Part 1. Verification and Validation

Part 2. Successful Metrics

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JCSDA Sumer Colloquium 2015

Outline

- Analysis and Forecast Verification
- What makes a good forecast?
- Verification against model fields
- Verification against observations
- Measures of Forecast Error
- Scorecards
- How to interpret common diagnostic plots

- Successful Metrics
- Case studies – benefits and pitfalls

Assessing Forecast Quality

- Allan Murphy, a pioneer in the field of forecast verification, wrote an essay on what makes a forecast "good" (Murphy, 1993). He distinguished three types of "goodness":

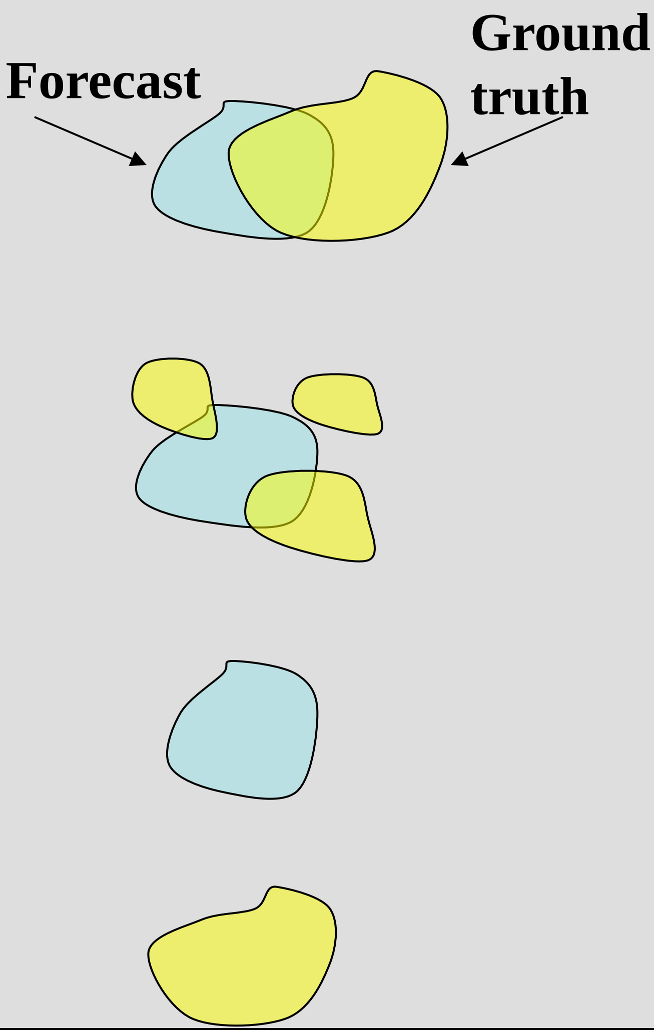
- ***Consistency*** - the degree to which the forecast corresponds to the forecaster's best judgement about the situation, based upon his/her knowledge base

- ***Quality*** - the degree to which the forecast corresponds to what actually happened

- ***Value*** - the degree to which the forecast helps a decision maker to realize some incremental economic and/or other benefit

1. Synoptic evaluation 2. Forecast Skill scores 3. Customer Metrics

Many types of errors exist



Well correlated fields, coverage/displacement/intensity error

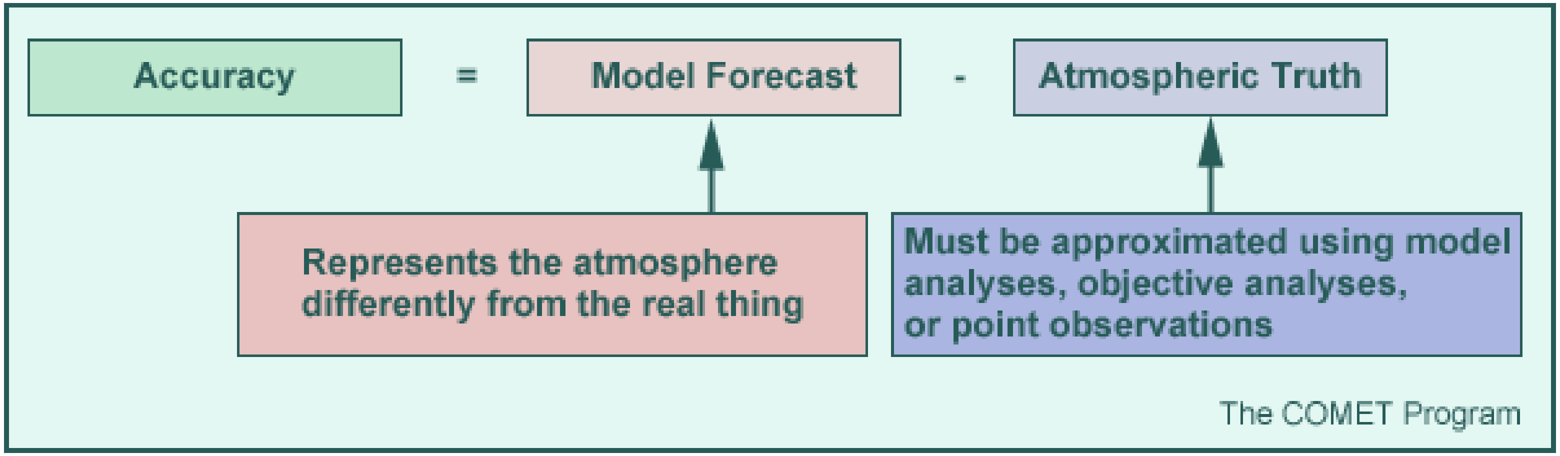
Poorly correlated fields, coverage/displacement/intensity error

False Alarm

Missed forecast

Graphic courtesy of Dr. Jason Nachamkin, NRL

Measuring Model Performance



- The goal of model assessment is to verify how well the model predicted the state of the atmosphere.
- To do this, one must not only understand the strengths and limitations of the model being evaluated, but also the accuracy and applicability of the verification data.
- Traditionally, model assessment tools use the following techniques and data sources to represent atmospheric truth, no one of which is clearly superior.
  - Model analyses
  - Independent objective analysis
  - Point observations

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Analysis and Forecast Verification

- **We want to estimate the errors in the analyses and forecasts**
  - Ideally, we would compare against "truth", but truth is unknown
  - Observations and analyses represent only an approximation of truth
  - Observations are sparse in space and time, and have random and systematic errors
  - Analyses have various sources of error due to errors in observations, model background, and the assumptions we must make regarding errors in observations and model background
  - In data sparse regions, or data denial studies, the analyses may be degraded and thus provide a misleading estimate of truth

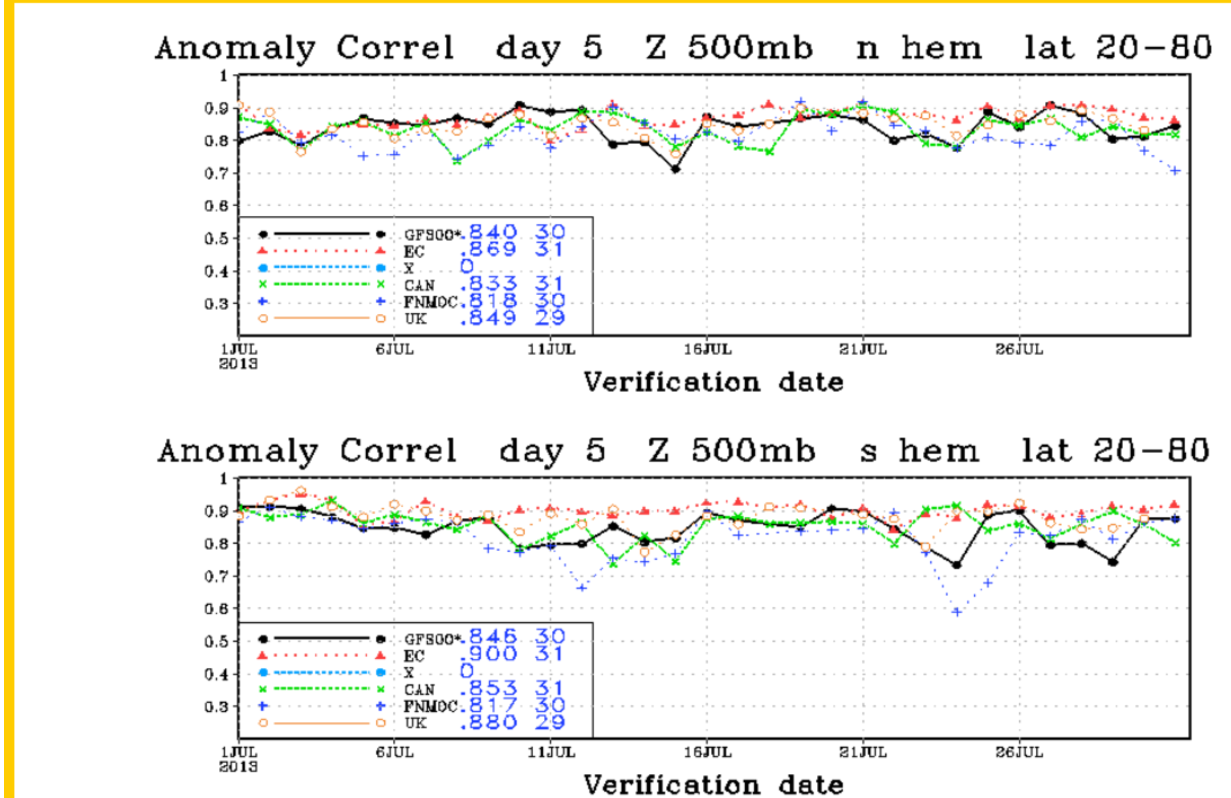
- **Model forecast verification against analyses**
  - One commonly used method is to compare the NWP forecasts against the analyses used to start each forecast (self-analysis)
  - In the limit, if no observations are assimilated, the forecast and verifying analyses are the same, implying that the forecast is perfect

Measuring Model Performance

- Anomaly correlation
- Root-mean-square error (RMSE) and verification against observations
- Scorecards
- Event verification (case studies)

The Most Viewed Graphic

Anomaly correlations for 5-day forecasts of 500-hPa heights for various models verifying during the last 31 days. Average values and number of forecasts are shown in insets.



