Improving Numerical Weather Forecasts by Clustering

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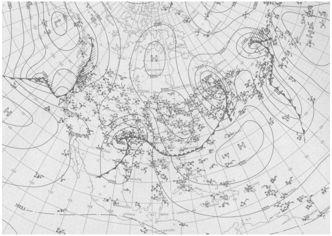
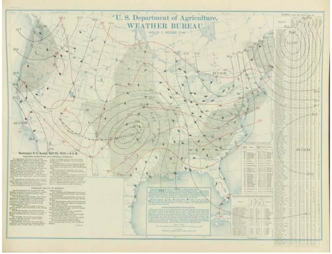
Traditional (judgmental) forecasting

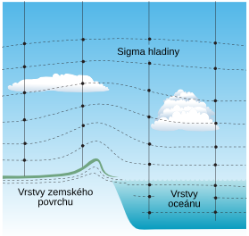




Forecast made by expert(s) using solely measurements and own knowledge/experience.

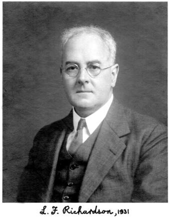
- Analyzing and modifying synoptic maps by hand
- Spot observations from previous day(s)
- Mostly general circulation
- Typical outputs:
    - Greater areas (hundreds of km)
    - Daily averages and/or extremes

Numerical weather prediction (NWP)



source: Australian Boureau of Meteorology

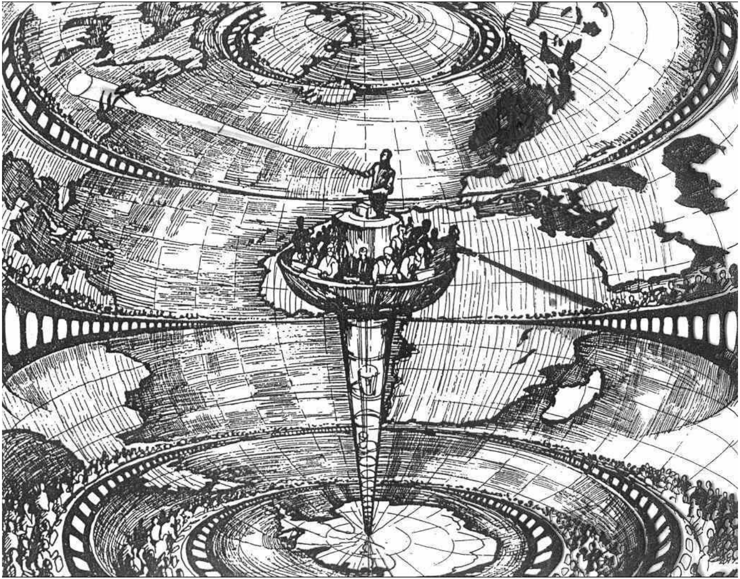
- State variables on a grid
- Navier–Stokes equations, thermodynamics
- L. F. Richardson, 1920's:



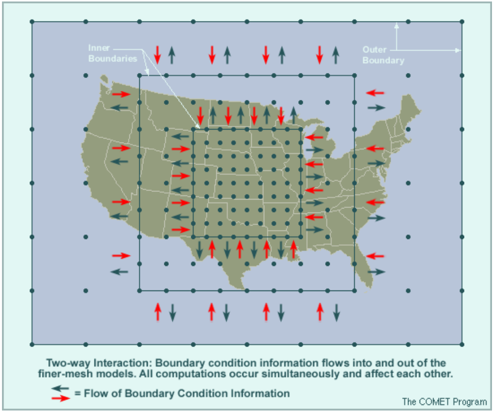
2 points, 6 hours forecast ⇒ 6 weeks computation

- Nowadays: resolution in order of km, weeks ahead

Richardson's NWP



Nested domains



1. Global models
   - data assimilation
   - probabilistic forecast
2. Mesoscale models (LAM)
   - grid nudging, nestdown and nesting

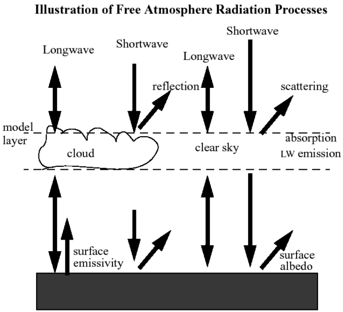
Parametrizations

- Parametrization = (statistical) simplification
- Processes of too small scale
- Modular
- Configuration and tuning

Example

Convection, PBL, ground surface, microphysics, radiative transfer.

