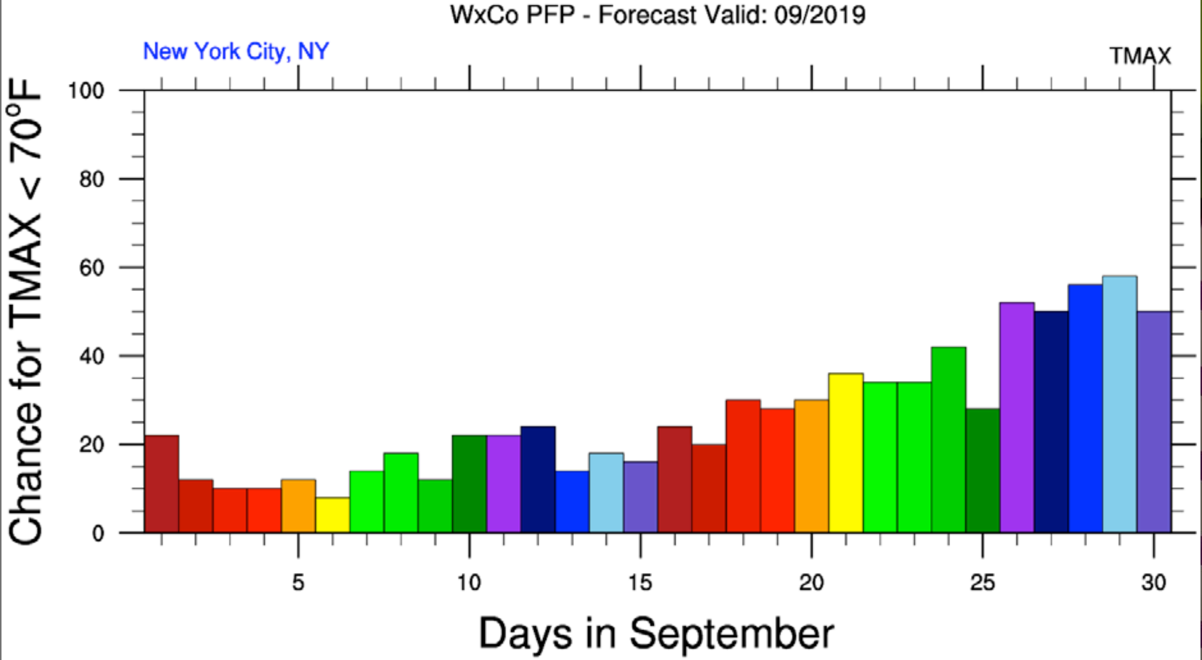
IBM

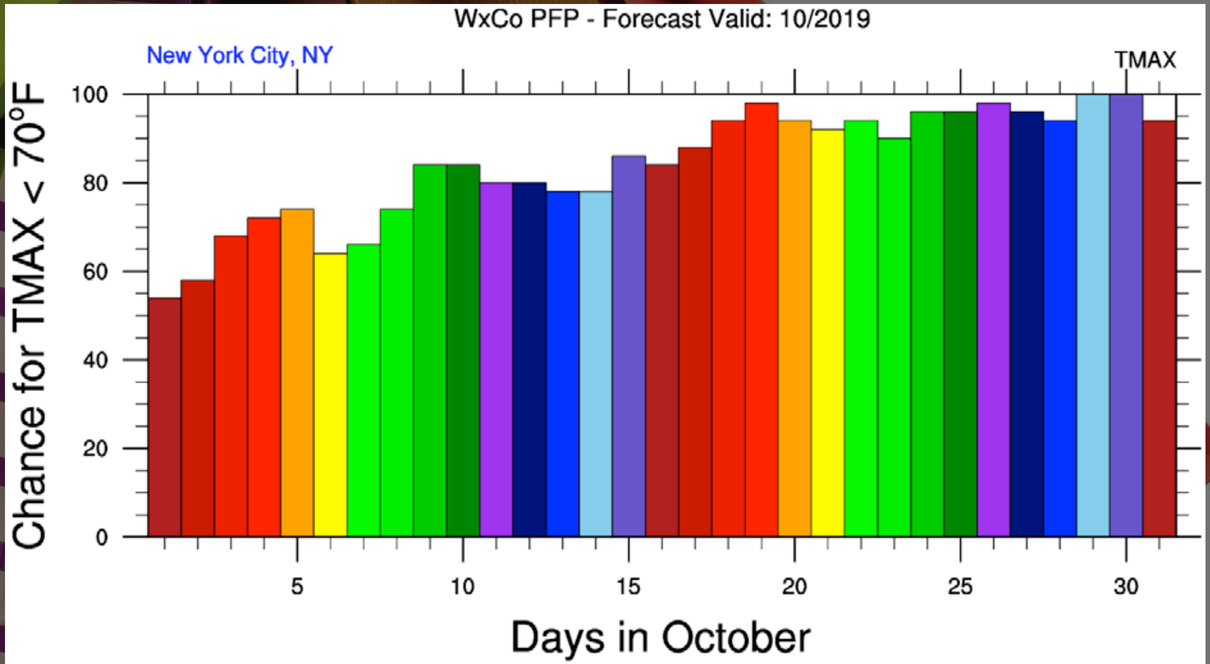
Retail Example: When to launch Fall Clothing Lines in NYC?

