Enhancing Atmospheric Transmittances Estimation for TOVs through Advanced Statistical Approaches

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May 9th, 2025

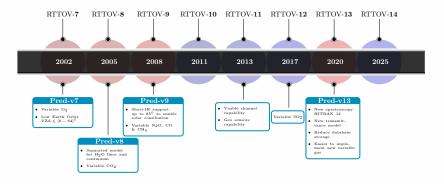


Motivations

- A pressing need exists to improve our understanding of the RTTOV coefficients generation process
 → Retired experts: Marco Matricardi, Pascal Brunel, Roger Saunders, John Eyre, Hal Woolf
- Many of our users treat the so-called RTTOV coefficients as a black-box
- Conduct a thorough investigation of all aspects of the process, focusing on efficiency, stability, and accuracy

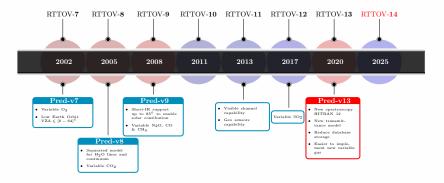
 This is still going on
- Suggest potential improvements based on the findings

Overview of RTTOV gas absorption's parametric models



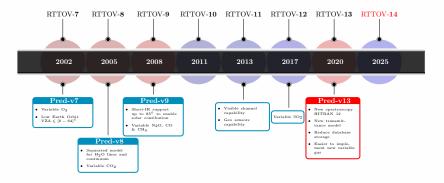
• New parametric model version are named after the RTTOV version in which they have been introduced.

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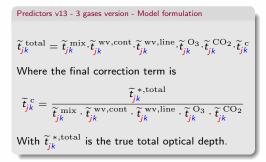
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- Retirement of Pred 7, 8 & 9 anticipated for RTTOV-v15

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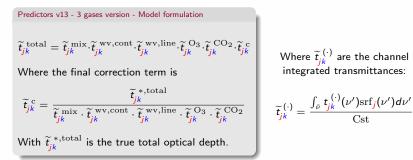


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- McMillin et al., Applied Optics, 1976, 1977, 1979, 1995a, 1995b, 2003
- Hocking et al., GMD, 2022

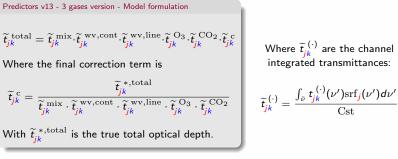
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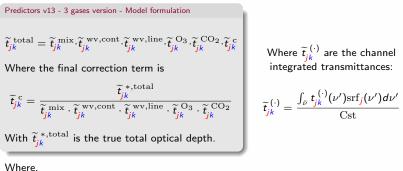
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Where,

$$\widetilde{t}^{(\cdot)} \in \Omega = \{ \widetilde{t}_{jk}^{\text{mix}}, \ \widetilde{t}_{jk}^{\text{wv,cont}}, \ \widetilde{t}_{jk}^{\text{wv,line}}, \ \widetilde{t}_{jk}^{\text{O}_3}, \ \widetilde{t}_{jk}^{\text{CO}_2}, \ \widetilde{t}_{jk}^{\text{c}_3} \}$$

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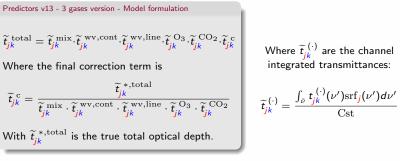


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RTTOV coefficients are estimated for each terms of Ω , each channels and each layers:

$$N_{tot} = N_j \times N_k \times \operatorname{Card}(\Omega)$$

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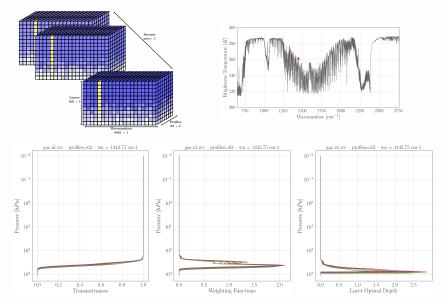
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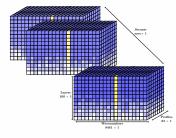
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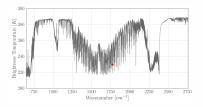
As an example... IASI pred 13 with 3 variable gases $N_{iasi} = 8461 \times 100 \times 6 = 5,076,600$

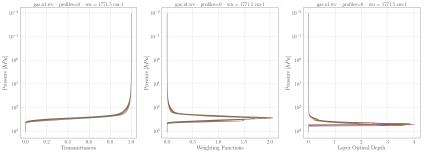
Channel Integrated transmittances datacubes



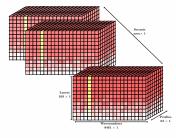
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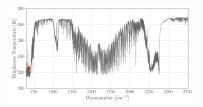


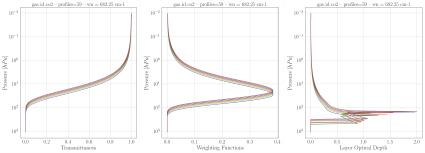




Channel Integrated transmittances datacubes







Theoretical fundation of the layer optical depth parameteric model

Layer optical depths $\widetilde{ au}^{*}$ $^{(.)}$ are modeled as a multilinear regression:

$$\widetilde{\boldsymbol{\tau}}_{jk}^{*(.)} = \boldsymbol{X}_k \boldsymbol{c}_{jk} + \boldsymbol{\epsilon}_{jk}$$

where,

•
$$\widetilde{ au}^{st~(.)}_{jk}$$
: true layer optical depth: $[({\sf N}_{\sf prof} imes{\sf N}_{\sf sec}) imes{1}]$