500 hPa Northern Hemisphere Geopotential Height Anomaly Correlation Coefficient is the most commonly used metric to compare NWP model skill

Anomaly Correlation Coefficient (ACC)

$$ACC = \frac{\sum(F - C)(A - C)}{\sqrt{\sum(F - C)^2 \sum(A - C)^2}}$$

Forecast is valid at the same time as the analysis
Analysis is an optimal estimate of the atmosphere given prior observations and forecasts.
Climatology is a long-term average given the "expected" state

- How well did the forecast values correspond to the observed values?
- Does not take forecast bias into account -- it is possible for a forecast with large errors to still have a good correlation coefficient with the observations. A good ACC does not guarantee accurate forecasts
- Sensitive to outliers.
- If there are no observations, then A = F, and ACC=1 (implying a perfect forecast)
- The choice of which verifying ***A***nalysis to use as well as the ***C***limatology to compare against can affect the numerical value of the score.

Anomaly Correlation

- Anomaly correlation (AC) is a measure of the similarity between forecast and observation (analysis) patterns using anomalies (departures from the climatological mean) for a particular parameter.

- AC is best used in global regimes, where the slowly changing portion of the flow (long-waves) dominates and yet does not have a major effect on the weather.

- By removing the longest waves (climatology) and examining the smaller-scale features (anomalies), AC can focus on the significant patterns.

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Anomaly Correlation

AC Advantages

- Good overall indicator of skill
- Widely used and accepted
- Independent of observation networks

AC Disadvantages

- Not very useful in the tropics
- Limited value for surface parameters
- Large penalty for small phase errors
- Rewards smooth and zonal forecasts
- Dependent on choice of climatology

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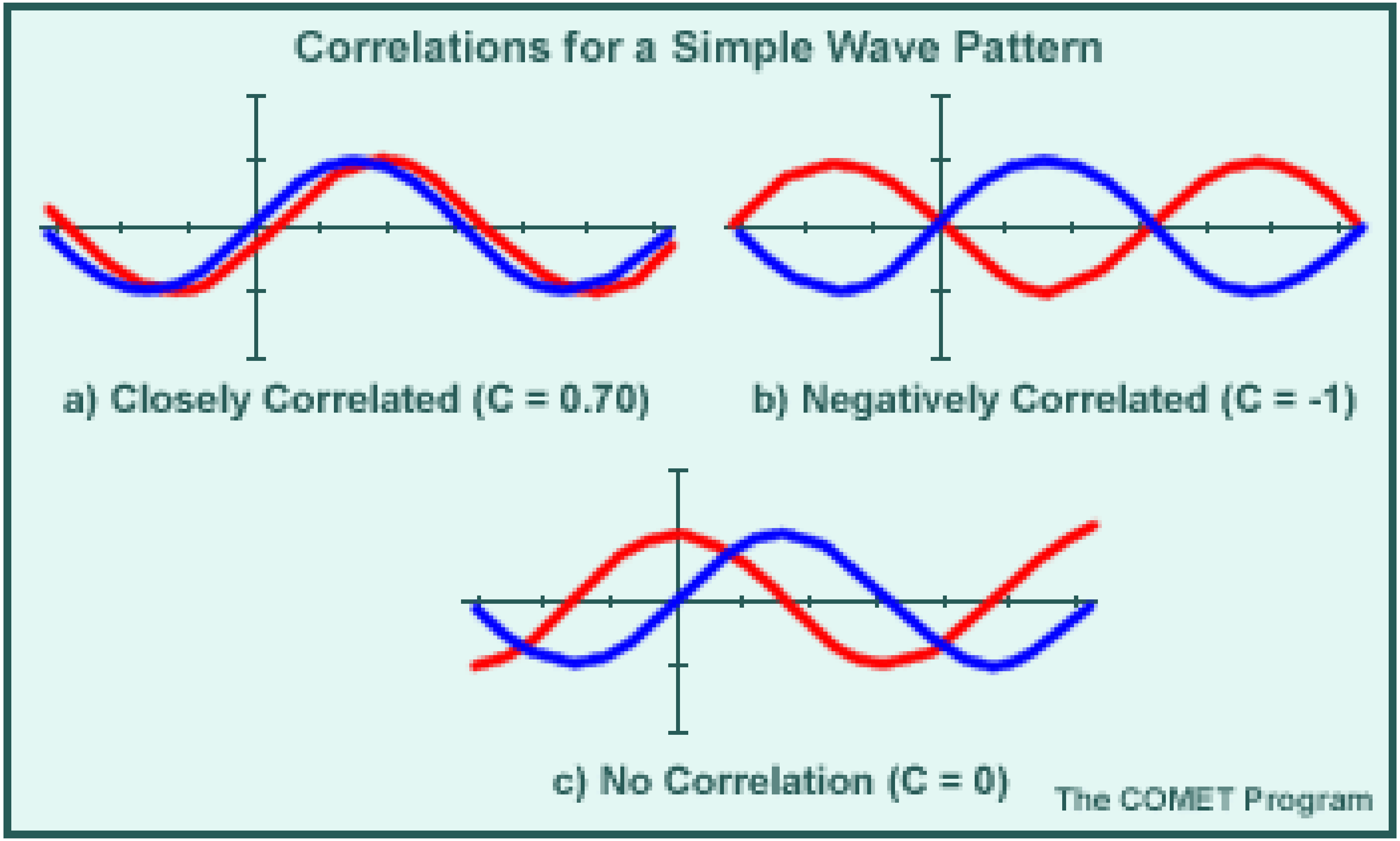
Large Penalty for Small Phase Speed Errors



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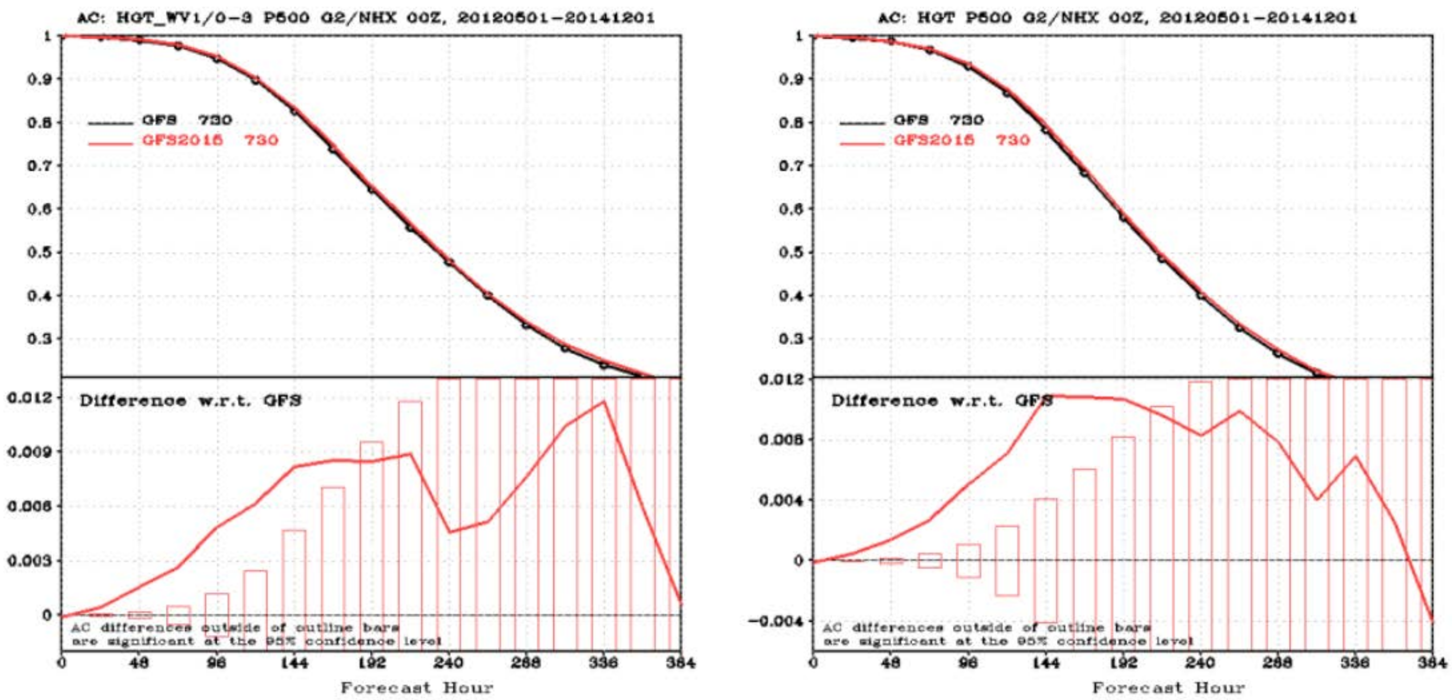
Example of GFS ACC plots



