



# Observations use in data assimilation and verification: *Similar but not the same*

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with contributions from my co-members of the WMO Joint Working Group on Forecast Verification Research (JWGFVR) and other Met Office staff

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ECMWF-JCSDA Workshop on assimilating satellite observations of clouds and precipitation in NWP models



## Outline

1. **Basic concepts** of verification
2. **Observations** – a nasty business?!
3. DA vs verification
4. Using **analyses** for verification
5. Dealing with **observations errors** (in verification)
6. A role of **satellite** observations?
7. Conclusions and recommendations

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# Basic verification concepts



## Why verify?

- **Administrative** purpose
  - Monitoring performance
  - Choice of model or model configuration (has the model improved?)
- **Scientific** purpose
  - Identifying and correcting model flaws
  - Forecast improvement
- **Economic** purpose
  - Improved decision making
  - “Feeding” decision models or decision support systems

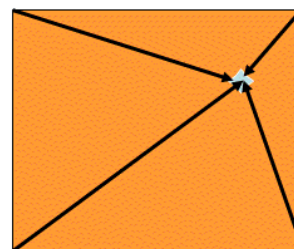
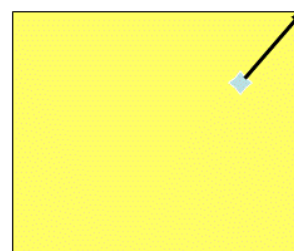


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## Matching forecasts and observations

- Point-to-grid and grid-to-point
- Matching approach can impact the results of the verification

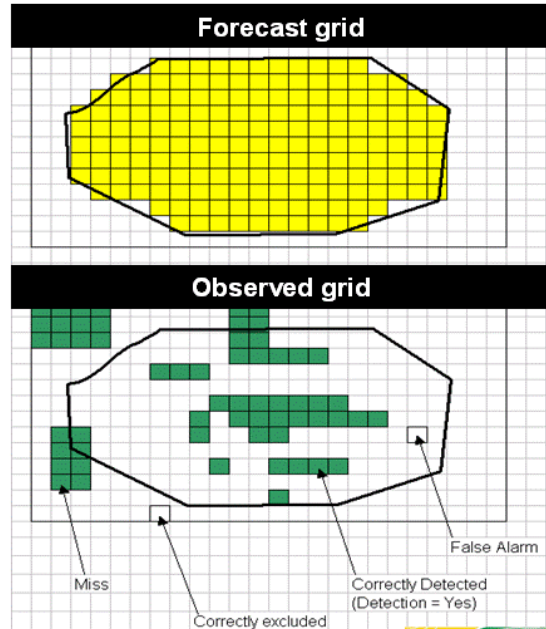


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# Matching forecasts and observations

- Grid-to-grid approach
  - Overlay forecast and observed grids
  - Match each forecast and observation

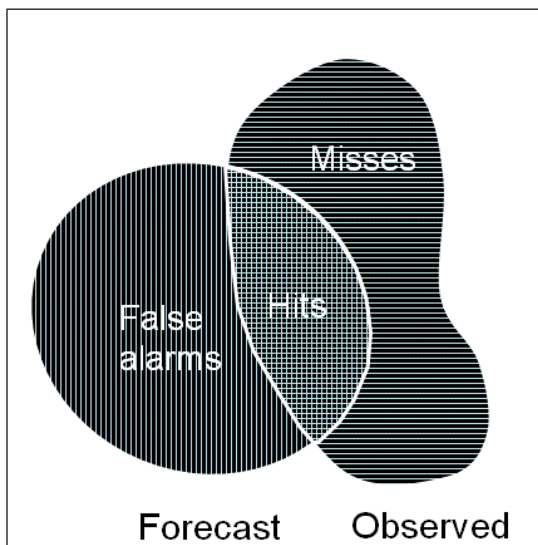


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# Traditional spatial verification using categorical scores

Compute statistics on forecast-observation pairs



|           |     | Observed |                   |
|-----------|-----|----------|-------------------|
|           |     | Yes      | no                |
| Predicted | yes | hits     | false alarms      |
|           | no  | misses   | correct negatives |

$$POD = \frac{\text{hits}}{\text{hits} + \text{misses}} \quad FBI = \frac{\text{hits} + \text{false alarms}}{\text{hits} + \text{misses}}$$

$$FAR = \frac{\text{false alarms}}{\text{hits} + \text{false alarms}}$$

$$TS = \frac{\text{hits}}{\text{hits} + \text{misses} + \text{false alarms}}$$

$$ETS = \frac{\text{hits} - \text{hits}_{\text{random}}}{\text{hits} + \text{misses} + \text{false alarms} - \text{hits}_{\text{random}}}$$

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## Traditional spatial verification

- **Requires an exact match** between forecasts and observations at every grid point.

