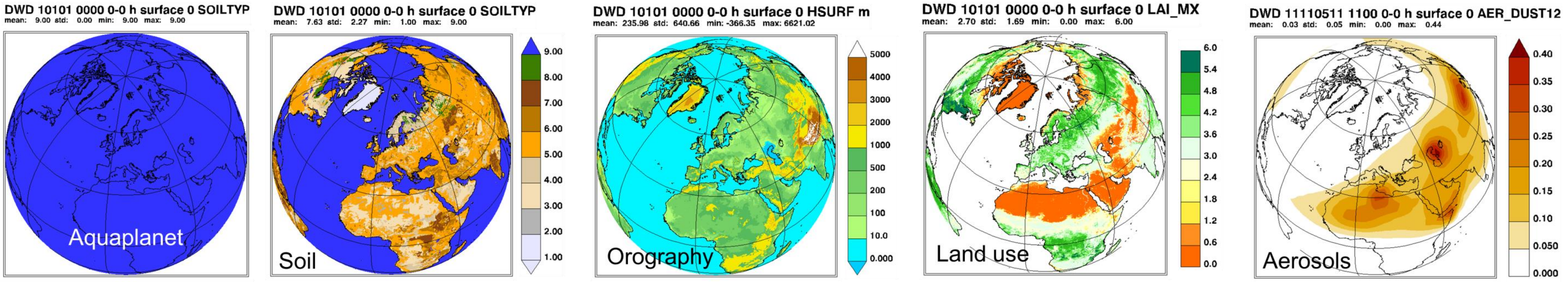
Advancing ancillary parameters and soil processes for numerical weather prediction at DWD