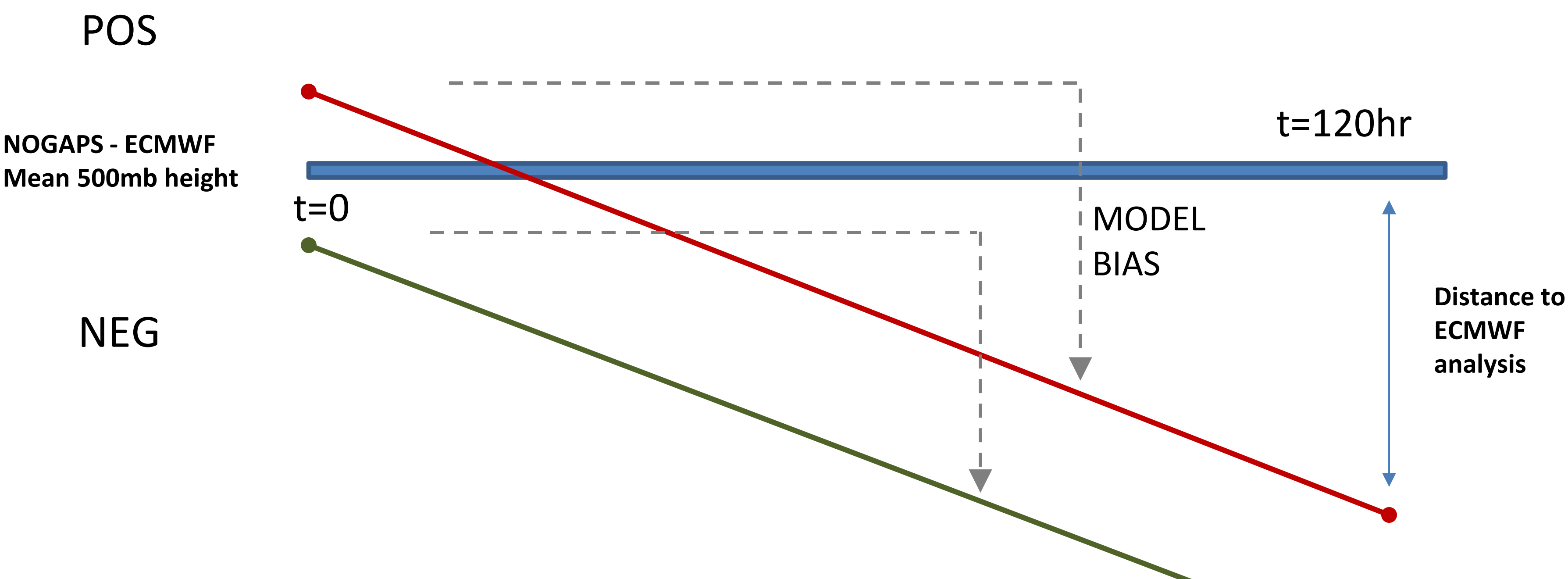
Top plot does not contain any information on statistical significance

Bottom plot – if the difference curve lies above (or below) the bars, then the results are statistically significant.

FORECAST MODEL BIAS can cause the skill of NAVGEM forecasts to be worse, even when the initial conditions are improved!

Example: error metric = global mean diff (NAVGEM-ECMWF) of 500hPa height

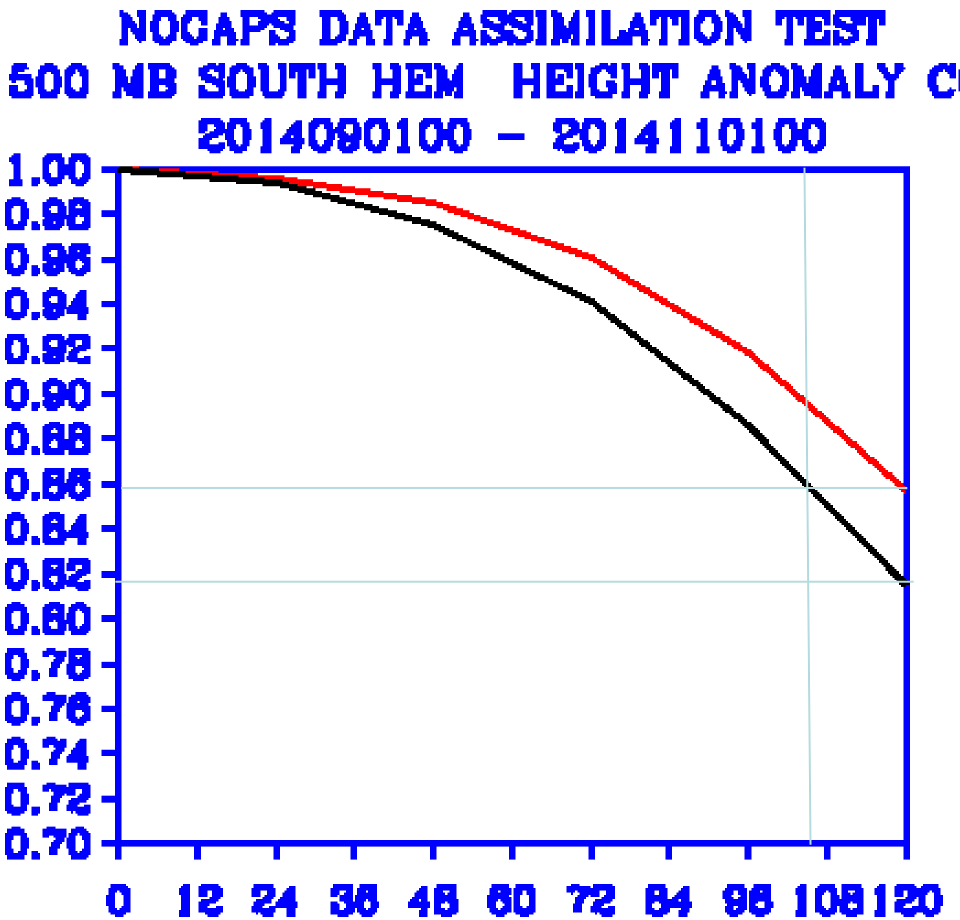
CONTROL (mean 500mb height too high at initial time; decreases due to forecast model bias and ends up slightly closer to ECMWF at 120hr)



EXPERIMENT (mean 500mb height too low at initial time (<u>but closer to truth</u>); decreases due to forecast model bias and ends up slightly farther from ECMWF at 120hr)

Slide from R. Langland

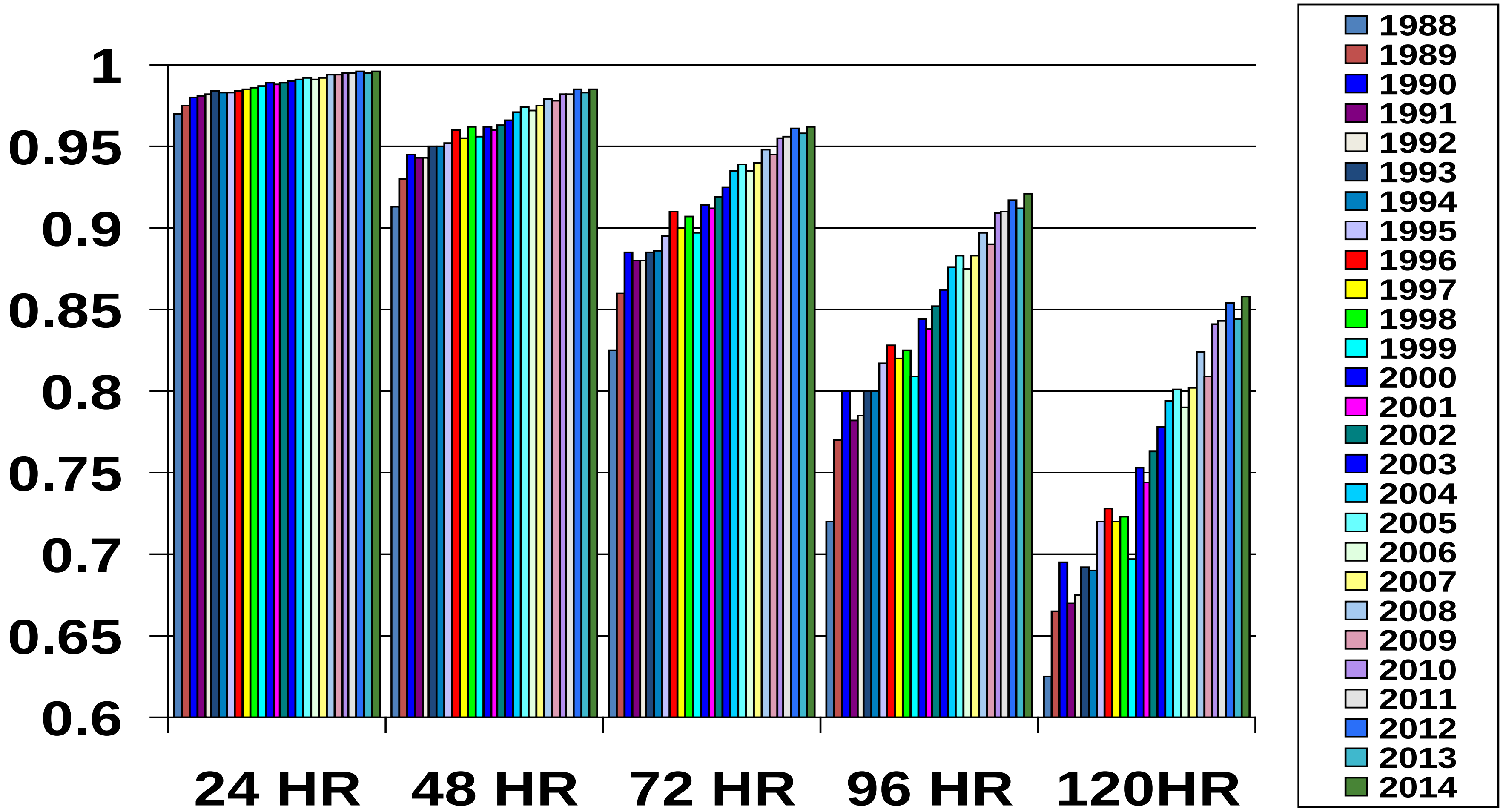
Forecast lead time vs. Anomaly Correlation “Die-off” Curves



