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Machine Learning for Parametrization

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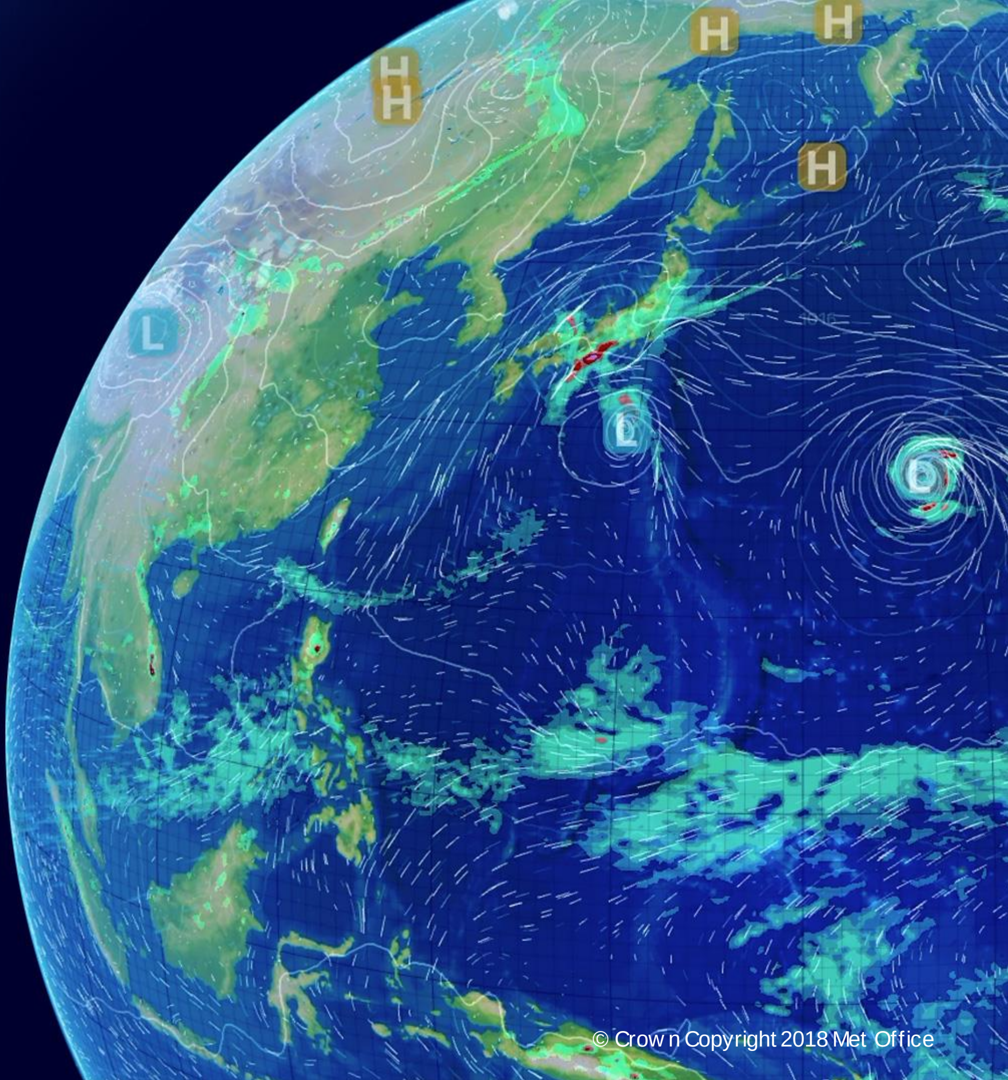

Aim of the project

- Can parametrization schemes be cheaply emulated using ML?
- Why parametrization?
  - Computational cost: N1280 on 530 nodes: 60% dynamics 35% physics.
  - Worst offenders: Convection, Boundary Layer, Microphysics, GW drag, Radiation
- Why emulate existing schemes?
  - (Almost) unlimited training data available
  - Known inputs
  - Potentially frees model developers from operational constraints.
- Why Radiation?