J. Helmert, L. Schlemmer, G. Zängl

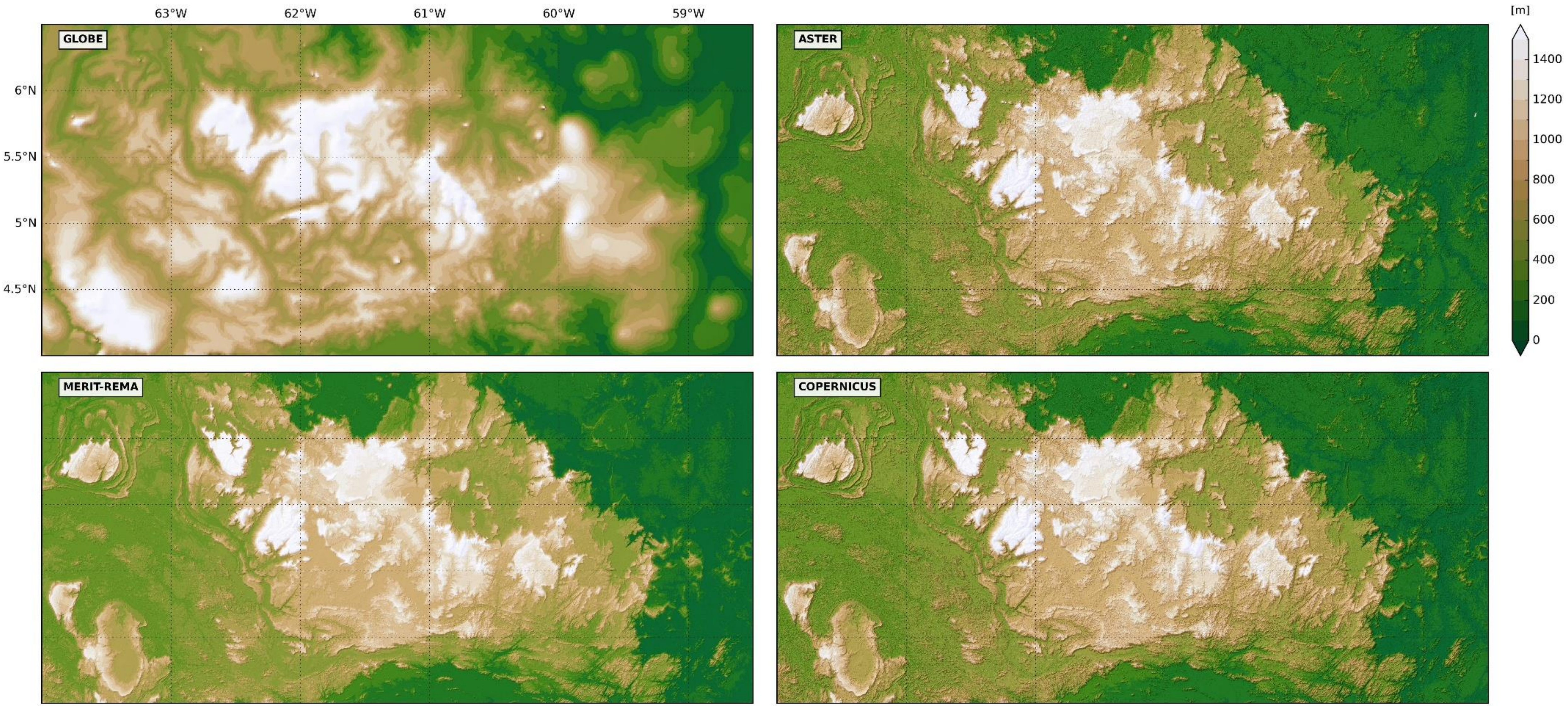
Importance of Geospatial Datasets

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



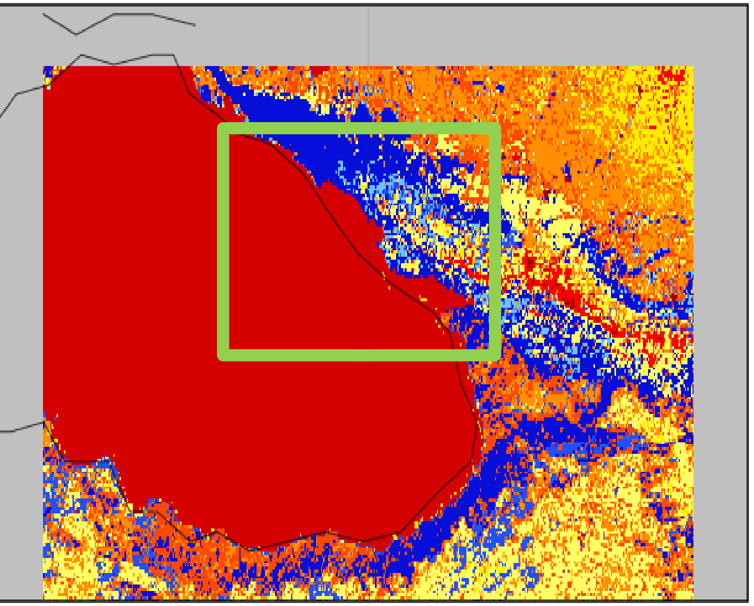
- Geospatial or ancillary or physiographic or external data are retrieved from high-resolution satellite information or land registers and are aggregated to the model’s global or limited-area grid.
- In a final processing step all available data are cross-checked for consistency (e.g., to exclude vegetation on glaciers).
- The required model parameters are very similar for NWP models, but the used data sources and the applied tools vary between different models – i.e. different mapping of geospatial information (Onvlee et al, 2014).
- External parameters provide foundational inputs but introduce biases due to resolution limits, heterogeneity, or outdated datasets (e.g., land use maps affecting roughness lengths).

Motivation: DEM uncertainties

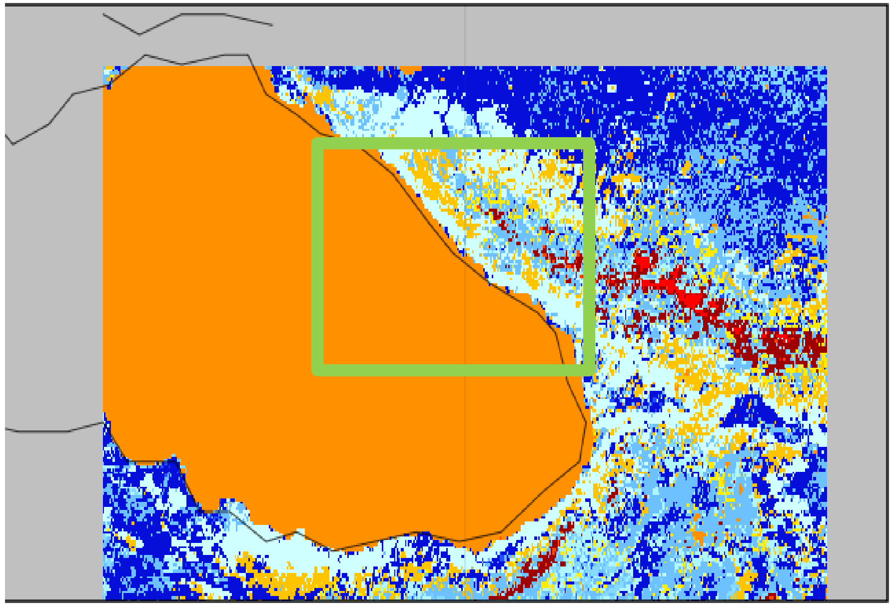


Ch. Steger, MeteoSwiss

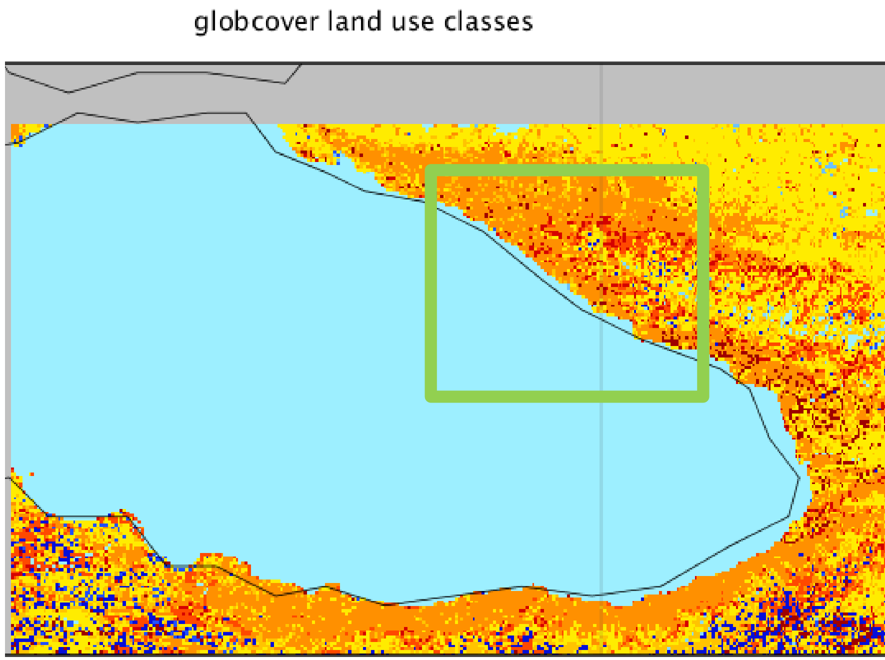
Motivation: Land-use uncertainties



GLC2000 land use classes



GLCC USGS land use / land cover system



Globcover 2009
(in ICON used to derive land-sea mask)

Problems in land-sea mask for GLC2000 at Black-Sea coastline

Motivation

- Systematic biases in NWP models like ICON often stem from uncertainties in external parameters (e.g., orography, albedo, land use, soil texture), leading to errors in near-surface forecasts (e.g., T2M, RH2M, FF10M).