— Control — Data denial

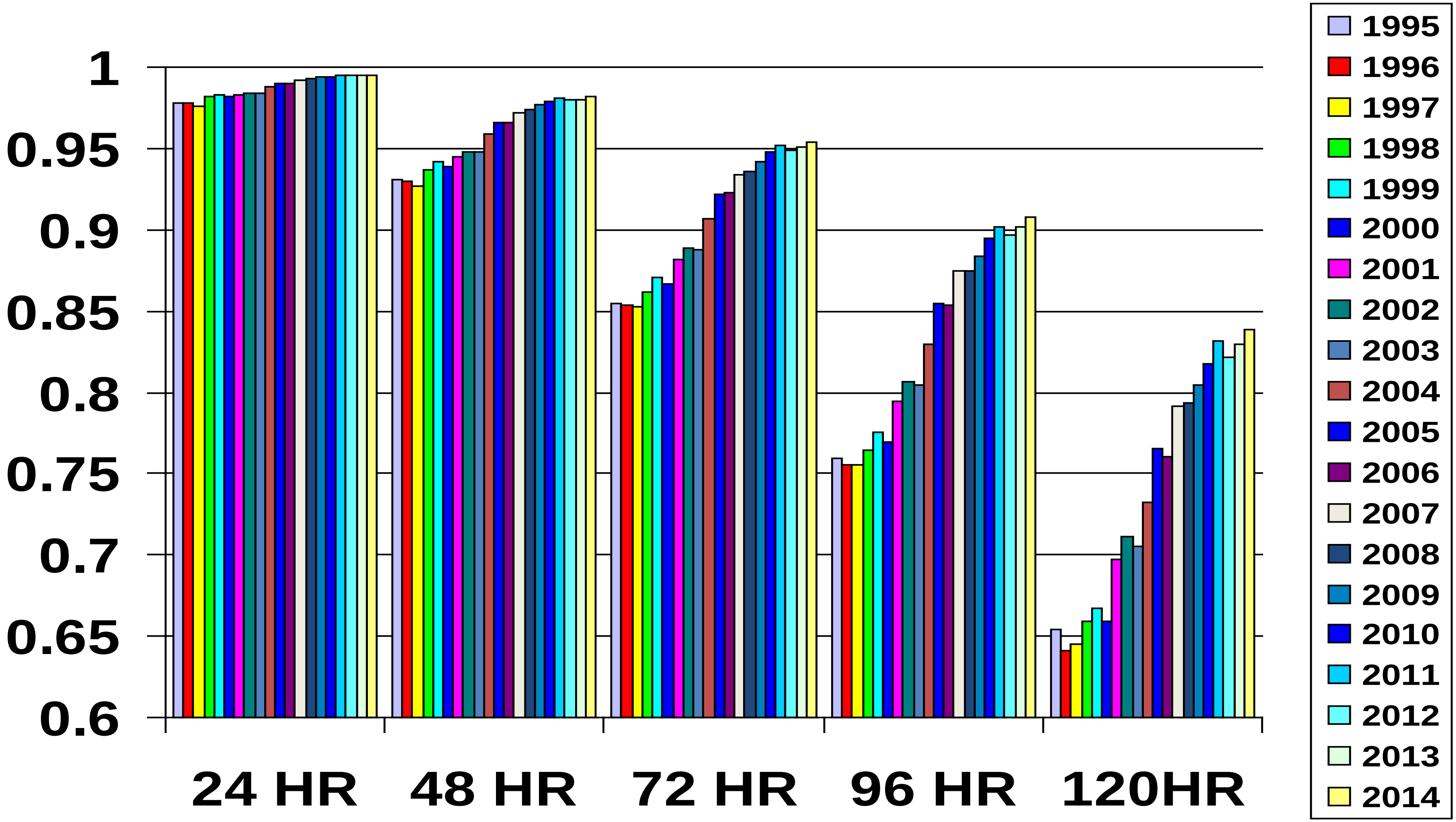
NOGAPS Annual Mean Forecast Statistics
N. Hemisphere 500 mb Heights

Anomaly Correlation



NOGAPS Annual Mean Forecast Statistics
S. Hemisphere 500 mb Heights

Anomaly Correlation



Root mean square error (RMSE)

$$\mathrm{RMSE} = \left[\frac{1}{N} \sum_{n=1}^{N} (f_n - o_n)^2 \right]^{1/2}$$

- **Root mean square error (RMSE)** is the square root of the average of the individual squared differences between the forecast (f_n) and observation (o_n), where N is the total number of forecast comparisons.
  - Weights positive and negative errors equally; measures total model error.
  - Includes both systematic component (bias) and random component (standard deviation).
  - Often used to evaluate the error in temperature, wind, and height forecasts.

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Measures of Forecast Error

$$\text{Mean Error} = \frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)$$

Mean absolute error - $$MAE = \frac{1}{N}\sum_{i=1}^{N}|F_i - O_i|$$

Root mean square error - $$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2}$$

Mean squared error - $$MSE = \frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2$$

- F is forecast value
- O is verifying value (analysis or observation)
- N is the number of points in the verifying area

From: http://www.cawcr.gov.au/projects/verification/#Types_of_forecasts_and_verifications

- Mean Error: average forecast error
- Mean Absolute Error (MAE): average magnitude of forecast error
- RMSE is a measure of the "average" forecast error
- RMSE does not indicate direction of errors, and is more strongly influenced by large errors (because it is a squared value)
- MSE can be decomposed into component error sources following Murphy (1988)

Limitation of Point-by-point RMS

$$\mathbf{MSE} = (\text{bias})^2 + (S_f)^2 + (S_o)^2 - 2\, S_f\, S_o\, r_{fo} \qquad \text{(Murphy 1988)}$$

S_f is the sample variance of the forecasts

S_o is the sample variance of the observations

r_{fo} is the sample correlation coefficient between forecasts and obs

- Forecast is penalized for high variability (flip side of the fact that forecast is rewarded for smoothness).

- Skill Scores Based on the Mean Square Error and Their Relationships to the Correlation Coefficient Allan H. Murphy *Monthly Weather Review* Volume 116, Issue 12 (December 1988) pp. 2417–2424

Self Analysis

Model analyses

- Designed to minimize forecast error growth within a modeling system rather than represent atmospheric observations as closely as possible
- Typically smoother than the actual atmospheric field
- Incorporate multiple types and sources of observations
- Observational data rejection of extreme events can seriously hamper the analysis and cause the atmosphere to be misrepresented. If the analysis is too heavily influenced by the first guess, the model will be validating itself.

Verification using model analyses can be problematic and unrepresentative when

- The resolutions of the analysis and forecast are not well matched (i.e., different resolution grids represent different area averages)
- The accuracy assessment generated from one model (using its own analyses) is compared against measures from another (using a different model-specific analysis), which makes the comparison inconsistent

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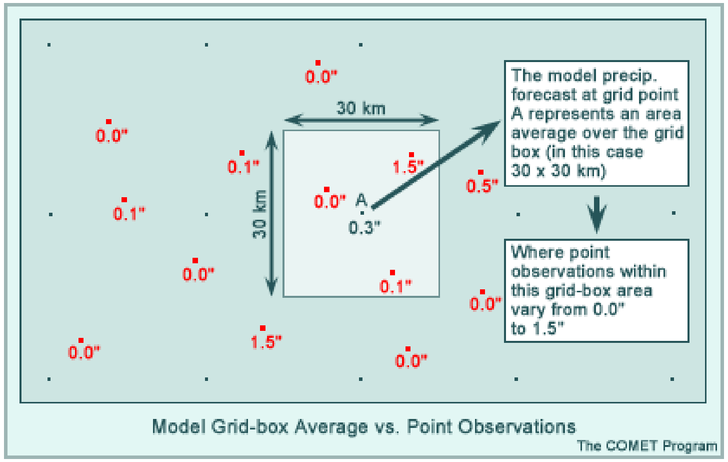
Verification against independent model

- How good is the quality of the other analysis?
- What is the purpose of that analysis?
  - MERRA 1 designed to provide consistent analysis over time, so did not assimilate new observation data sets
  - Political reasons for choice
- ECMWF analyses provides a statistical method for comparison (calibration) between the runs
- Let X=(Baseline-ECMWF)
- Let Y=(Denial-ECMWF)
- Define Error between baseline and denial as Error = (Baseline-Denial) = B - D
- Error = X-Y = (Baseline-ECMWF) - (Denial-ECMWF) = (B –E) – (D + E) = B - D

Verification Against Observations



A Complicated Comparison

Point Observations - direct measurements at discrete points, but contain:

- Instrument errors
- Errors of representativeness (how well a point observation represents the state of the atmosphere around a particular location).

To compare model forecasts to observations, one of the following must be done:

- Model data must be interpolated to the observation point
- Model data must be taken from the nearest grid-point
- Observational data within each grid box must be averaged

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Verification Against Observations

- Model values at discrete grid points represent an average over a grid-box area, but observations are for a point.

- Model **surface** data are averaged to fit the model topography, which is a smoothed representation of the actual terrain, but **surface observational data** "fit" the actual surface terrain.

- Sometimes additional errors of representativeness enter the verification process if model data used to compute verification is derived from lower-resolution post-processed grids. This may lead to an underestimate of performance, especially for low-level parameters and precipitation.