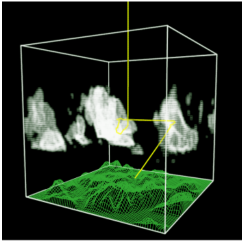
Modeling radiative transfer



Main processes

- Absorption
- Scattering
- Reflection

- Subgrid level



Important inputs

Solar geometry, albedo, atmospheric water, aerosols, ozone

Deficiencies of all–purpose NWPs

Model variables

state (prognostic) variables × derived (diagnostic) variables

- Not all model variables are regularly and properly evaluated
- Even derived variables might be tuned for model internals (e.g. radiation → heat fluxes)
- Well-captured overall weather state doesn't imply precise prediction of each variable

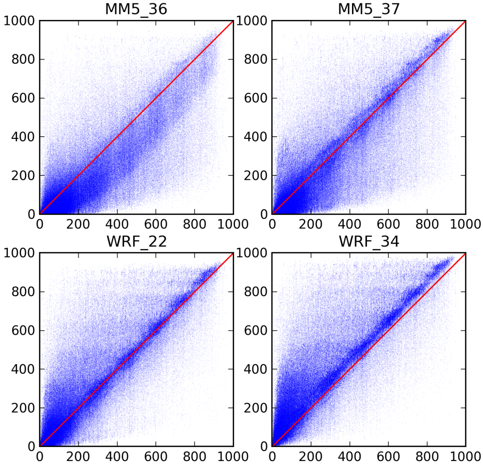
Postprocessing

- Measured error in many variables can be reduced by statistical postprocessing
  - local bias (spatial representativity)
  - similar weather patterns
- Shortwave irradiance errors: stratification (E. Lorenz et al.)
  - solar zenith angle ϑ_t
  - clearness (clear-sky) index k_t

$$GHI_t = ETR_t \cdot k_t \cdot \cos \vartheta_t$$

Multi–model prediction

- Combination of models with uncorrelated errors = strong improvement
  - different initial & boundary conditions
- Some improvement even with strongly correlated models
- MM5 and WRF: various radiation schemes and model versions



Weather classification and clustering

- Localized weather classification
  - Pasquill–Gifford stability class
- Synoptic classification
  - standardized, yet based subjective similarity
- NWP based clustering
  - analog ensembles (probabilistic forecast)

Experiment design

Idea: Combine weather type clustering, postprocessing and multi–model forecasting

Goals: Explore relative advantages of different NWPs under different weather conditions, outline possible model improvement

Conditions:

- Clustering input variables based on loosely defined target (expected relative model performance)
- High dimensionality of input data
- Explanatory result expected – shouldn't use e.g. PCA

Method

1. Use CART regression tree (forest) learning with vector of model deviations as a target variable
2. Identify clusters defined by leaf nodes
3. Optimize weights for linear combination of models within each cluster
    - bias removed directly
    - relative model performance expected indirectly (depth and branching limits)

Input data

Measurements:

- Hourly averages of global horizontal irradiation (GHI)
- 15 professional weather stations operated by CHMI

Forecasts:

- Four NWP models: MM5 3.6, MM5 3.7, WRF 2.2, WRF 3.4
- Identical nested domains
  - 9×9 km horizontal resolution covering Czech Republic
  - 27×27 km covering central Europe
  - NCEP GFS initial and boundary conditions
- Simulated operational regime
  - new forecast every 6 hours, 48 hour horizon
  - May 2011 to April 2012

Split by date: 20 × 18-day segments (15 days training + 3 days validation)

Meteorological variables for clustering

Meteorological variables:

- Air temperature at 2 m
- Air humidity at 2 m
- Wind at 10 m
- Precipitation amount
- Surface air pressure
- Planetary boundary layer height
- Water vapor & different precipitation types
  - low, medium and high altitude

Other predictors:

- Clearness index
- Extraterrestrial solar radiation
- Solar geometry
- Season indicator
- Latitude and longitude
- Terrain height

Experiment results and control results

Model	RMSE $[W \cdot m^{-2}]$ in-sample	RMSE $[W \cdot m^{-2}]$ out-sample
MM5 3.6		158.0
MM5 3.6 ⊙	140.4	144.0
MM5 3.7		146.5
MM5 3.7 ⊙	141.4	149.3
WRF 2.2		140.7
WRF 2.2 ⊙	123.1	121.6
WRF 3.4		167.9
WRF 3.4 ⊙	131.4	133.7
Simple combination	115.1	115.4
Combination of ⊙	114.3	115.7
Stratified combination	113.6	115.8
Random forests	106.3	113.2

⊙ = bias correction on stratified data

Further research

- Complex spatial information
  - only point forecasts used so far
  - spatial averages, differences and variances: metalearning of sizes and (relative) positions of areas
- Purposely excluded: localized learning
  - usually huge improvement against local measurements
  - not so usable for analyzing behavior