- The behavior of consumers (shoppers) is correlated with weather.
- Consumers will often not buy Fall/Winter clothing when max temperatures are greater than (70F).
- In order to maximize revenue, the timing of issuance of seasonal clothing lines is dependent on temperatures in a given region.

Retail Example: When to launch Fall Clothing Lines in NYC?

- Summing the counts of across Prototypes of when Max Temperatures <70F, you can assess the probability of when temperatures will be cold enough to warrant Fall shoppers.

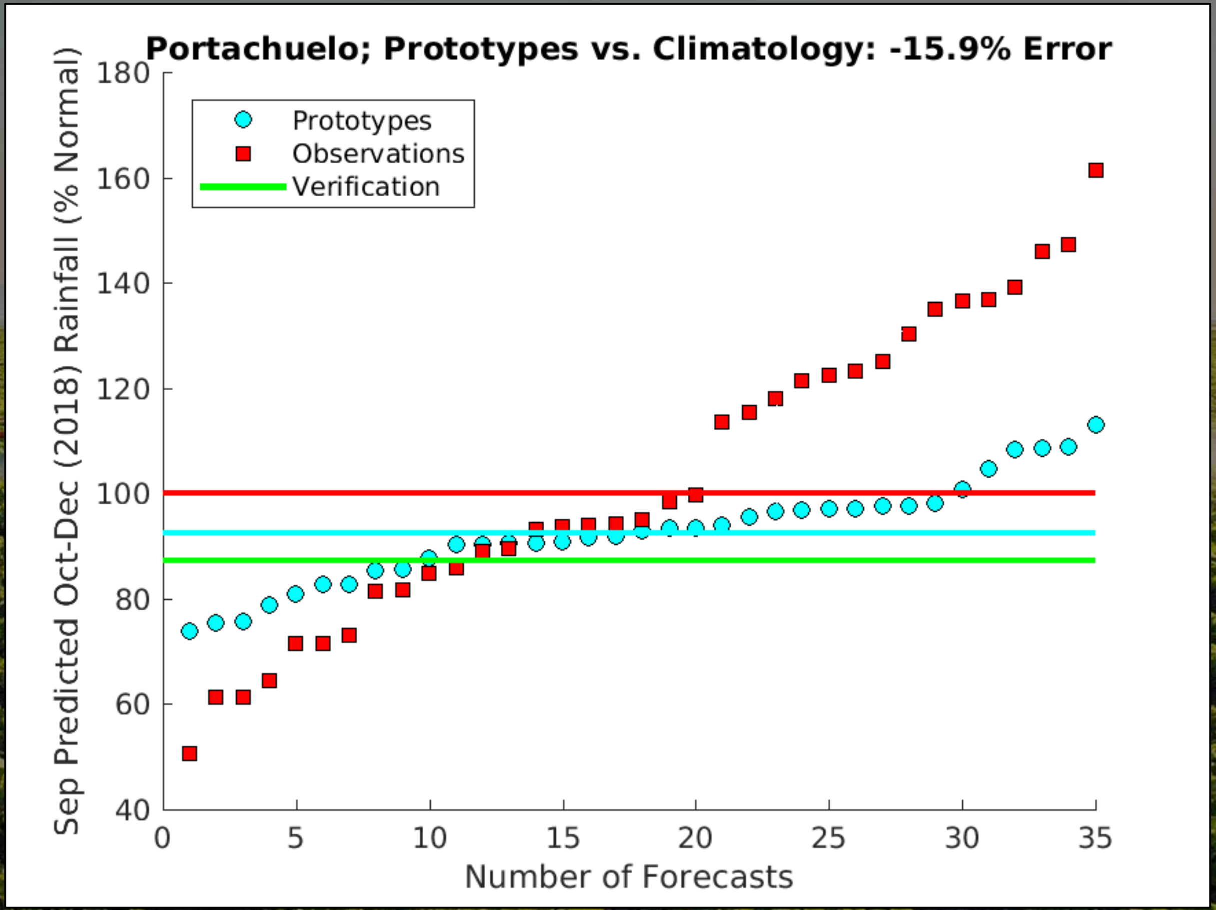




August 2019 Initialization

Agriculture Example

- Calibrated forecasts are sharper than using historical observations (industry standard for B2B avenues such as Agriculture).
- Portachuelo, Columbia Farm example
  - Uses historical observations to understand risk to forecast for upcoming season.
- Seasonal PFP Prototypes show higher sharpness and lower CRPS compared to historical observation distribution.



Climatological Rainfall Event

Seasonal PFP Prototype (forecast)

IBM

Thank You

Contact info:

Email: Michael.Ventrice@us.ibm.com

@MJVentrice on twitter