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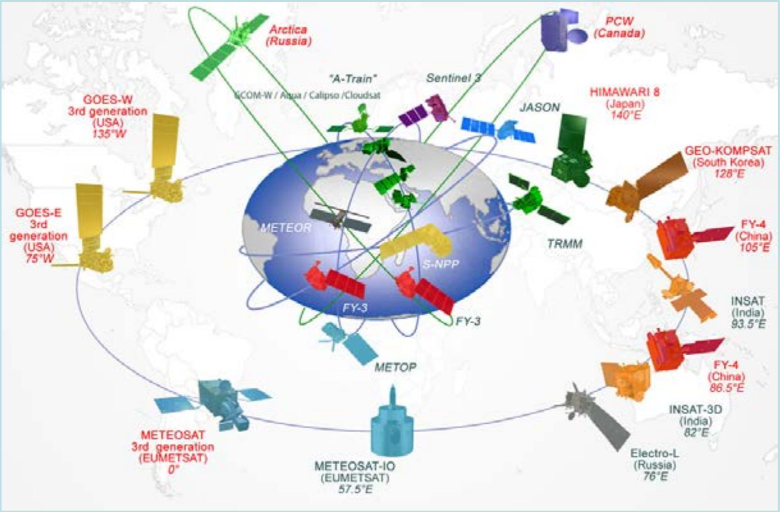
Overview of Environmental Satellites

Primary Atmospheric Sensors for NWP



Geostationary (GEO) Satellites

- ✓ Multi-purpose VIS/IR/WV imagery : Atmospheric Motion Vectors (AMVs), SST, clouds, aerosols, land surface & ocean properties

Low Earth Orbiting (LEO) Satellites

- ✓ Multi-purpose VIS/IR/WV imagery: AMVs, SST, clouds, aerosols, land surface & ocean/sea-ice properties
- ✓ IR temperature/humidity sounding : temperature and humidity profiling, ozone profiling, some trace constituents
- ✓ MW temperature/humidity sounding: temperature and humidity profiling
- ✓ Multi-purpose and low frequency MW imagery: TC intensity and position, ocean surface winds, integrated water vapor, SST, sea-surface salinity, soil moisture, sea-ice
- ✓ Radio occultation sounding: temperature and humidity profiling
- ✓ Sea-surface winds by active and passive MW: ocean surface wind speed and direction
- ✓ Other relevant sensor data includes altimetry for SSH and SWH, ocean color, space weather, etc…

Global and Mesoscale Observing Systems

Global: 3.3 million obs assimilated per 6-hr analysis cycle

Conventional Data Types (10%)

- Radiosondes and Pilot Balloons (Pibals)
- Dropsondes
- Land and Ship Surface Obs
- Fixed and Drifting Buoys
- Aircraft Obs
  - AIREPS, ADS
  - AMDAR, MDCRS
- Synthetic Obs (TC Bogus)

Special Sensor Data Types

- Radar Observations
  - Doppler Radial Winds
  - Radar Reflectivity
- UAV/UAS Observations
- High density hurricane & Winter Storm obs
- Mesonet surface obs

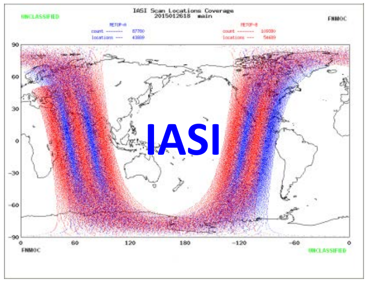
Satellite Data Types (90%)

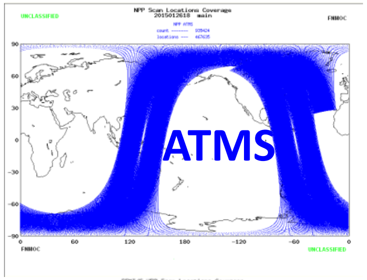
- Surface Winds
  - Scatterometer, ASCAT
  - SSMIS (4)
  - WindSat
- Feature Tracked Winds
  - Geostationary (5 satellites)
  - Polar - AVHRR, MODIS, VIIRS (8)
  - Combined leo/geo winds (CIMSS)
- Total Water Vapor
  - SSMI/SSMIS (4)
  - WindSat
- GPS Bending Angle (10)
- IR Sounding Radiances
  - AIRS, IASI and CrIS
- MW Sounding Radiances
  - AMSU-A (Ch 4-14) (6)
  - SSMIS (Ch 2-7,9-11,22-24) (3)
  - MHS 183 GHz (4)
  - ATMS (1)

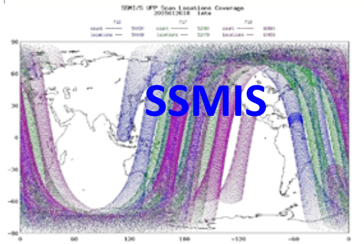
Satellite Data Coverage

Complementary not Redundant

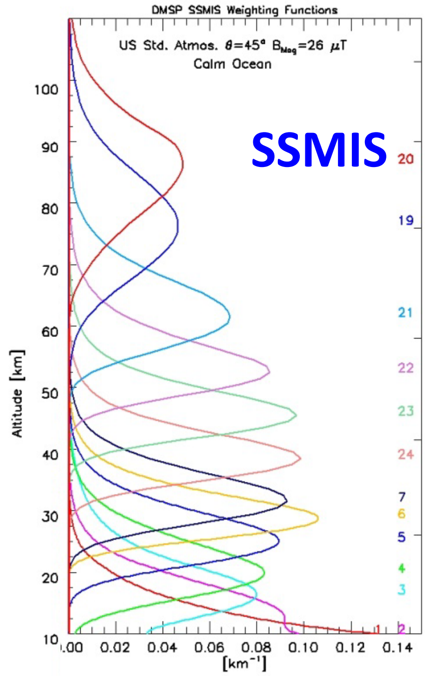
LEO (Polar) Infrared and Microwave Sounders





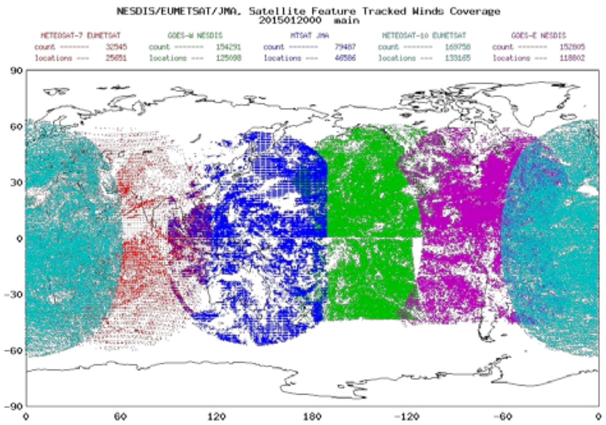


Two satellite constellation gives better data coverage than one, and three is even better



Sounders give vertical temperature and humidity information

Geostationary Imagers



- Geostationary imagers give good horizontal and temporal coverage, but limited vertical (profile) information.

- LEO imagers also have limited profile information

Examples for a 6-hr window at 18 UTC

NRL/FNMOC Scorecard

- **Objective scoring used to guide decisions for model upgrades**
  - Verification against buoy surface observations, radiosondes, self-analysis for different levels and lead times, plus tropical cyclone track forecasts
  - Weights for each metric (e.g. buoy winds) range from 1 to 4 (positive for a “win”, zero for no statistical difference)
  - Differences must be statistically significant
  - Differences must meet minimum threshold requirements (e.g. 5% for wind vectors)
  - Proposed system changes must be neutral or better
  - A perfect score would be +28
  - A perfect score does NOT imply perfect forecasts!
  - Scorecard using “self-analysis” does not distinguish between e.g. 5% and 25% worse
  - ECMWF analyses are often used by NRL as the comparison (verifying) analyses so that we can highlight differences between the model runs

Evaluating Forecast Quality

"Score Card"

Type	Level	Area	Parameter	Error-Type	Fcst Tau	Weight
Field	Surface	Tropics	Tropical cyclone	Track error	96 hrs	4
Field	500 hPa	N Hem	Height	AC	96 hrs	4
Field	1000 hPa	N Hem	Height	AC	96 hrs	1
Field	500 hPa	S Hem	Height	AC	96 hrs	1
Field	1000 hPa	S Hem	Height	AC	96 hrs	1
Field	850 hPa	Tropics	Wind	Vector RMS	72 hrs	2
Field	200 hPa	Tropics	Wind	Vector RMS	72 hrs	1
Field	850 hPa	N Hem	Wind	Vector RMS	72 hrs	1
Field	200 hPa	N Hem	Wind	Vector RMS	72 hrs	1
Buoy	Surface	Global	Wind	Speed Error	72 hrs	2
Raob	850 hPa	Global	Wind	RMS	72 hrs	1
Raob	250 hPa	Global	Wind	RMS	72 hrs	1
Raob	850 hPa	Global	Temperature	RMS	72 hrs	1
Raob	250 hPa	Global	Temperature	RMS	72 hrs	1
Raob	500 hPa	Global	Height	RMS	72 hrs	1
Raob	100 hPa	Global	Height	RMS	72 hrs	1

“No MeteoSat-7/10 Redundancy” vs. “Control”

Modified FNMOC Scorecard Score = -1 (out of 28)

Reference	Level	Region	Variable	Lead time	Level type	Metric	Weight	Score
ECMWF Analysis	200.0	Northern Hemisphere	Wind	72	pressure	Vector RMS Error	1	0
ECMWF Analysis	200.0	Tropics	Wind	72	pressure	Vector RMS Error	1	0
ECMWF Analysis	500.0	Northern Hemisphere	Geopotential Height	96	pressure	Anomaly Correlation	4	0
ECMWF Analysis	500.0	Southern Hemisphere	Geopotential Height	96	pressure	Anomaly Correlation	1	0
ECMWF Analysis	850.0	Northern Hemisphere	Wind	72	pressure	Vector RMS Error	1	0
ECMWF Analysis	850.0	Tropics	Wind	72	pressure	Vector RMS Error	2	0
ECMWF Analysis	1000.0	Northern Hemisphere	Geopotential Height	96	pressure	Anomaly Correlation	1	0
ECMWF Analysis	1000.0	Southern Hemisphere	Geopotential Height	96	pressure	Anomaly Correlation	1	0
Fixed Buoy	None	Northern Hemisphere	Wind Speed	72	surface	Mean Error	2	0
Fixed Buoy	None	Southern Hemisphere	Wind Speed	72	surface	Mean Error	2	0
Fixed Buoy	None	Tropics	Wind Speed	72	surface	Mean Error	2	0
Radiosondes	100.0	Global	Geopotential Height	72	pressure	RMS Error	1	-1
Radiosondes	250.0	Global	Air Temperature	72	pressure	RMS Error	1	0
Radiosondes	250.0	Global	Wind	72	pressure	Vector RMS Error	1	0
Radiosondes	500.0	Global	Geopotential Height	72	pressure	RMS Error	1	0
Radiosondes	850.0	Global	Air Temperature	72	pressure	RMS Error	1	0
Radiosondes	850.0	Global	Wind	72	pressure	Vector RMS Error	1	0

