An idealised setup for future experiments in satellite data assimilation research

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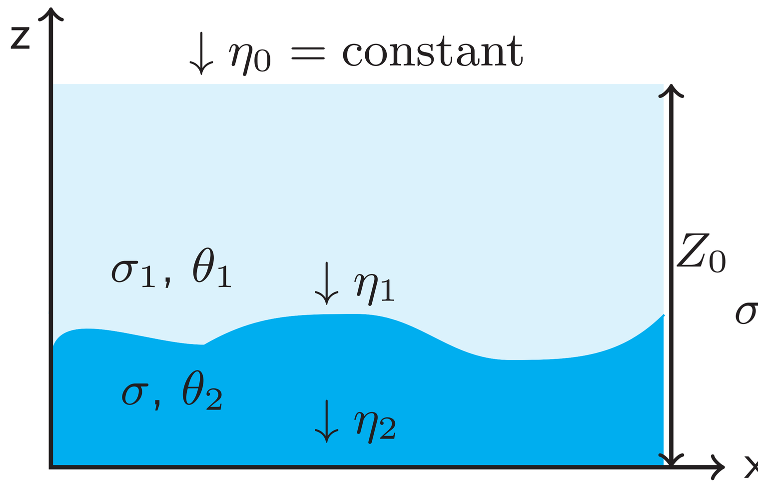
1. Objective

Operational data assimilation (DA) schemes rely significantly on satellite data. Our aim is to investigate **the impact of satellite observations of different spatial-temporal scales**: is there a case for concentrating effort into the assimilation of small-scale features over the large-scale dynamics, or vice versa?

2. The 'isenRSW' model

We conduct our study with an **idealised model**: an isentropic 1.5D 1.5-layer model based on modified shallow water equations, able to mimic convection and precipitation (**no topography**). This is an updated version of the model developed by Kent et al. (2017).



$$T_i = \theta_i \eta_i^{\kappa},\ i = 1, 2$$
$$\kappa = \frac{R}{c_p}$$
$$\sigma_i = \frac{p_{ref}}{g}(\eta_i - \eta_{i-1})$$

In the sketch above: θ_i is the potential temperature, η_i the (non-dimensional) pressure, T_i the temperature, R the specific gas constant for dry air, c_p the heat coefficient at constant pressure, g is the gravity acceleration and p_{ref} is a reference pressure. The non-dim system of eqs. reads:

$$(\sigma)_t + (\sigma u)_x = 0, \tag{1a}$$
$$(\sigma u)_t + \left(\sigma u^2 + \mathcal{M}(\sigma)\right)_x + \sigma c_0^2 r_x = \frac{1}{\mathrm{Ro}}\sigma v, \tag{1b}$$
$$(\sigma v)_t + (\sigma u v)_x = -\frac{1}{\mathrm{Ro}}\sigma u, \tag{1c}$$
$$(\sigma r)_t + (\sigma u r)_x + \beta \sigma u_x + \alpha \sigma r = 0, \tag{1d}$$

in which: Ro is the Rossby number, $\mathcal{M}$ the effective pressure, σ is the layer pseudo-density, u and v are the zonal and the meridional velocities and r is the 'mass rain fraction': a proxy for precipitation. **Convection and rain are triggered by a threshold mechanism** for σ:

$$\mathcal{M}(\sigma) = \begin{cases} \mathcal{M}(\sigma) & \text{if } \sigma < \sigma_c, \\ \mathcal{M}(\sigma_c) & \text{if } \sigma \geq \sigma_c, \end{cases} \tag{2}$$

$$\beta = \begin{cases} \tilde{\beta} & \text{if } \sigma \geq \sigma_r, u_x < 0, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

with $\sigma_c < \sigma_r$. α, $\tilde{\beta}$ and c_0^2 are additional model parameters controlling: the removal of rain (α), its production ($\tilde{\beta}$) and the suppression of convection (c_0^2), respectively.

3. Data assimilation with the 'isenRSW' model

We exploit a **twin-setting** configuration and use a **Deterministic Ensemble Kalman Filter** (DEnKF, as per Sakov & Oke, 2008) for data assimilation.

Model $\xrightarrow{\text{high-res}}$ Nature run x^t $\longrightarrow$ Observations y^o $\longrightarrow$ EnKF

Model $\xrightarrow{\text{low-res}}$ Forecast x^f $\longrightarrow$ EnKF

4. The observing system

A set of pseudo-observations is derived from the nature run at each analysis step. The observation vector $\mathbf{y}^o$ is made of **ground** and **satellite** observations.