- Adaptive Parameter Tuning (APT) has proven to address these by leveraging data assimilation (DA) to dynamically optimize parameters, improving forecast accuracy and operational reliability, as demonstrated in DWD implementations since 2022.

- This talk highlights APT's role in bridging data assimilation, ancillary data, and physics parameterization, offering a pathway to more robust Earth system modeling amid growing climate variability.

Zängl, G. (2023) Adaptive tuning of uncertain parameters in a numerical weather prediction model based upon data assimilation. Quarterly Journal of the Royal Meteorological Society, 149(756), 2861–2880. Available from: https://doi.org/10.1002/qj.4535

Adaptive Parameter Tuning (APT) Background

• APT is an innovative extension of data assimilation (DA) in the ICON model, designed to reduce systematic forecast errors by dynamically optimizing uncertain model parameters.

• In addition to traditional DA, which adjusts prognostic variables (e.g., temperature, humidity), APT uses DA information to tune physical parameters indirectly.

• Developed by Günther Zängl and team at DWD, APT has been operational since 2022 for T2M/RH2M (May 2022) and wind speed (November 2022), with extensions ongoing as of 2025.

• Core idea: Time-filtered DA increments (e.g., over 2.5 days) serve as proxies for model biases, allowing adaptive adjustments without permanent parameter changes.

• **Limitations**: Requires assimilation of relevant and (bias-free) observations

Motivation: Goal of APT

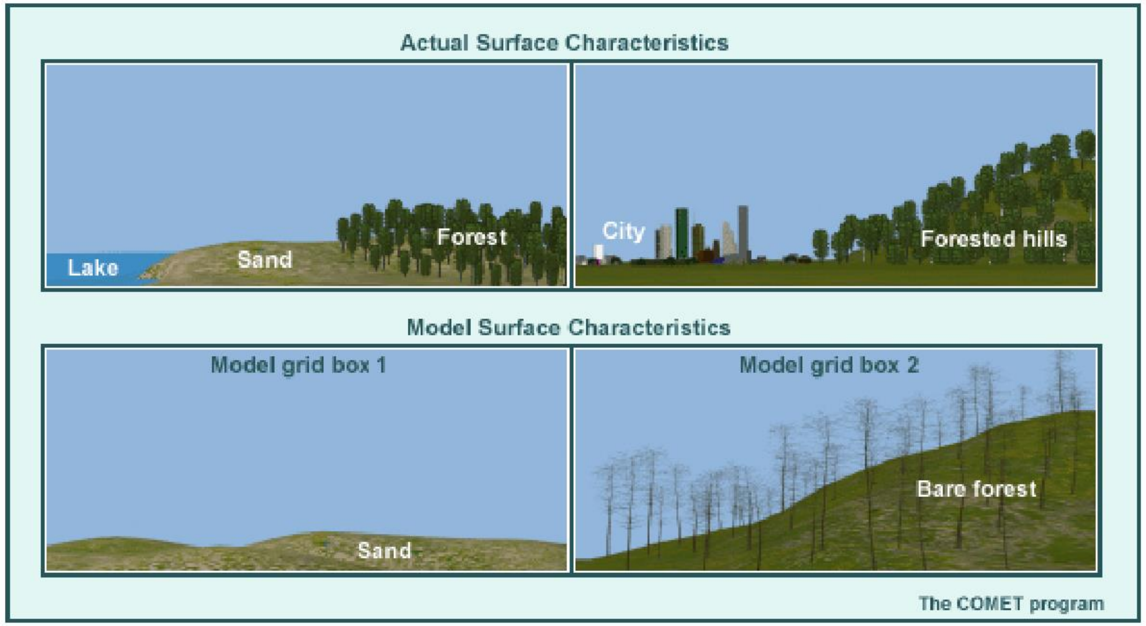


Figure: Representation of surface characteristics (COMET® Website at http://meted.ucar.edu/)

- Compensates for limitations in external parameter data, such as incomplete representation of natural variability (e.g., soil texture heterogeneity or orographic subgrid effects).

- Amplifies benefit of higher-resolution external data (e.g., orography upgrades in 2022 improved lower-tropospheric forecasts).

- Overall: APT evolves external parameters from static inputs to dynamically optimized ones, enhancing NWP reliability in diverse terrains and climates.

- Using time-filtered DA increments as bias proxies to adaptively tune derived parameters (e.g., soil heat capacity, snow albedo), creating a dynamic correction that compensates for external data imperfections without altering core datasets.