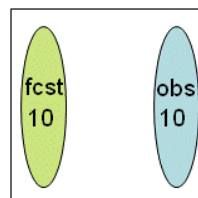
- Problem of **"double penalty"** - event predicted where it did not occur, no event predicted where it did occur
- Traditional scores do not say very much about the source or nature of the errors



**Hi res forecast**  
RMS ~ 4.7  
POD=0, FAR=1  
TS=0



**Low res forecast**  
RMS ~ 2.7  
POD~1, FAR~0.7  
TS~0.3



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## How parameter characteristics dictate the metrics

### Precipitation

- **Positively bounded** quantity approximately log-normally distributed
- **Variety of sources:** gauges, radar, satellite
- **Highly discontinuous** in space and time, possibly sparse; difficult to verify due to potentially large space-time errors.
- Continuous metrics (e.g. rmse) not recommended
- Focus on rain areas, thresholds, spatial methods

### Cloud

- Cloud cover
  - **Bounded** (cloud fraction 0-1) but mostly discretised (0-8 okta)
  - **Complex 3-D structure** with discrete structures in space and time, usually simplified into total cloud amount (TCA)
  - Continuous metrics not recommended, ideally suited to 3 x 3 categorical contingency analyses.
- Radiances
  - Continuous parameter which could be assessed using continuous, categorical or spatial methods.

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# Observations



## The monster(s) in the closet...

- In attempting to assess model forecast skill, what are we losing/risking by ignoring observation uncertainty?
- What can we gain by considering it?
  - (Confusion?)
- Can we afford to ignore it?
  - No!



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Courtesy, Barb Brown



## Observations are *NOT* perfect!

- **Observations error** vs **predictability** and forecast error/uncertainty
- **Different observation types** of the same parameter (manual or automated) can impact results
- Typical **instrument errors** are:
  - For temperature:  $\pm 0.1^\circ\text{C}$
  - For wind speed: speed dependent errors but  $\sim \pm 0.5 \text{ m/s}$
  - For precipitation (gauges):  $\pm 0.1 \text{ mm}$  (half tip) but 2 -- 50%
  - For cloud cover: ???
- Then there are **further issues of shielding/exposure** etc
- In some instances "forecast" errors are very similar to instrument limits – so, should the forecast get the blame?



## Sources of error and uncertainty

- Biases in frequency or value ✓
- **Instrument error** ?
- Random error or noise ✓
- Reporting errors ✓
- **Reporting of errors** ?
- **Subjective obs** (e.g., impact-based observations) ?
- Representativeness error ✓
- Precision error ✓
- **Conversion/transformation error** ? ✓
- **Analysis error** ? ✓
- Other?

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## Effects of observation errors

- Observation errors add uncertainty to the verification results
  - *True forecast skill is unknown (an imperfect model / ensemble may score better!)*
  - *Extra dispersion of observation PDF*
- Effects on verification results
  - *RMSE – overestimated*
  - *Spread – more ob outliers make ensemble look under-dispersed*
  - *Reliability – poorer*
  - *Resolution – greater in BS decomposition, but ROC area poorer*
  - *CRPS – poorer mean values*
- Can we remove the effects of observation error?
- More samples help with reliability estimates
- **Quantify actual observation errors as far as possible**