Tropical Cyclone Track Error Lead 4 0

“No MeteoSat-7/10 redundancy” score is similar to “Control”, but this does not imply that other metrics would not be affected by loss of MeteoSat-7 (aerosols, waves, imagery)

UK NWP INDEX
Used for Short Term Regional Area

The Index is a weighted average of

- 1.5m temperature
- 10m wind speed & direction
- Precipitation yes/no (6 hour buckets)
  - 0.2 mm or more
  - 1.0 mm or more
  - 4.0 mm or more
- Total cloud amount
  - 2.5 oktas or more
  - 4.5 oktas or more
  - 6.5 oktas or more
- Near-surface visibility
  - 200 m or worse
  - 1000 m or worse
  - 5000 m or worse

Skill score
$1 - r_f^2/r_p^2$

Categorical
2x2 contingency table
Equitable Threat Score

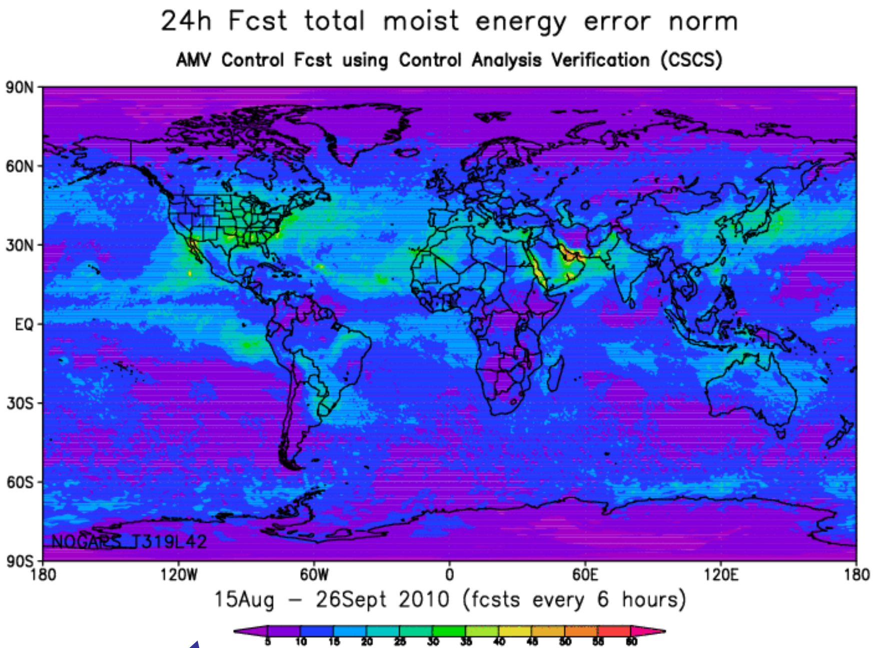
Verification data

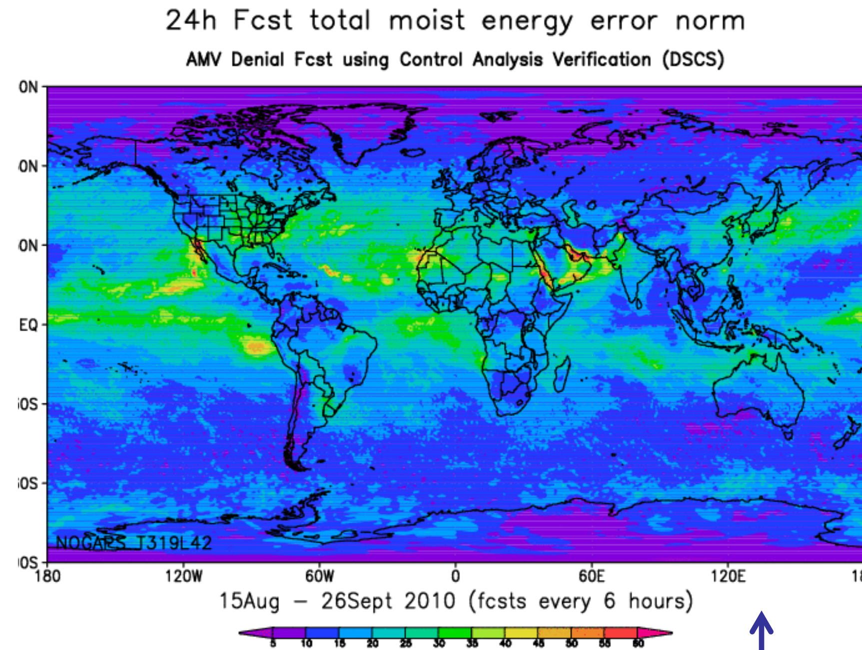
- From 42 station positions across the UK
- Using 36 months of forecasts
- Binned by analysis time
- Calculated for tau 6, 12, 18, and 24

- Allows parameters to be weighted according to their importance to operations.

Comparison Challenges for Data Denial Experiments

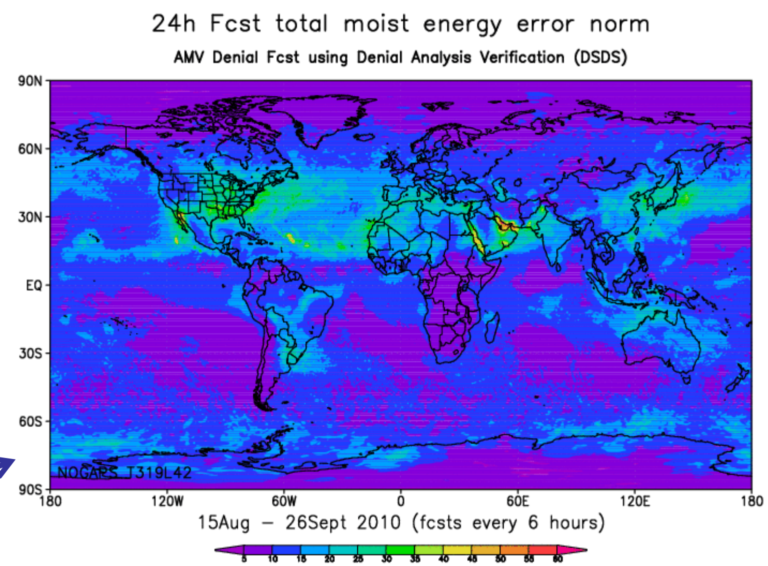
- Many standard verification techniques essentially assume that either model forecast is equally likely – typically we are trying to decide which of two proposed system variations is better overall.
  - Typically the differences between the two analyses are even smaller
- When a significant proportion of the observations are withheld
  - Resulting baseline versus denial forecast differences are no longer small
  - Baseline and denial analyses may be quite different
  - Verification against self-analysis is problematic (verifying forecast against the initial analysis – starting point for the forecast)
- In the limit, an analysis with no observations assimilated will verify best – for certain metrics
  - With data assimilation, the observations are used to correct the model forecast with “truth”. In the absence of those corrections, the model tends verify well with itself.
- In a true data denial situation, we wouldn’t have a wealth of diverse observations to verify quality of either the analyses or forecasts





Baseline Error:
Control verified
against control

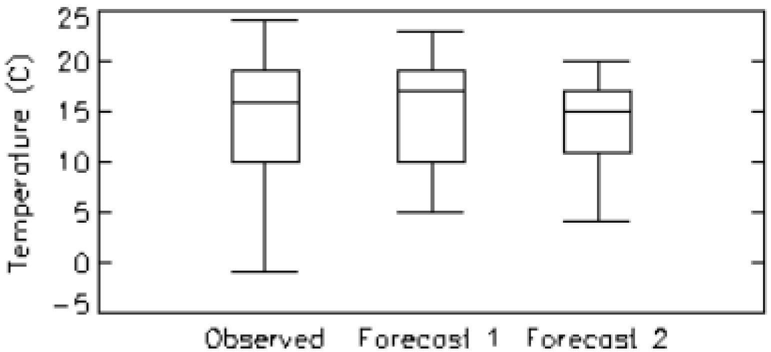
True Error:
Denial verified
against control



Misleading Error:
Denial verified
against denial

Removal of Satellite Winds results in a large departure from the control state in the tropics.

Box Plots/Bars and Whiskers



- ***Box plot -*** Plot boxes to show the range of data falling between the 25th and 75th percentiles, horizontal line inside the box showing the median value, and the whiskers showing the complete range of the data.

- ***Answers the question:*** *How well did the distribution of forecast values correspond to the distribution of observed values?*

- **Characteristics:** Shows similarity between location, spread, and skewness of forecast and observed distributions. Does not give information on the correspondence between the forecasts and observations. Box plots give information similar to histograms.