Tuned Parameters and Relation to External data

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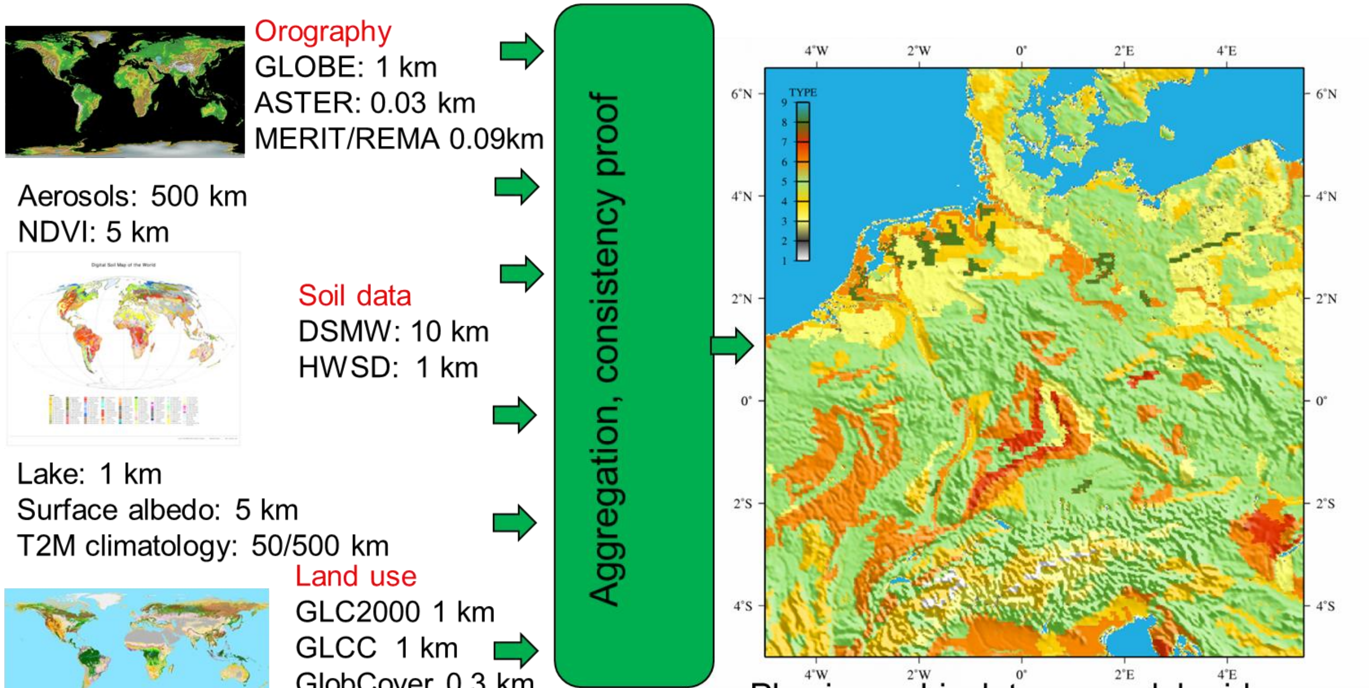
APT targets parameters derived from external sources:



Physiographic data on model grid

Vegetation-related: Minimum stomata resistance, vegetation roughness length (from land use maps).

- **Soil-related**: Heat capacity, heat conductivities, minimum evaporation resistance, hydraulic diffusivity (from soil texture classifications).

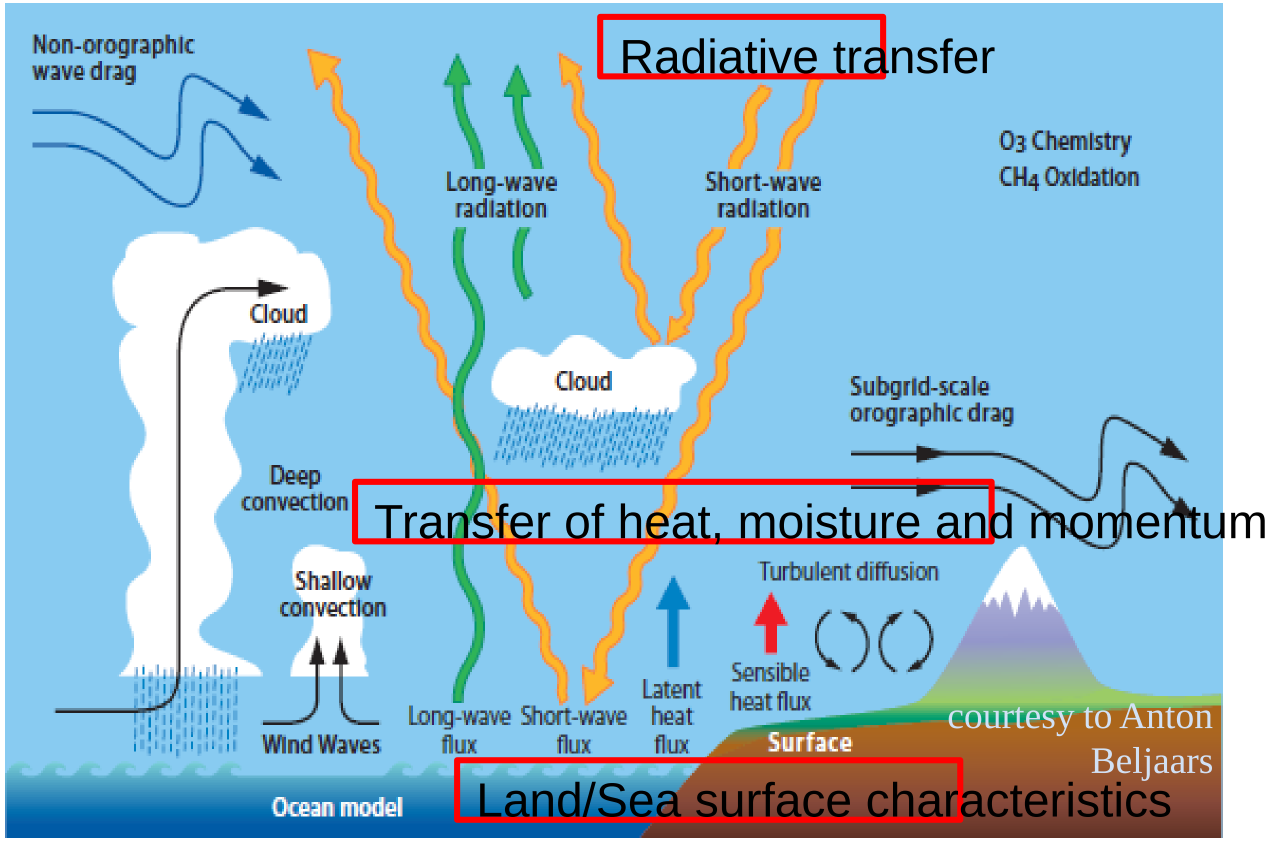
- **Snow/Ice-related**: Snow and sea-ice albedo (influenced by land cover and albedo datasets).