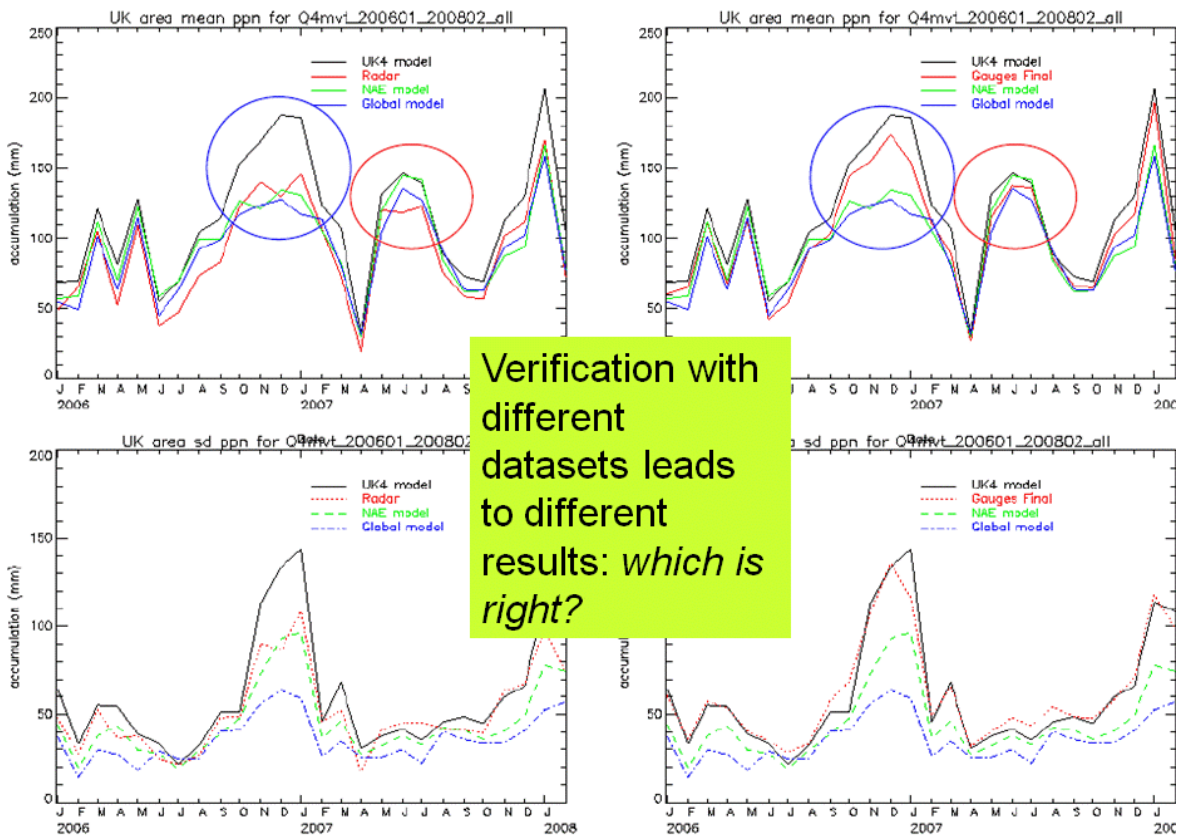
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# The pitfalls of observations type



## Fact sheet

- Manual surface observations are a “dying breed”.
- Using sparse and irregularly distributed observations for verifying high-resolution models leads to potentially disappointing results. *“Where is the benefit of high-resolution?”*
- **Cloud and precipitation are two of the most difficult parameters to predict accurately**, yet the impact of cloud biases (in particular) have huge **knock-on effects** on other parameters, such as temperature.
- Using different observation types for verifying the same model parameter will give different results. *[How does one deal with this?]*

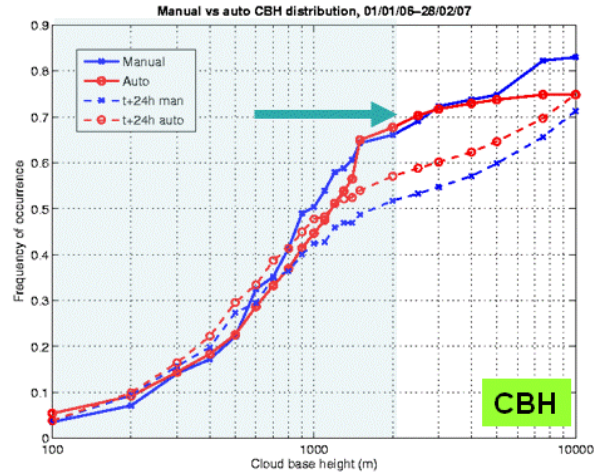
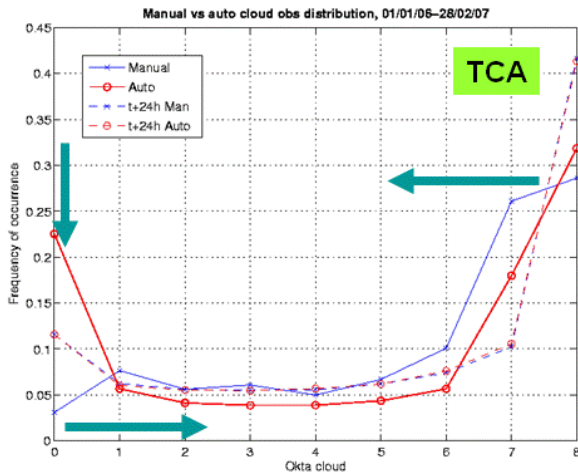


Verification with different datasets leads to different results: which is right?