Satellite observations

Derived from the pseudo-density σ, we recreate vertically integrated **passive microwave radiation** B_{sat} (see section 5) and use the Rayleigh-Jeans law as radiative scheme. The non-dimensional radiation in each layer B_i is:

$$B_i = \eta_i^{\kappa}. \tag{4}$$

To mimic polar-orbiting satellites, 1D approximation: our satellite moves at constant v_{sat} and reenters the domain periodically (of length L). Observations B_{sat} at time t will be located at:

$$x_{sat} = v_{sat} \cdot t \bmod L. \tag{5}$$

Each B_{sat} observation is a **weighted contribution from each layer** (see also section 5) and is also a **weighted horizontal average** that tries to reproduce a satellite's Field of View (FOV) of width Δx:

$$B_{sat}(x_{sat}) = \frac{\int_{x_{sat}-\Delta x/2}^{x_{sat}+\Delta x/2} B(x) w(x)\, \mathrm{d}x}{\int_{x_{sat}-\Delta x/2}^{x_{sat}+\Delta x/2} w(x) \mathrm{d}x}, \tag{6}$$

in which $w(x)$ is Gaussian function centered on $x_s at$ with a width comparable to Δx.

Ground observations

Variables such as u, v and r are assimilated at fixed evenly spaced locations along the domain (e.g. one each $\sim 50-80$ km, N.B. tunable) at each analysis step.

5. Modeling clouds

We exploit the 1.5-layer configuration to generate pseudo-vertically integrated values of radiance:

$$B_{sat} = \alpha_1 \cdot B_1 + \alpha_2 \cdot B_2. \tag{7}$$

α_1 and α_2 (see Figure 2, left panel) are chosen such that our system can mimic the response of passive microwave radiation to the presence of both non-precipitating and precipitating clouds, exploiting the convection and the rain threshold σ_c and σ_r:

$$\begin{aligned} \sigma < \sigma_c < \sigma_r \quad & \text{clear} - \text{sky conditions}; \\ \sigma_c < \sigma < \sigma_r \quad & \text{non} - \text{precipitating clouds}; \\ \sigma_c < \sigma_r < \sigma \quad & \text{precipitating clouds}. \end{aligned}$$

Generally speaking, emitted microwave radiation is absorbed by non-precipitating clouds and scattered by precipitating ones. Above low-emissivity surfaces (i.e. the ocean), this turns into an increase in the radiance reaching the sensor in the presence of non-precipitating clouds and a decrease when precipitating clouds are present. This is the physical mechanism we are trying to imitate (see Figure 2, center panel).

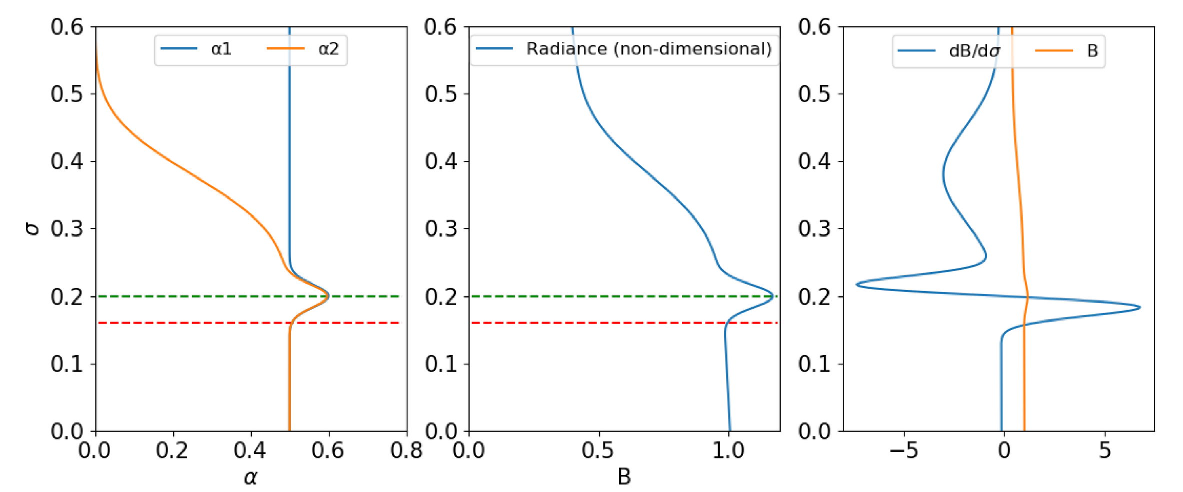


Figure 1: Plots of α_1, α_2 (left panel), B_{sat} (central panel) and $\partial_\sigma B_{sat}$ (right panel) as a function of the pseudo-density in the bottom layer σ. The red and green dotted lines indicate the convection (σ_c) and the rain thresholds (σ_r), respectively.

6. Observation operator

A Deterministic Ensemble Kalman filter is used and the linearisation of the observation operator (i.e., $\mathbf{H} = \nabla \mathcal{H}$) is performed to compute the Kalmain Gain $\mathbf{K}$, so that ensemble covariance localisation can be mantained in physical space. The right panel of Figure 2 shows the only non-trivial element of this (sparse) matrix, namely $\frac{\partial B_{sat}}{\partial \sigma}$, as a function of σ. The fully non-linear observation operator is used in the innovation vector.

7. The nature run

The nature run is the high-resolution deterministic model integration from which we derive the pseudo-observations to be used in the data assimilation scheme. The one shown below represents a dynamically interesting case (with continuous production of convection and rain) and will be used in our future forecast-assimilation experiments.