- **Orography-related**: SSO blocking tendency at lowest model level (from high-resolution orography data, upgraded to 3" resolution in 2022).

- **Other**: Leaf Area Index (LAI), root depth, snow-cover fraction diagnosis.

These parameters embed external data uncertainties: E.g., land use maps may not capture subgrid heterogeneity, leading to biases in evaporation or friction that APT corrects adaptively.

Requirements for Ancillary Data by APT

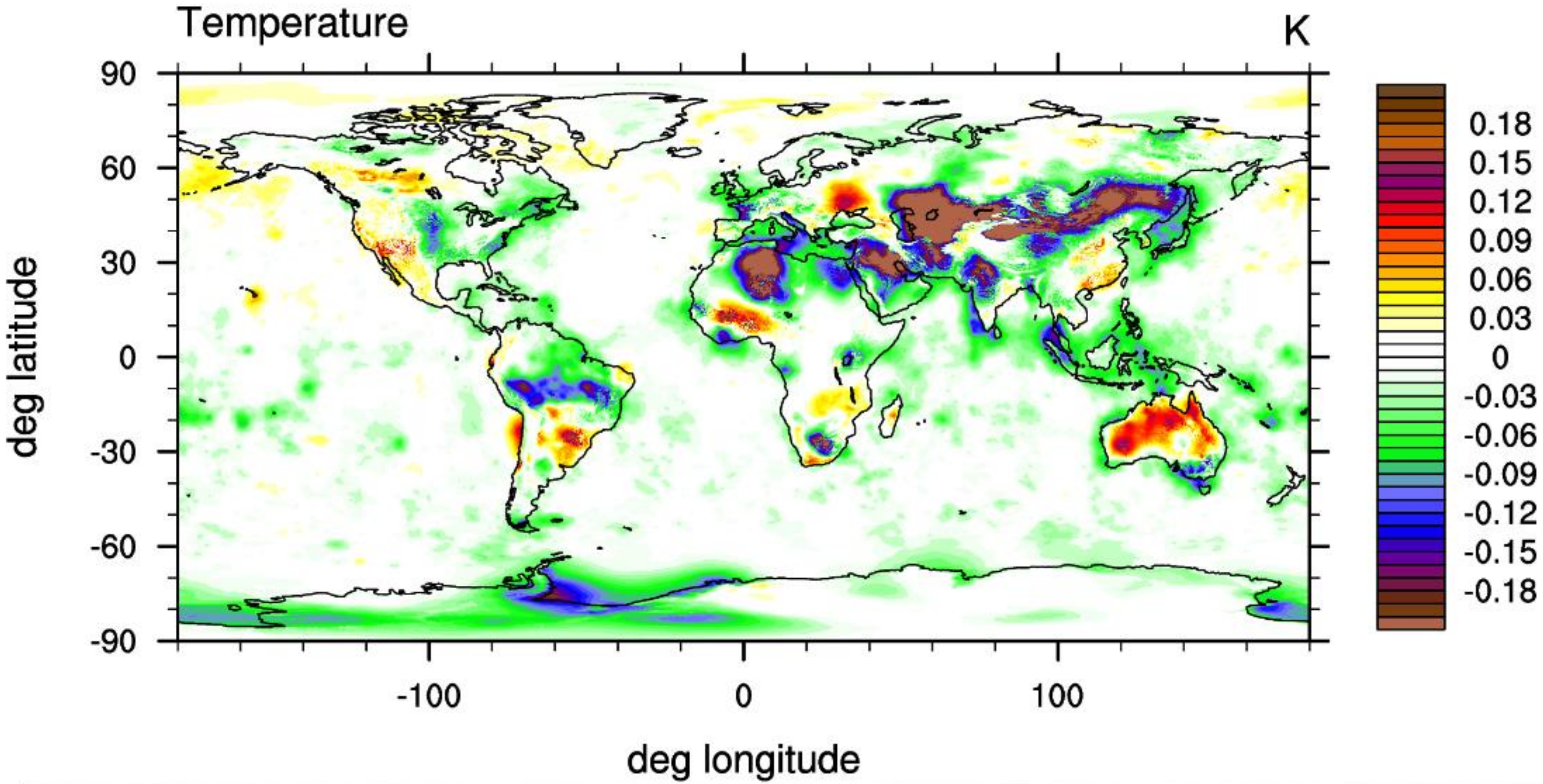


- **Local Bias-Parameter Relationship**: Must have a strong, local link between the parameter and the bias (e.g., stomata resistance land-use data directly affects T2M/RH2M biases).

- **Assimilation Support**: Relevant variables (T2M, RH2M, FF10M) must be assimilated; parameters adjustable via multiplicative factors without violating physical constraints.

- **Data Quality and Derivability**: Parameters derived from external datasets (e.g., land use, roughness, soil texture for conductivity) but with acknowledged uncertainties

Exp. Results without APT (increments for temp)



Average over November 2020

negative values correspond to an underestimated diurnal temperature amplitude

Exp. Results with APT (increments for temp)