# TCA and CBH distributions

- 14 months of data for Block 03 stations
- Auto obs have greater proportion of no cloud (due to instrument limitations, can't see high cloud)
- Observers hedge away from the "boundaries".
- For CBH artificial cloud ceiling visible in cdf

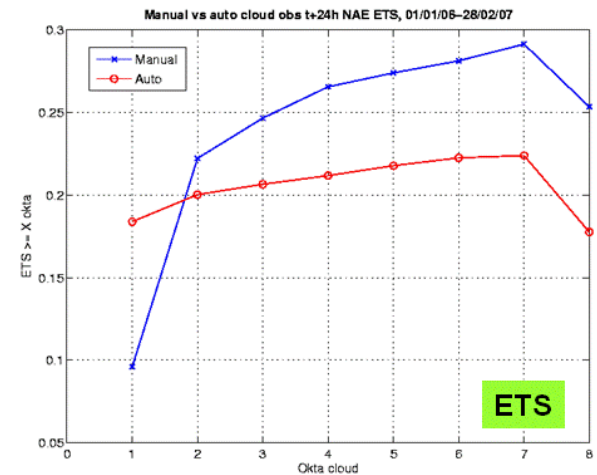
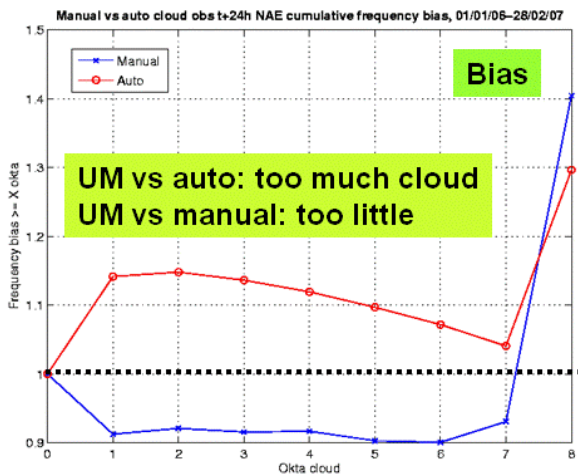


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# How does ob type affect verification measures?

In the UM we discovered that use of manual and auto TCA leads to biases of equal but opposite magnitudes.



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# DA vs verification



## Observations treatment

- DA and verification **both require observations** *BUT* the type, treatment, temporal resolution of observations used may be quite different.
- **Verification (in near real-time) relies heavily on the obs QC that DA provides**, using assigned flags to determine whether an ob is safe to use (other non-DA based obs QC takes a lot longer)
- **Independent observations analysis systems** (that do not rely on model background checking) are rarely available.



## Observations treatment in DA

1. Observations received, check whether in time window, unit conversion and re-mapping
2. QC – **“probability of gross error”**
  - Updating of “reject lists”
  - Background checking (O-B) and buddy checking etc
  - Update obs QC flags
3. Data thinning for satellite obs (in both space and time) – all satellite obs tend to be QC'd



# Impacts of observations handling

## DA

- ✓ **Error tolerant** but sensitive to gross errors
- ✓ O-B at observation time
- ✓ PGE different for each model so observation sets may differ
- ✓ DA is run at **coarser** resolution than the forecast
- ✓ Linear model assumptions and interpolation methods
- ✓ Error inflation
- ✓ Thinning results in a self-selecting partial non-random sample