UM radiation scheme: SOCRATES

- Expensive - full calculation is only run hourly in global UM
- Stand-alone code - can be driven offline
- High resolution configuration can be used to generate ‘truth’ data for training (narrow-band model):
  - Current Global UM (GA7) configuration: 9 bands in LW, 6 bands in SW
  - Narrow-band configuration: 300 bands in LW, 260 bands in SW
- Community model used in many other centres

Data pipeline

- Global model GA7 at N320 (640 x 480, ~40km grid spacing)

1. 4 sample dates (winter, summer, spring, 2 different years)
2. Extract clear-sky columns (and day columns for SW)
3. Create offline driving files for SOCRATES inputs (T, p, q, etc.).
4. Mass mixing ratios (MMRs) for GH gases (CO_2, O_3, CFCs etc.) randomly perturbed.
5. Random 50K sub sample for quick development / testing.
6. SOCRATES driven offline using GA7 and narrow-band configurations.

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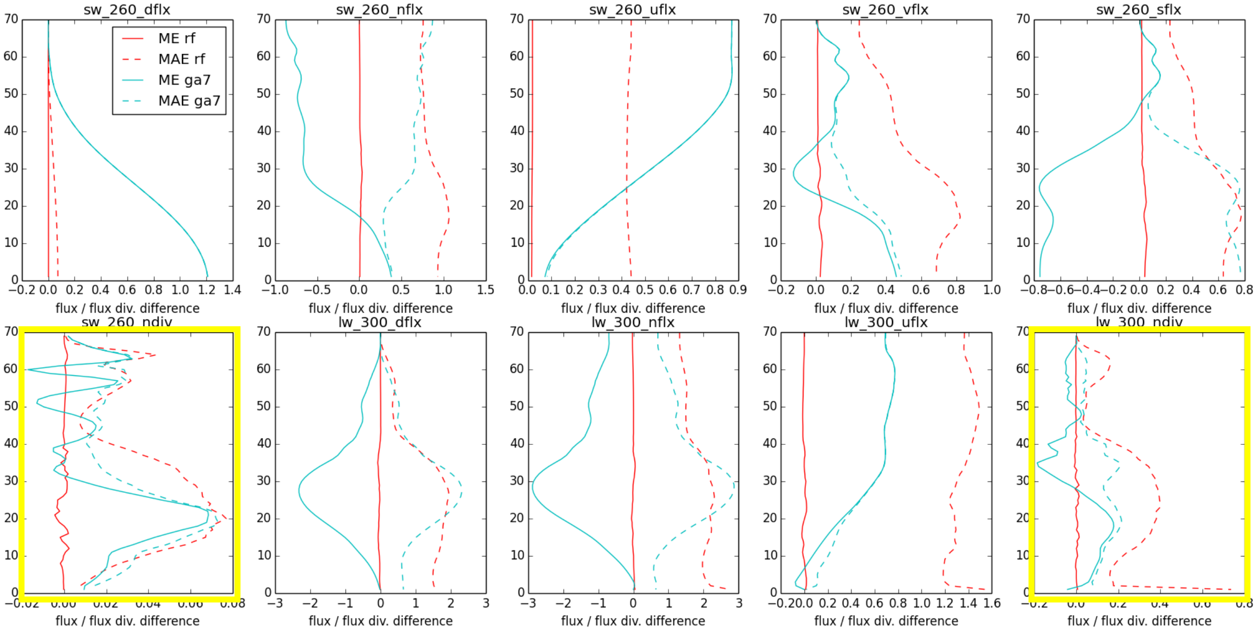
Results – random forest regressor

- Vertical profiles of flux differences w.r.t narrow-band model (0 = surface)
- Mean Error / bias (ME)
- Mean Absolute Error (MAE)
- RF emulator has very low bias and similar MAE to GA7

- Flux divergence (highlighted plots) was targeted directly. It is critical to model dynamics



Where next?

- Inclusion of clouds / aerosols
  - Clouds are a major source of uncertainty – currently handled by a Monte-Carlo sampling strategy in SOCRATES (See SOCRATES technical guide).
- Custom loss functions
  - All errors were treated equally in these tests, but in an operational setting errors near the surface are more important, so some kind of weighting profile is needed (e.g. Hogan, R.J., 2010, J. Atmos. Sci., 67, 2086–2100, https://doi.org/10.1175/2010JAS3202.1)
- Alternative ML methods
  - A single hidden layer MLP did not perform as well as the RF on this test data set, but other methods (particularly ANNs) may perform better with more training data.
- Feature engineering
  - No attempt was made to modify the input features, and there is considerable redundancy in some (e.g. state variables defined on both levels and layers), so some sort of feature manipulation (e.g. feature engineering, or the use of convolutional NNs) could be beneficial.