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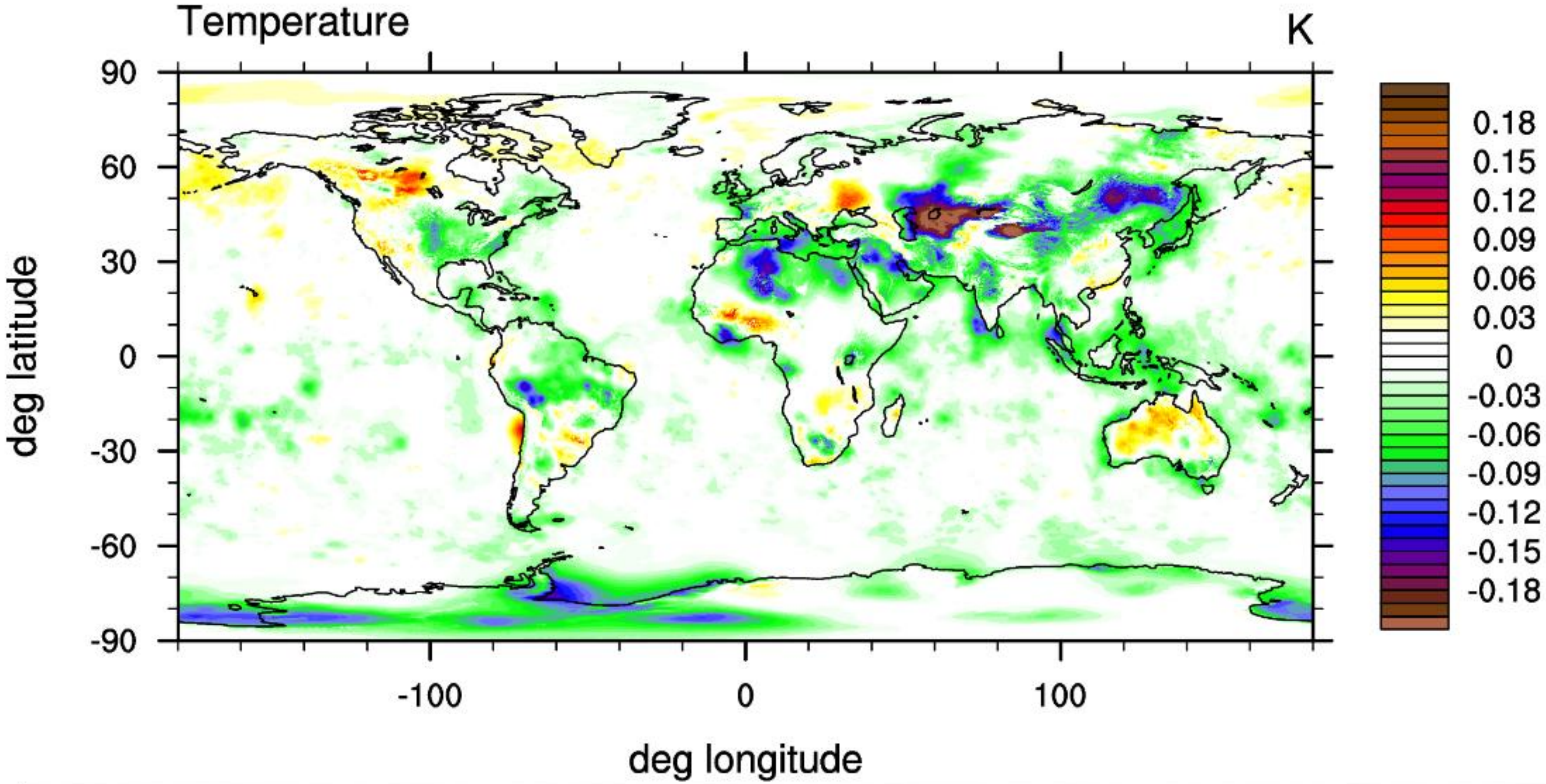


Average over November 2020

negative values correspond to an underestimated diurnal temperature amplitude;

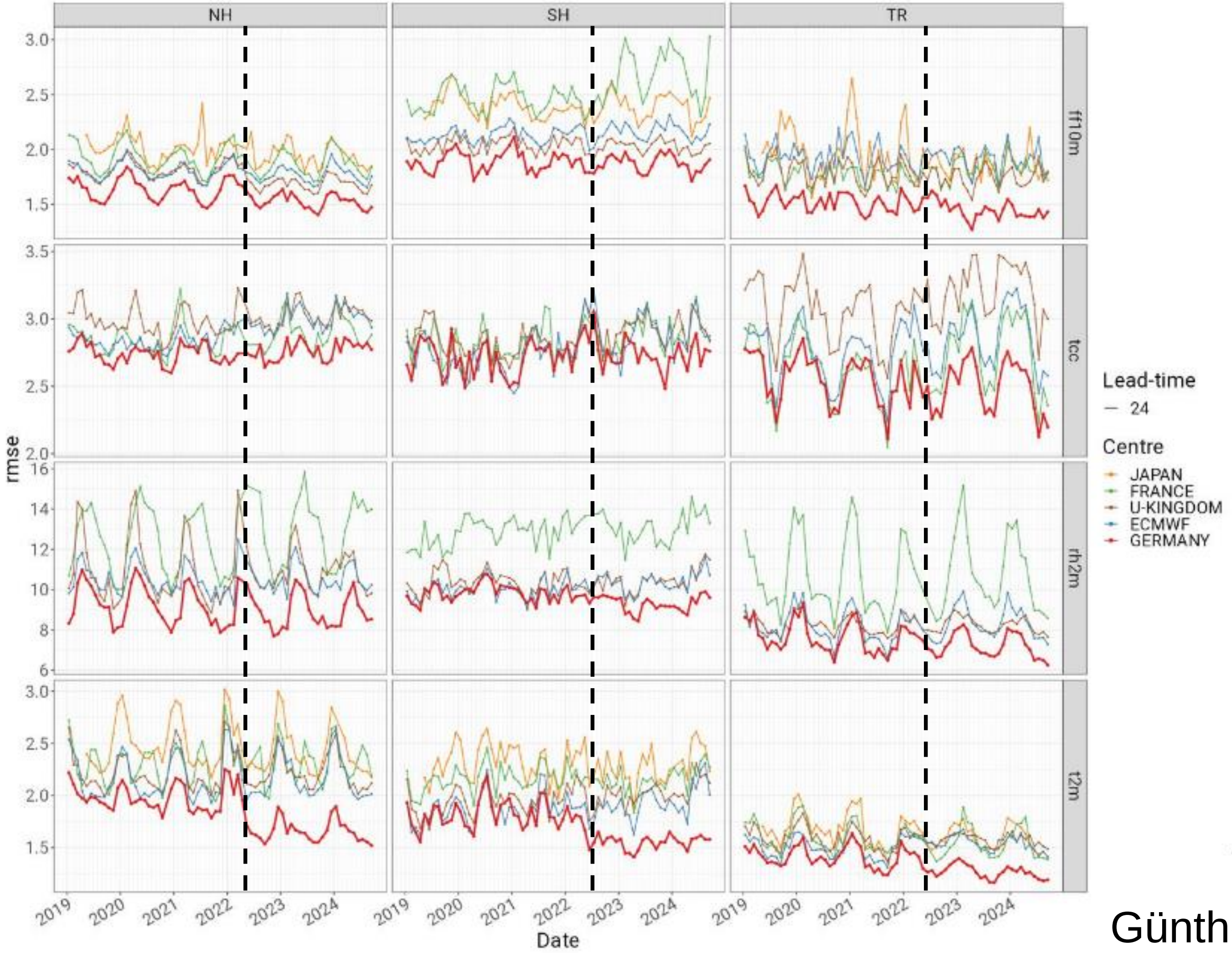
the filtered 3-hourly assimilation increment typically has about 1/4 the amplitude of the model bias (with model-DA coupling)