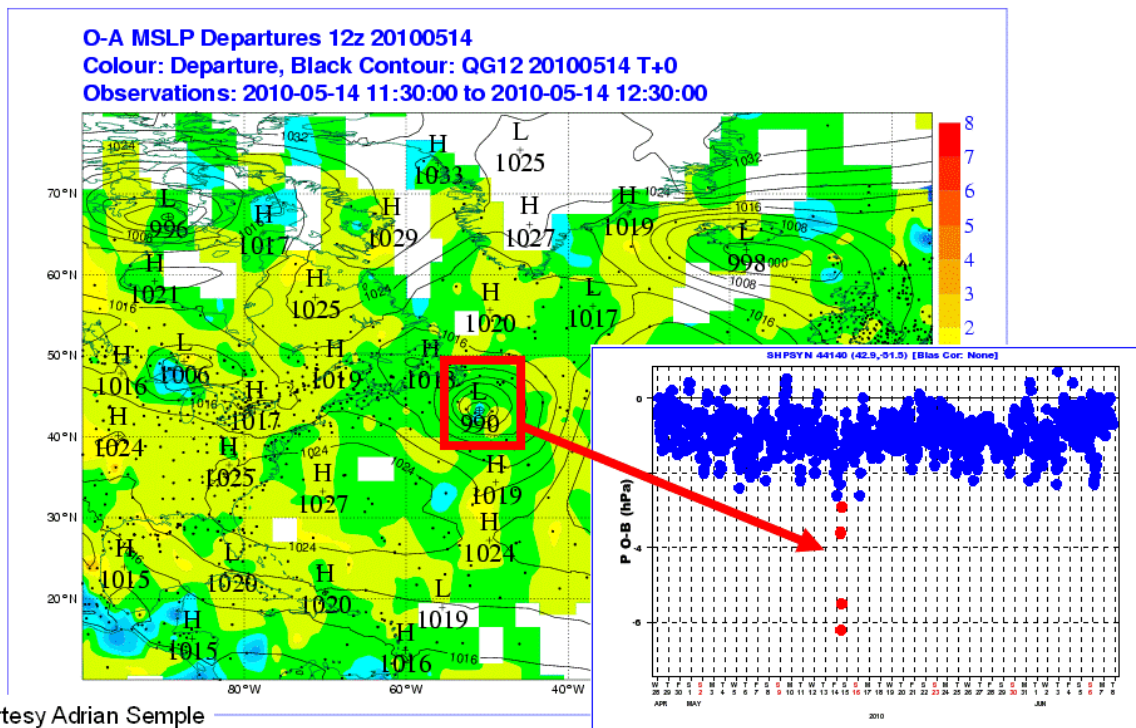
## Verification

- ✗ **Error intolerant**, dependent on DA QC flags
- ✓ F-A at validity time
- ✗ Want the same obs for comparison of different models
- ✓ Forecast models are at **finer** resolution
- ✓ Impacts the QC flags so good observations may be rejected
- ✗ Forecast skill under-estimated
- ✓ Issues with non-independence

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# Data filtering for assimilation and QC





# Case study: OPERA European radar composite

- Two strands:
  - Data assimilation
  - Verification

• **Stage 1: establish quality and advise on usefulness, make suggestions for improvements**

| Region         | OPERA vs Operational | No Precip vs Operational |
|----------------|----------------------|--------------------------|
| NAE            | -0.02%               | +0.01%                   |
| Mes            | -0.13%               | -0.13%                   |
| UK Index List  | -0.42%               | -0.69%                   |
| WMO block 3    | -0.27%               | -0.32%                   |
| Scandinavia    | -0.07%               | 0.0%                     |
| France         | -0.26%               | -0.02%                   |
| Iberia         | +0.85%               | +1.60%                   |
| Germany        | -0.29%               | -0.05%                   |
| Central Europe | -0.21%               | -0.13%                   |
| Eastern Europe | +0.21%               | +0.29%                   |

**Negative impact over UK –**  
OPERA degraded product compared to Nimrod

**Negative impact over France –**  
OPERA is degraded product compared to Oper

**Positive impact over Spain and Eastern Europe -**  
OPERA represents additional info available here

From Mittermaier et al, 2008

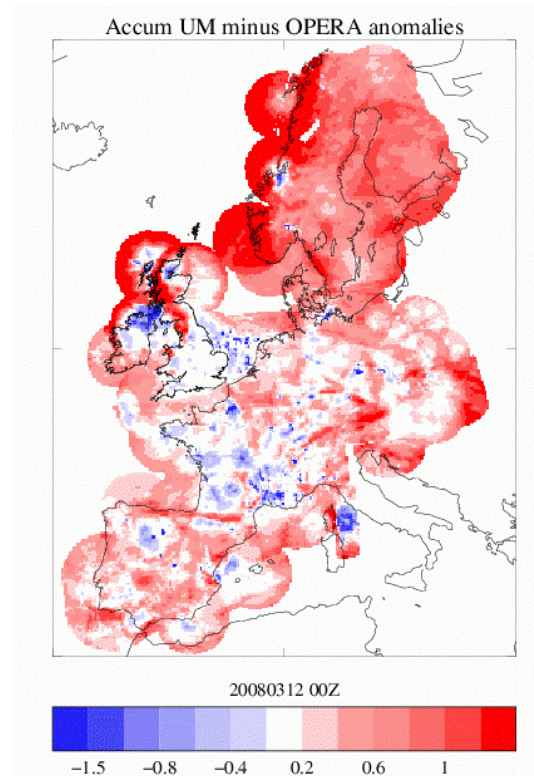


## OPERA anomalies

- **Use the model forecasts as truth** to consider observations inconsistencies and errors.
- **35 days** accumulated normalised anomalies
- Computed from detrended model forecasts and OPERA accumulations.
- Pick out areas of:
  - **Range problems** and **cold season bias**
  - **Anaprop**
  - **Bright band**

From Mittermaier et al, 2008

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# The dreaded “verifying analysis”



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## Analyses: different flavours

- **Forecast analysis:** here the purpose is provide the best estimate of the atmospheric state for the *model to produce the best possible forecast sequence*.
- **Observations analysis:** here the objective is to *match the observations as precisely as possible* to produce the best possible high-resolution estimate of the current atmospheric state. No forecast is produced from this. Variational and statistical techniques are used, but the use of model background fields is optional.
- **Re-analysis:** here the desire is to fix the method for creating the analysis, and produce a *retrospective dataset of analyses* which are used for model re-runs (of old case studies) and validation.