Part 1. Verification and Validation

Part 2. Successful Metrics

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Metrics – Potential and Pitfalls

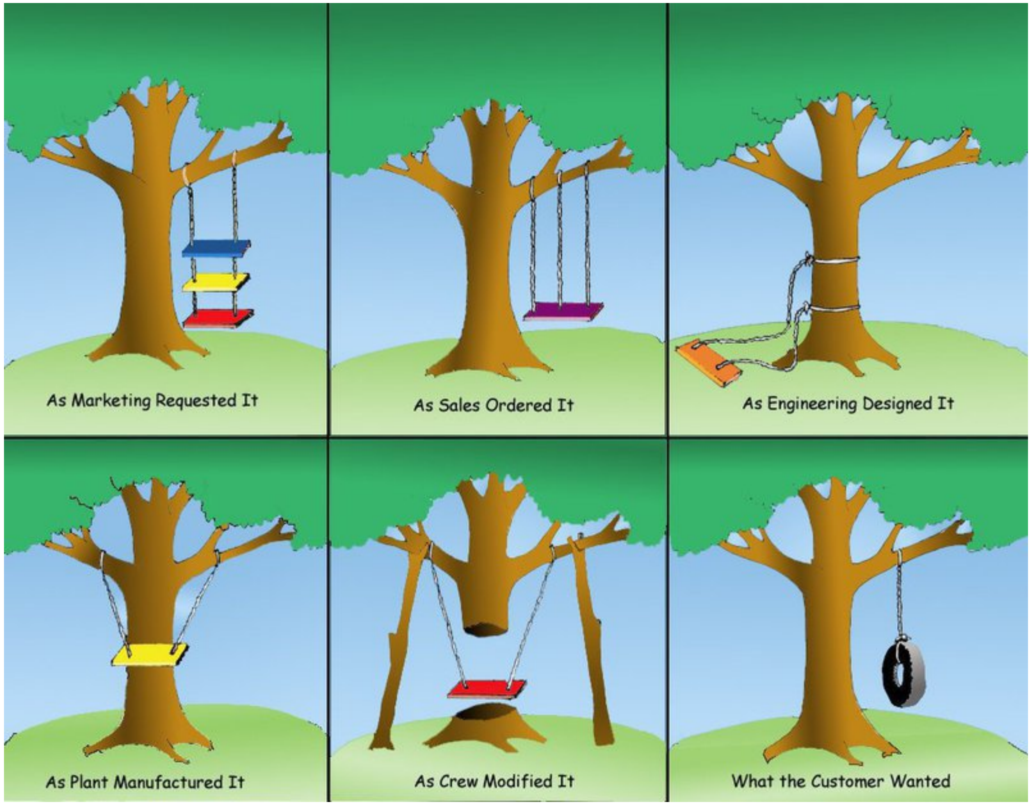
- Metrics – how to translate forecast or analysis skill into what the customer needs
- Metrics are often a proxy for something else
- Tropical cyclone intensity is a proxy for radius of maximum winds, storm surge potential, significant wave heights
- NWP centers often do not have the capability to translate NWP output into the customer products
- NWP centers may not have the information to translate forecast improvements into metrics
  - E.g. 50 nm improvement in average TC track prediction
  - Millions of dollars saved because coastline was not evacuated
  - Billions lost because of a missed forecast

Knowing your customer

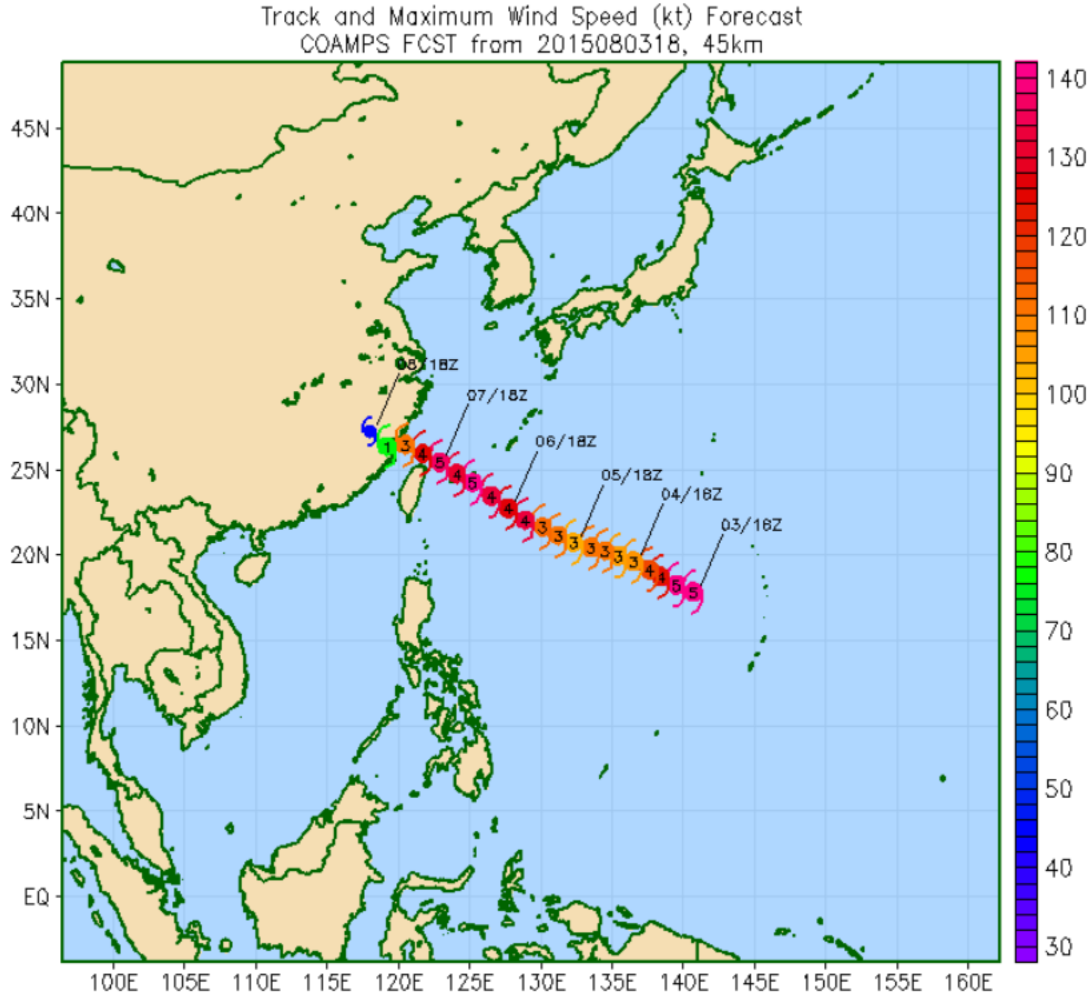
- Who is paying for your research?
- What is their expected outcome?
- What is the hoped for outcome?
- How to balance scientific integrity against customer wishes
- Are the customer expectations reasonable (e.g. AMSU-A impact NOGAPS)?
- Translating technical jargon into customer friendly language
- Accepting guidance and suggestions gracefully
- Building a rapport with your customer
  - Recognizing that the customer may have a great idea, but not have the technical background or jargon to ask the question

Packaging

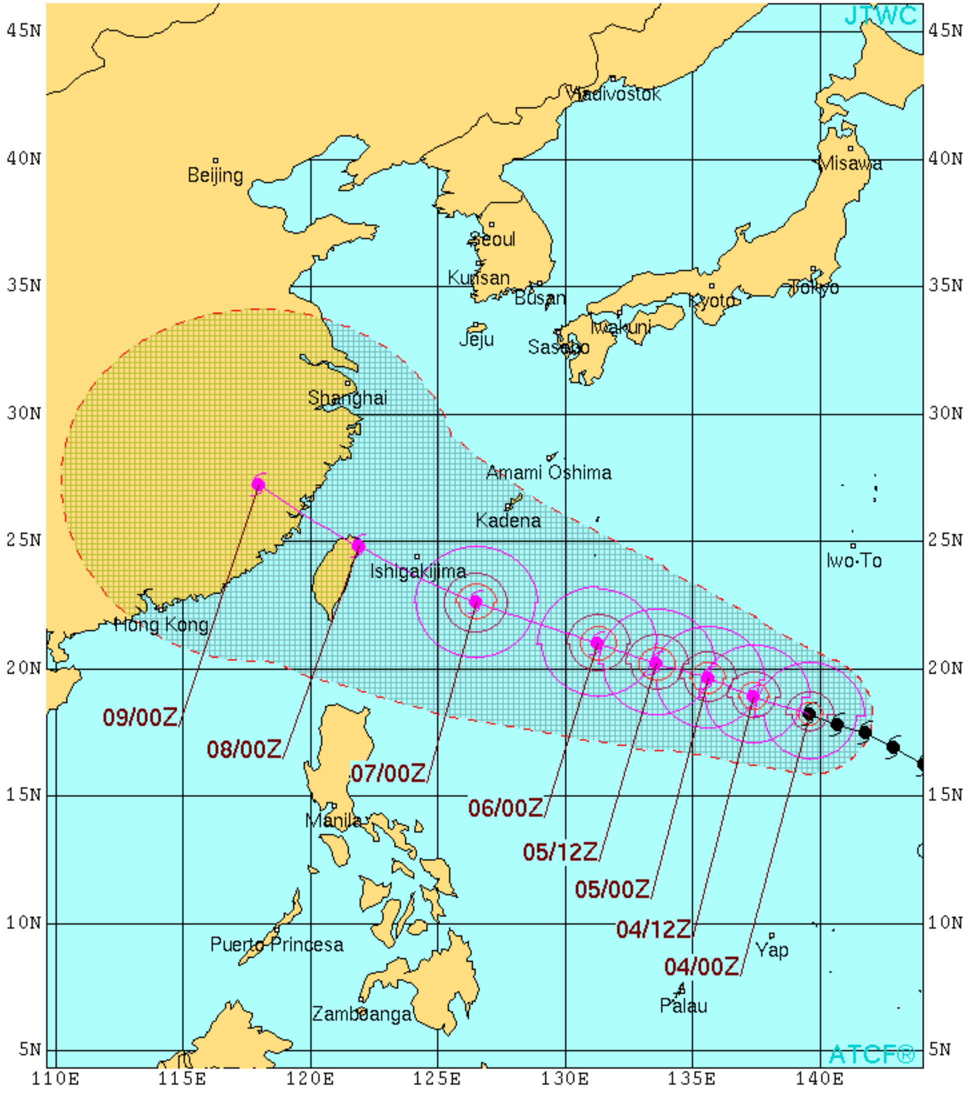
- The customer requested this, … this was what was delivered



Packaging can make a difference



Graphic from JTWC

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SUPER TYPHOON 13W (SOUDELOR) WARNING #20
WTPN31 PGTW 040300
040000Z POSIT: NEAR 18.2N 139.6E
MOVING 290 DEGREES TRUE AT 11 KNOTS
MAXIMUM SIGNIFICANT WAVE HEIGHT: 50 FEET
04/00Z, WINDS 155 KTS, GUSTS TO 190 KTS
04/12Z, WINDS 160 KTS, GUSTS TO 195 KTS
05/00Z, WINDS 160 KTS, GUSTS TO 195 KTS
05/12Z, WINDS 155 KTS, GUSTS TO 190 KTS
06/00Z, WINDS 145 KTS, GUSTS TO 175 KTS
07/00Z, WINDS 130 KTS, GUSTS TO 160 KTS
08/00Z, WINDS 110 KTS, GUSTS TO 135 KTS
09/00Z, WINDS 070 KTS, GUSTS TO 085 KTS