Motivation

WMO (WGNE) intercomparison for SYNOP scores

WMO verification against SYNOP
Valid-time: 0UTC

24h forecasts, validity time 00 UTC



10m wind speed

cloud cover

2m humidity

2m temperature

DWD

ECMWF

UKMO

JMA

Météo France

Implications for Surface Physics Developments

- APT shifts parameterization development toward adaptive, data-driven approaches, reducing reliance on fixed tunings that may perform unevenly across regions.

- Enhances land surface schemes (e.g., TERRA in ICON) by addressing ambiguities in external data, improving representations of fluxes (heat, moisture, momentum).

- Mitigates "ambivalent tuning" (better in one area, worse in another) by local optimizations, e.g., for Bowen ratio or diurnal cycles.

- Encourages integration of DA in physics design: Future schemes could incorporate APT-friendly parameters, like variable albedo or soil properties, for better bias correction.

- 2025 updates (e.g., land-tile averaging in DA, interception evaporation retuning) show APT driving refinements in subgrid processes, boosting forecast skill in land-atmosphere interactions.

Conclusion

• External parameters provide foundational inputs but introduce biases due to resolution limits, heterogeneity, or outdated datasets (e.g., land use maps affecting roughness lengths).

• APT connects by using time-filtered DA increments as bias proxies to adaptively tune derived parameters creating a feedback loop that compensates for external data imperfections without altering core datasets.

Implications for Future Development:

• Experience shows that APT cannot replace advanced physical parameterizations with appropriate physical dependencies and accurate process descriptions. Bug fixes and improvements at the level of individual processes still have beneficial impact on the forecast skill.

• Encourages hybrid DA-physics approaches: Future parameterizations could be designed APT-ready, with built-in adaptability for external uncertainties.

Broader impact: Enhances resilience in NWP for extreme events; promotes better external data integration (e.g., satellite-derived updates); potential expansion to other models or climate simulations.

Thank you

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Motivation

Problem

- Need a relationship between particle based mathematical equations and fields from model and measurements
- Consider field quantity $T(x,y,z,t)$: total differential provides development in time for the property temperature T of the particle

$$\boxed{\frac{dT}{dt} = \frac{\partial T}{\partial x}\frac{dx}{dt} + \frac{\partial T}{\partial y}\frac{dy}{dt} + \frac{\partial T}{\partial z}\frac{dz}{dt} + \frac{\partial T}{\partial t}\frac{dt}{dt} \quad \Big| \quad \frac{d\vec{x}}{dt} = \vec{v}}$$

$$\boxed{\frac{dT}{dt} = \frac{\partial T}{\partial t} + \vec{v}\,\vec{\nabla} T}$$

$\frac{\partial T}{\partial t} = 0$ stationary field

$\frac{dT}{dt} = 0$ conservative property

$\frac{\partial T}{\partial t} = -\vec{v}\,\vec{\nabla} T$ Adv. only

$\frac{dT}{dt}$ development of particle property

$\frac{\partial T}{\partial t}$ development of the T field

$\vec{v}\,\vec{\nabla} T$ advective development
particle moves with $\vec{v}$ through T field

Impact cases for forecast

Change of the field temperature at one point

Data assimilation, APT

$$\boxed{\frac{\partial T}{\partial t}} = \boxed{\frac{dT}{dt}} - \boxed{\vec{v}\,\vec{\nabla} T}$$

Impact of the particle temperature

- Sensible and latent heating or cooling, condensation, evaporation
  - Diurnal cycle of solar irradiation near surface
  - Precipitation processes

Impact of the temperature advection

- Change of the air mass (frontal passage)
  - Large temperature gradients and wind speed in winter

Implementation details

Basic formula for filtered increments:

simple Newtonian relaxation approach

$$\psi_{\mathrm{fi}}(t) = \psi_{\mathrm{fi}}(t - dt_{\mathrm{ana}}) + \frac{dt_{\mathrm{ana}}}{dt_{\mathrm{filt}}}[\psi_{\mathrm{i}}(t) - \psi_{\mathrm{fi}}(t - dt_{\mathrm{ana}})], \quad (1)$$

where ψ represents T, wind speed FF, or relative humidity RH, and subscripts i and fi signify analysis increments and filtered increments respectively; t is the validity time, $dt_{\mathrm{ana}} = 3\,\mathrm{hr}$ is the analysis interval (1 hr for ICON-D2), and $dt_{\mathrm{filt}} = 2.5\,\mathrm{days}$ is the filtering time-scale.