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## Why do we want to use gridded analyses for verification?

- **Sample size and coverage** – get the “bigger picture”
- **Ease of use** – “hides” the observations, QC process has been done, consistent etc
- **Availability** - most created as part of the forecast process
- **Improved sampling of spatially discontinuous parameters** e.g. cloud and precipitation
- High-resolution models suffer from poor verification results when compared at isolated points

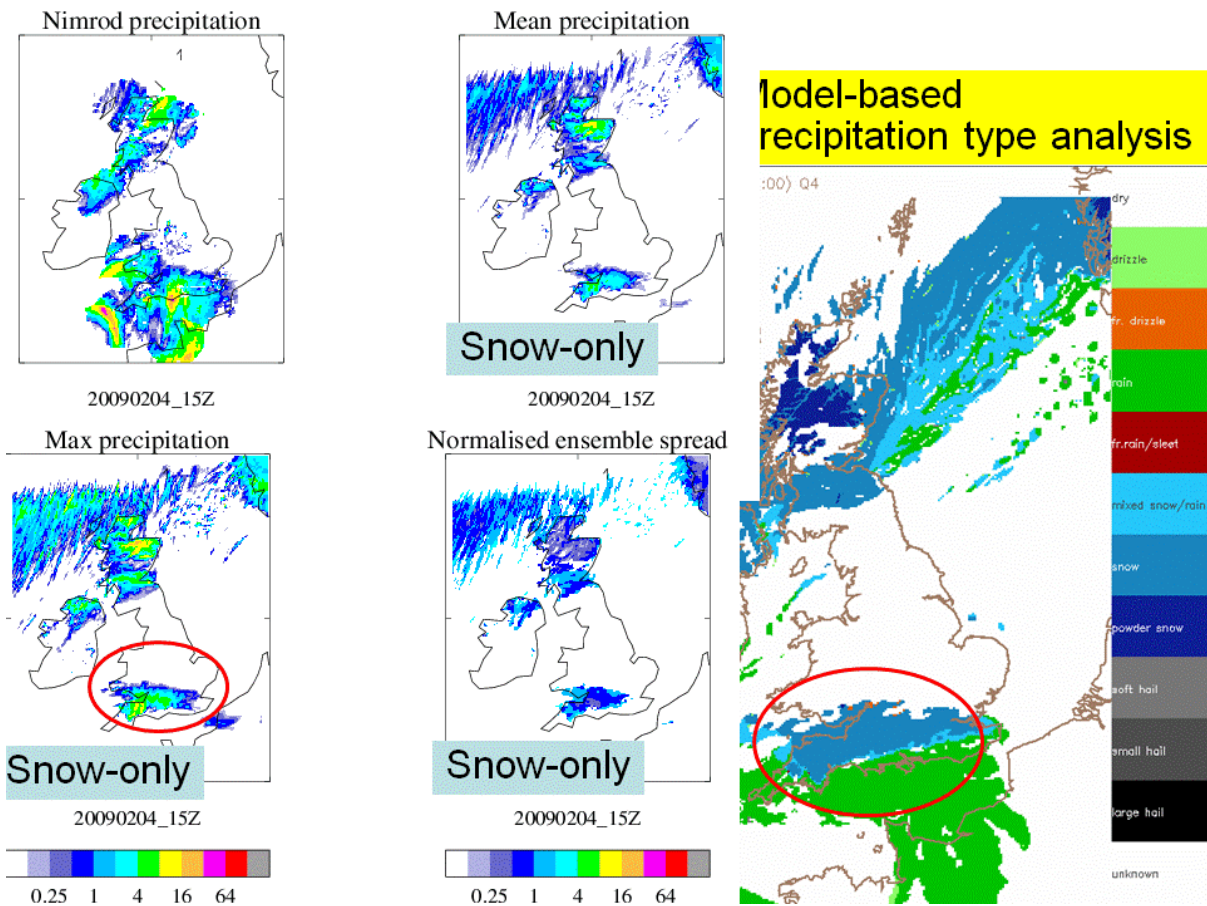




# The issues with using analyses

- **Non-independence**, adjacent grid points correlated in space and time. This reduces the degrees of freedom of verifying sample.
- **Local effects** not always well captured, or too much local (spurious?) detail – **resolution**
- **Method** - created as part of the forecast process. Need to verify the analysis, can only do this at observations locations. Even so, **is this form of “truth” accurate elsewhere?** How does one know? **Need for cross-validation**; impact of **observations denial**?