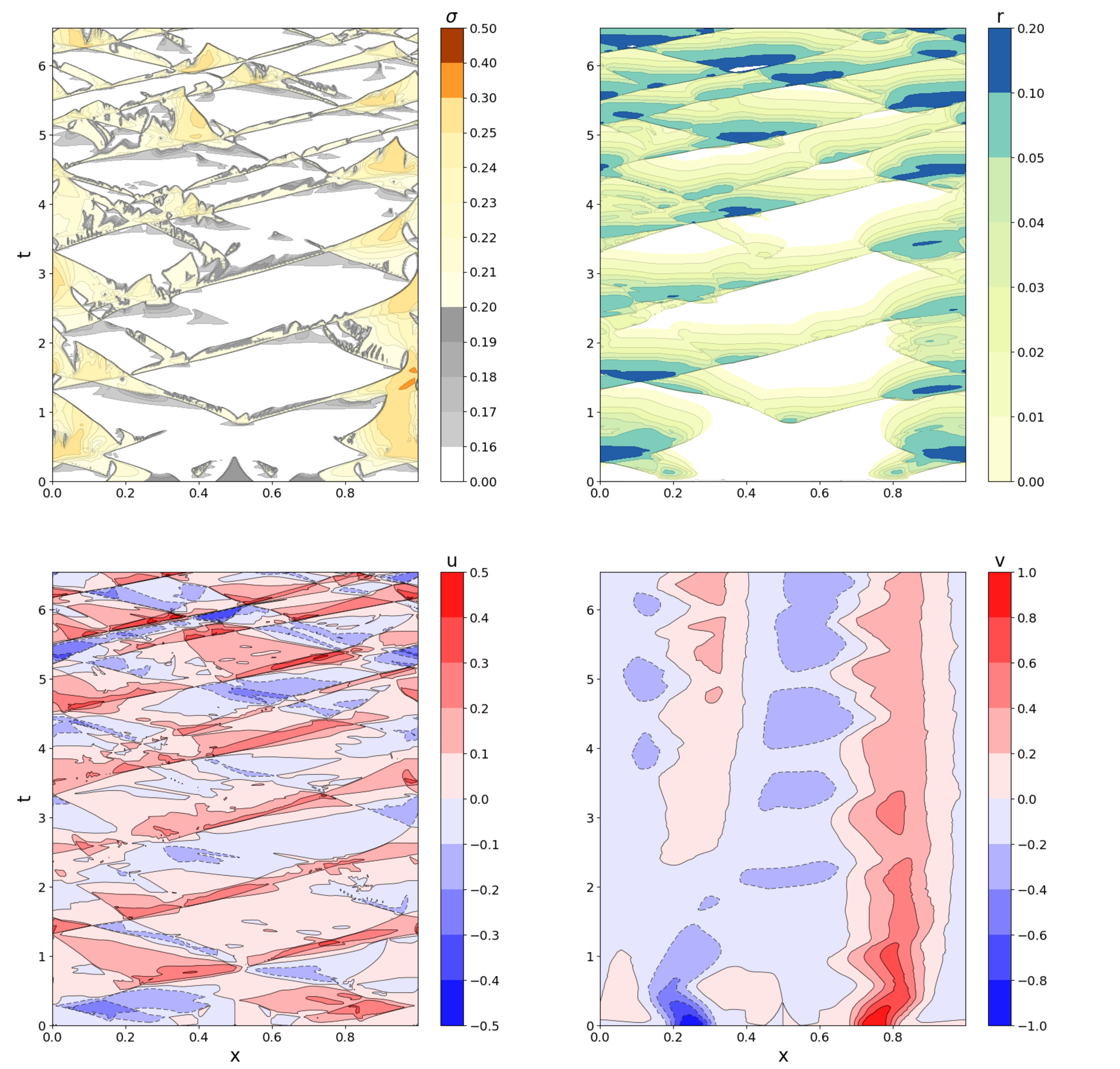


Figure 2: Hövmoller plots of the model evolution for each variable. Model parameters: $\theta_1 = 300$ K, $\theta_2 = 290$ K, $Z_0 = 11000\ m$, $\eta_0 = 0.22$, $\sigma_c = 0.16$, $\sigma_r = 0.2$, $\alpha = 5.0$, $\tilde{\beta} = 0.8$, $c_0^2 = 2.0$, $\mathrm{Ro} = 0.4$.

8. Conclusions

- We have developed an isentropic 1.5-layer model to conduct future forecast-assimilation experiments relevant for satellite DA research;
- We have shown a dynamically interesting nature run simulation, our test-bed for future experiments;
- We have recreated a complex observing system that mimics satellite observations of passive microwave radiation taking also into account the effect of clouds and precipitation.

9. Future work

Starting from the setup described here, idealised forecast-assimilation experiments will follow, to investigate the impact of satellite observations of different scales: for example, this can be achieved by varying Δx. The addition of more satellite observations to the observing system will be explored if required.

References:

[1] Kent, T., Bokhove, O., & Tobias, S. (2017). Dynamics of an idealized fluid model for investigating convective-scale data assimilation. Tellus A: Dynamic Meteorology and Oceanography, 69(1), 1369332.

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