Cosine-weighted temperature increments:

proxy for diurnal cycle bias of T2M

$$T_{\mathrm{wfi}}(t) = T_{\mathrm{wfi}}(t - dt_{\mathrm{ana}}) + \frac{dt_{\mathrm{ana}}}{dt_{\mathrm{filt}}} \times \left[T_{\mathrm{i}}(t)\cos\left(\frac{2\pi}{86{,}400}t_{\mathrm{loc}}\right) - T_{\mathrm{wfi}}(t - dt_{\mathrm{ana}})\right], \quad (2)$$

where t_{loc} denotes local time (in seconds) at a given model grid point. The sign convention is such that negative values of T_{wfi} correspond to an underestimated diurnal temperature amplitude.

The time-filtered assimilation increments are assumed to be proportional (with opposite sign) to the model bias in a free forecast. To the extent that this assumption is valid, they can be taken as a predictor for APT.

Implementation details

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For surface friction, the formulation that was found to provide the best results is given by

$$f_{sf} = \frac{1}{1 + 2.5 f_{ai} FF_{fi}} \quad (3)$$

for negative FF_{fi} and

$$f_{sf} = 1 - 2.5 f_{ai} FF_{fi} \quad (4)$$

for positive FF_{fi}

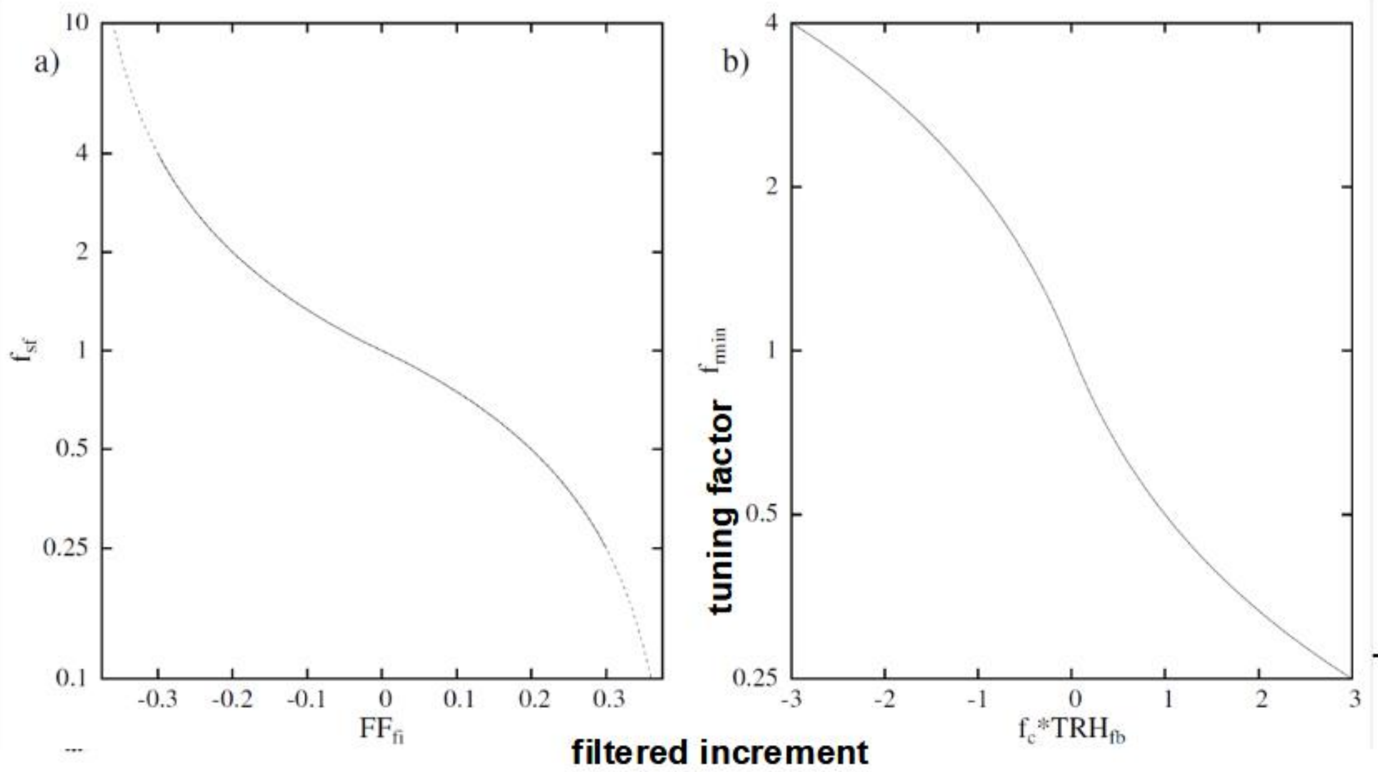
Based upon TRH_{fb}, the minimum evaporation resistances of bare soil and plant stomata, $rmin_{bs}$ and $rmin_{pl}$ are modified with the multiplicative factor

$$f_{rmin} = \frac{1}{1 + f_c TRH_{fb}} \quad (6)$$

for positive TRH_{fb} and

$$f_{rmin} = 1 - f_c TRH_{fb} \quad (7)$$

for negative TRH_{fb}



Based upon the time-filtered assimilation increments, the selected uncertain model parameters are varied around their default value (derived from external data) using a force-restore approach with multiplicative factors.

A filtered increment of zero implies that the parameter attains its original value. There is no permanent modification as in LETKF-based approaches tested in other studies.