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# Dealing with observations errors in verification



## Approaches for coping with observational uncertainty

- **Indirect estimation** of observations uncertainties through verification approaches
- Incorporation of uncertainty information into verification metrics and **developing new methods that lessen the impact** (e.g. Roberts and Lean MWR, 2008, ICP special collection in WF)
- **Treat observations as probabilistic** (e.g. Candille and Talagrand)
- **Assimilation** approaches
- **Perturbing ensemble members** with observation error



## Direct approaches for coping with observational uncertainty

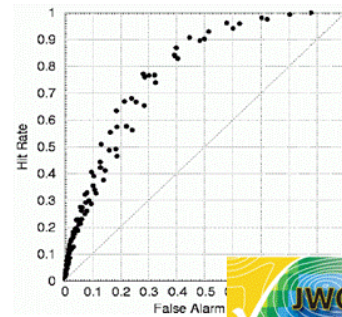
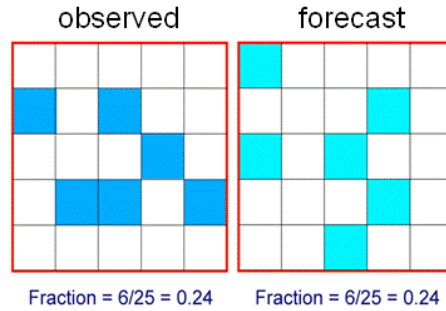
- Compare forecast error to known observation error. Can we be as simplistic as:
  - If forecast error is smaller than obs error then
    - A good forecast ✓
  - If forecast error is larger, then
    - A bad forecast ✗
- **What about testing improvements?** How can you know you are making the forecasts better when the improvement signal is in the “noise”?



# Indirect approaches for coping with observational uncertainty

(Roberts and Lean, 2008)

- **Neighbourhood** or fuzzy verification approaches
- Other spatial methods (see the special collection in WF on the Inter-Comparison Project (ICP) of spatial verification methods)



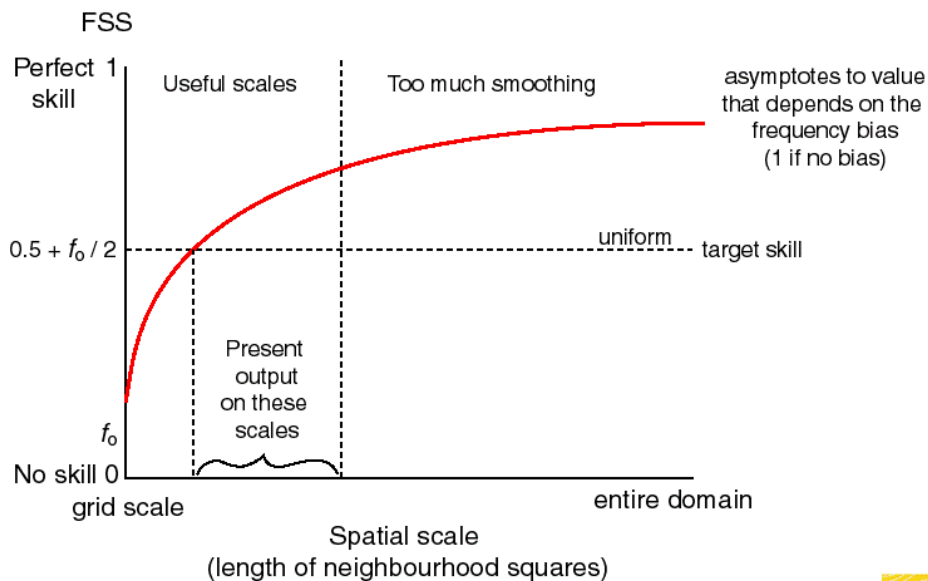
(Atger, 2001)

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# Fractions skill score

(Roberts and Lean, MWR, 2008)



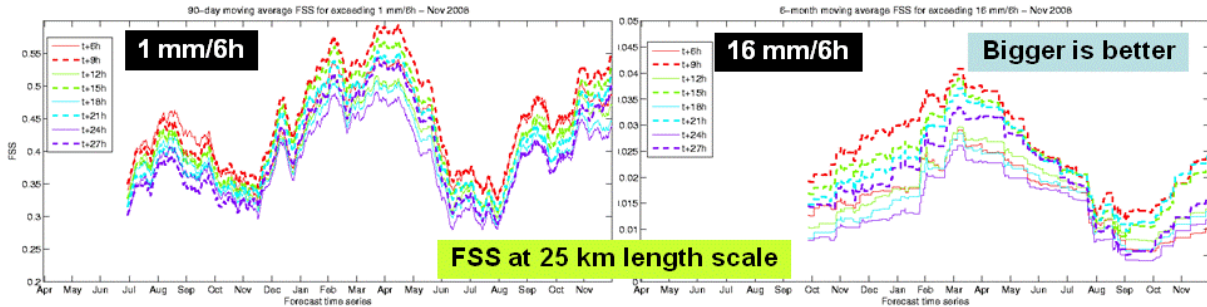
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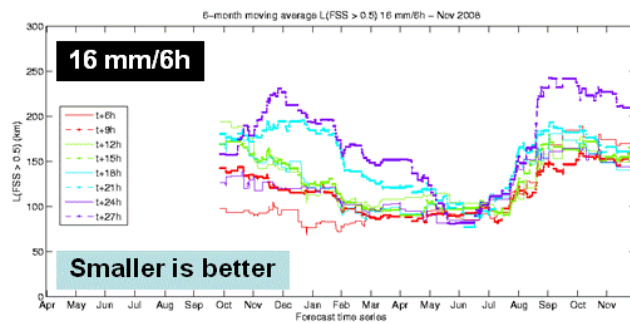