CPA TO:                NM     DTG
KADENA_AB             242   07/03Z
TAIPEI                  6   08/02Z
HONG_KONG             359   08/23Z
```

```
O LESS THAN 34 KNOTS
  34-63 KNOTS
  MORE THAN 63 KNOTS
PAST 6 HOURLY CYCLONE POSITS IN BLACK
FORECAST CYCLONE POSITS IN COLOR
```

Sensitivity versus Impact

- Sensitivity
  - Is there a difference between forecasts from different scenarios?
  - Case studies (An example would be Superstorm Sandy)
  - Field experiments typically fall into this category

- Impact
  - Would these results translate to other situations?
  - Results are statistically significant (e.g. 95% confidence level)
  - Differences meet threshold criteria (e.g. 5% decrease in RMS error)
  - Sufficient sample size
  - Sufficient sampling of different seasons, and weather regimes
  - Tropical cyclone are usually verified for multiple seasons and ocean basins
  - Validation against some representation of truth
  - Criteria used for model and data assimilation updates to be accepted for operational transition

Case Studies

- NWP studies use for forecast/DA verification and transition candidates typically comprise a minimum of 2 months cycling DA and forecast model verification over two seasons
- More often include up to a year of retrospective runs
  - Achieve statistical significance,
  - Verification over summer/winter and transition seasons gives confidence that upgrade benefits will carry into the future
- Tropical cyclone validation usually includes multiple seasons and multiple basins (36 storms over 4 years) to get a representative sample
- In contrast, case studies consist of a limited number of forecasts
- Cherry picking results – choosing results to support a desired conclusion
  - The case selected may not represent statistics over a larger sample size
  - If results are better than the overall statistics, this (1) sets up unreasonable expectations, (2) can oversell a particular capability
  - If the results are worse that overall statistics, then program managers may decide there is no payoff for what is being tested.

Data Impact Studies

- Data Impact studies usually fall somewhere in between model upgrade testing and case studies
- Sample question, what is the impact of the expected polar-orbiting satellite gap?
- The ultimate customer may be a Congress
- Results are usually needed within a matter of months – scope of study is often determined by time allotted and computational and human resources
- Choose (wisely) the appropriate tools to answer the question
- Be realistic – these studies often prove more difficult than expected
- Take time to define the study scope before starting

Metrics

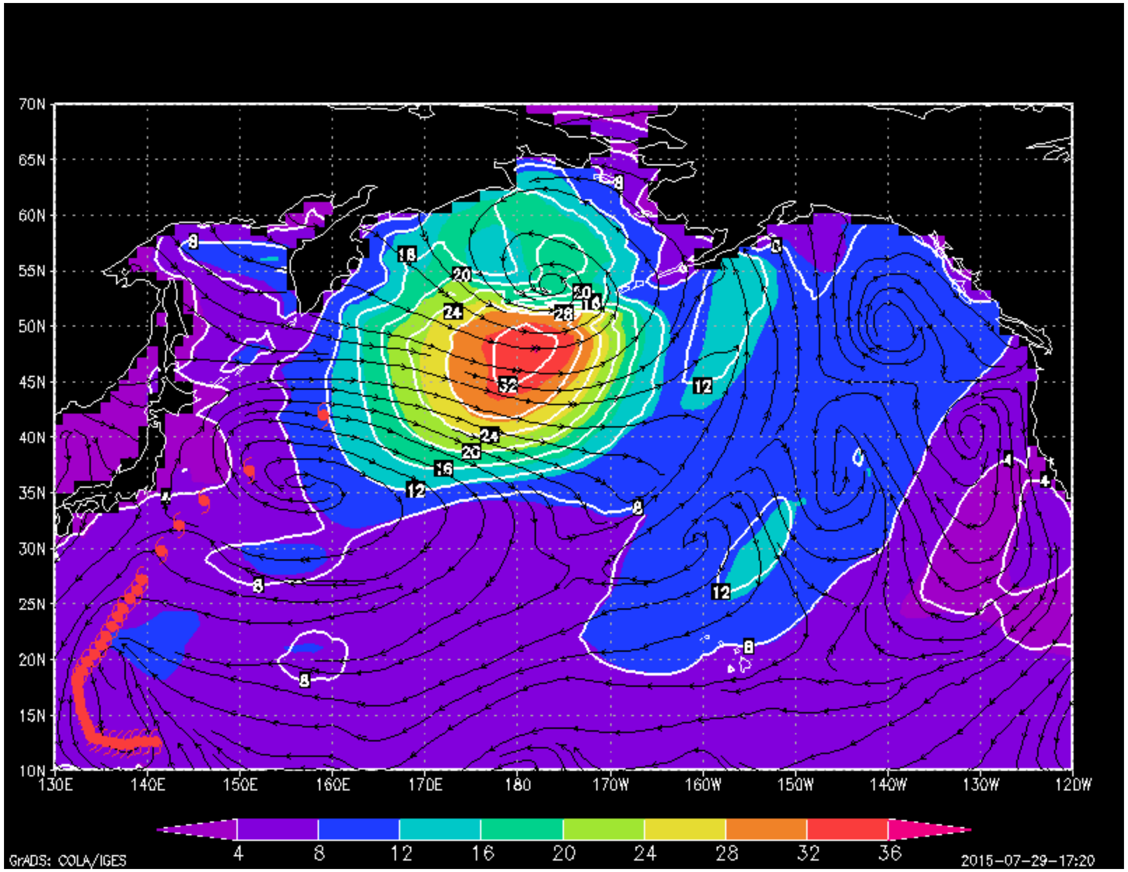
<u>Global</u> Atmospheric Forecast Model (NAVGEM)

- Forecast and analysis verification against baseline/comparison analyses
- Forecast and analysis verification against observations
- Dust and aerosol forecast verification against observations and baseline analyses
- Wave model forecast verification against wave observations and baseline analyses
- Ship routing – high seas warnings
- Observation Impact – which observations reduce forecast error most effectively
- Earth Orientation Parameters

<u>Regional</u> COAMPS-TC

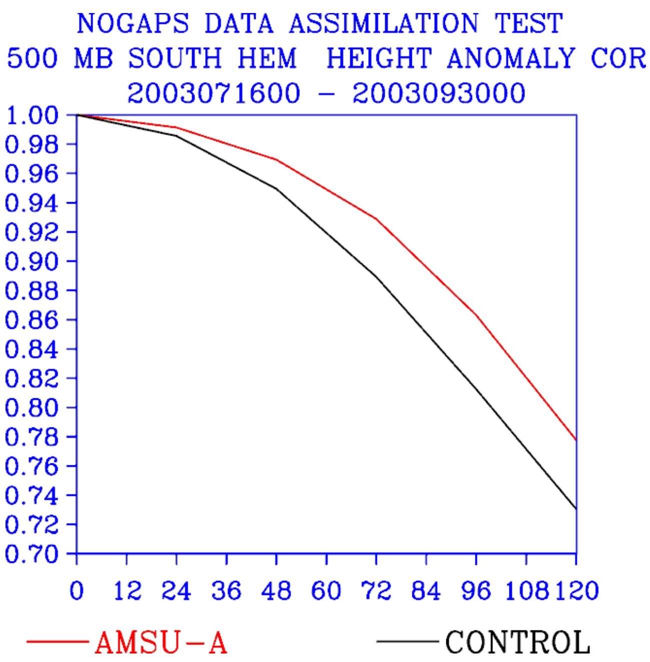
- TC track, intensity and structure verification against post-storm “Best Track” positions
- Tropical Cyclone forecaster guidance

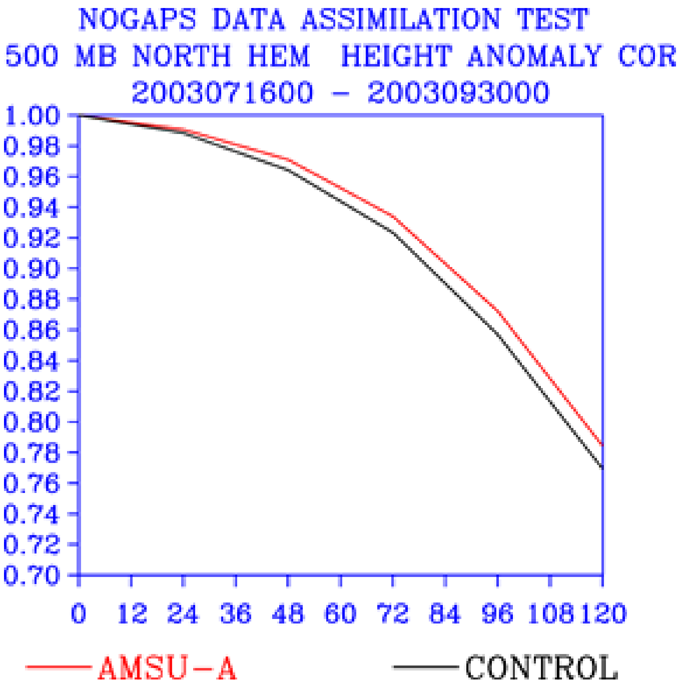
Wavewatch III forced by Global Model



Cause and effect – the ocean waves reflect the atmospheric wind forcing

Managing Expectations





Southern Hemisphere 500 hPa height AC vs. forecast hour for the summer 2003 case. The test run (AMSU-A) includes NAVDAS assimilation of AMSU-A radiances as described in Section 2. The control run assimilated NESDIS ATOVS retrievals with NAVDAS.

Discussion

- Do you know who your customer is?
- Several workshops have been held recently to connect NWP forecast to users
  - NASA CYGNSS Applications Workshop
  - NASA Workshop in April
  - NOAA ongoing initiative
  - Navy Remote Sensing Roadmaps
  - National Institutes of Health are providing special training on communicating science