# A “belt-and-braces” approach

Bundle up all sources of error, no direct attribution



- Is high-resolution (dashed) better than coarser resolution?
- Length scale which is skilful?



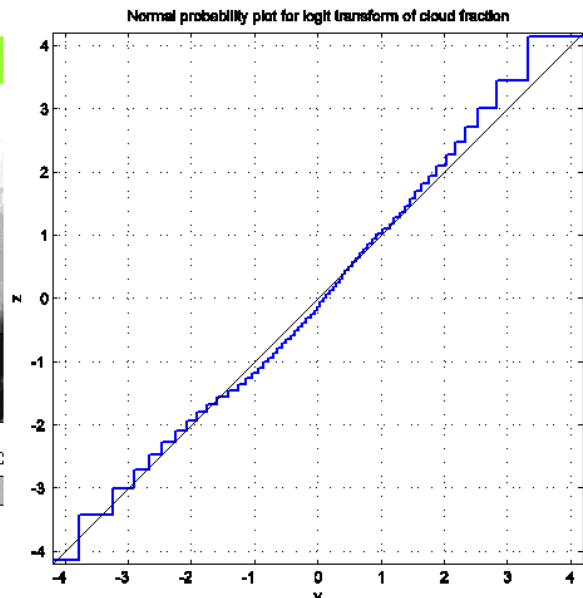
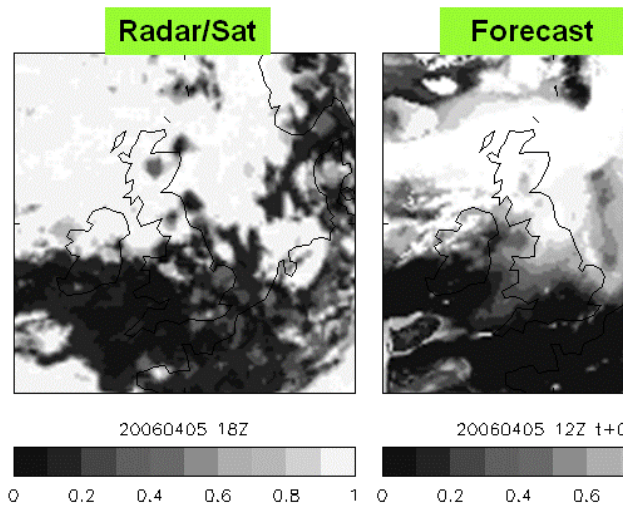
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## Remotely sensed cloud products: the way forward?



### Intensity-scale method

(Casati et al, 2004)







## Conclusions

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1. Verification is much **more strongly dependent on the availability of quality observations**.
2. The **characteristics** of the (model) parameters and the observations required to assess them, **must be well understood** for verification, if the results are to be meaningful (i.e. assessing forecast skill).
3. **Interpretation of conflicting results** from different observation types present a considerable challenge and must be treated with care.
4. Increased horizontal (and vertical) model resolution necessitates a search for new verification data sources. **New data sources will require new verification tools and strategies. A LOT OF PROGRESS HAS BEEN MADE.**
5. **Satellites** may provide a useful dataset of remote cloud characteristics, both for the end user and the model physics developer.

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## Strategic direction

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- **The concept of using satellite observations needs to be proven to be computationally statistically viable.**
- **Spatial verification methods** need to be:
  - Used for routine verification of high-resolution precipitation forecasts, to prove that they are indeed getting better.
  - Proven for other variables, using analyses or gridded data sets.
- **Error sources** and magnitudes need to be better understood and quantified.
- **Prevent good observations from being rejected!** Investigate how observations are tagged.
- **Instigate best practice for data denial** to test credibility of analyses.
- Invest more in the development of **“independent” analyses**.
- **Generic uncertainty measures** need to be developed that can be sensibly incorporated into the standard routine verification processes.
- **Greater use of error bars and use of hypothesis testing** for assessing the impact of model changes.

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