•
$$c_{jk}^{(.)}$$
: model parameters (RTTOV Coefficients): $[\mathsf{N}_{\mathsf{pred}} imes 1]$

- $X_k^{(.)}$: set of predictors depending on atmospheric model state and a specific gas: $[N_{pred} \times (N_{prof} \times N_{sec})]$
- $\epsilon_{ik}^{(.)}$: additive noise (i.e. gaussian distributed): $[(N_{prof} \times N_{sec}) \times 1]$

Predictors/Features for the water vapour lines

The water vapour lines predictors are:

$$\boldsymbol{X}_{k}^{\text{wv,line}} = \begin{bmatrix} \left(\begin{matrix} \sec(\theta)W_{r,k} \right)^{2} \\ \sec(\theta)W_{w,k} \\ \left((\sec\theta)W_{w,k} \right)^{2} \\ \sec(\theta)W_{r,k} \\ \delta T_{k} \\ \sqrt{\sec(\theta)W_{r,k}} \\ \delta T_{k} \\ \sqrt{\sec(\theta)W_{r,k}} \\ \sec(\theta)W_{r,k} \\ \sec(\theta)W_{r,k} \\ (\sec(\theta)W_{r,k})^{1.5} \\ (\sec(\theta)W_{r,k})^{1.5} \\ \delta T_{k} \\ \sqrt{\sec(\theta)W_{r,k}} \\ \delta T_{k} \\ (\sec(\theta)W_{r,k})^{1.25} \\ \sec(\theta)W_{r,k}^{2} \\ \sqrt{\sec(\theta)W_{r,k}} \\ \sqrt{\sec(\theta)W_{r,k}} \\ W_{r,k} \\ W_{wr,k} \\ \end{bmatrix}$$

- W_r , W_w , W_{wt} quantities depending on Water Vapour concentration
- δT depends on distance to the mean Temperature profile

Formulation of the coefficients estimation problem

Omitting j and k indexes.

The layer optical depth model parameters are estimated such as:

 $\widehat{c}^{(\cdot)} = \operatorname*{arg\,min}_{c} \mathcal{J}(c)$

where ${\cal J}$ is a weighted quadratic function:

$$\mathcal{J}(c) = \underbrace{\left(\widetilde{\boldsymbol{\tau}}^* - \widetilde{\boldsymbol{\tau}}^{(\cdot)}(c)\right)^t W\left(\widetilde{\boldsymbol{\tau}}^* - \widetilde{\boldsymbol{\tau}}^{(\cdot)}(c)\right)}_{\text{weighted fit to target value}} + \underbrace{\alpha \ c^t c}_{\text{regularization}}$$

weighted fit to target value

Where:

- $ilde{ au}^*$ are the true layer optical depth (target simulated with LBLRTM)
- $\widetilde{ au}^{(\cdot)}(c)$ are the model layer optical depth
- W is a diagonal matrix of weights
- The L_2 regularization term penalizes the "high values" of coefficients and is controlled by an hyperparameter α

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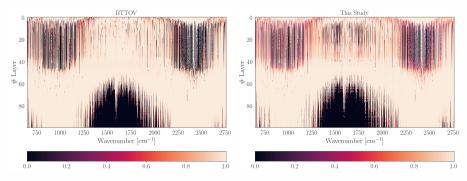
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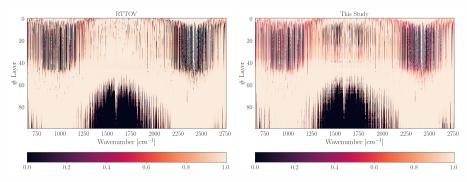
Coefficients estimation - Goodness of fit on Water Vapour datacube



Coefficient of determination of RTTOV versus using Singular Value Decomposition

- RTTOV (Direct computation of an inverse matrix) & Singular Value Decomposition shares some similar features in the overall metrics
- What are the differences ? We theoretically solve the same inverse problem...

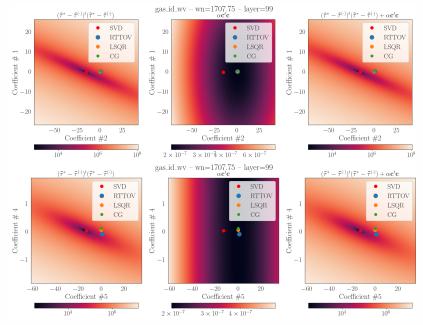
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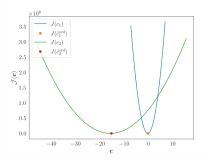
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- What are the differences ? We theoretically solve the same inverse problem...
- It turns out that we don't really but that is not the full story!

Coefficients estimation - The impact of solver

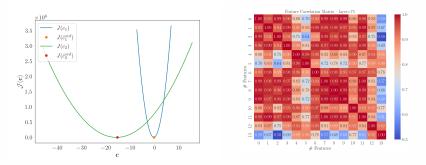


Coefficients estimation - An ill-conditioned problem



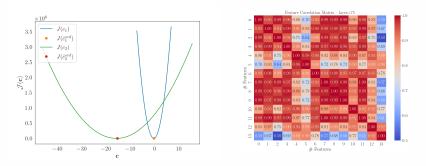
- Sensitivity to different coefficients can vary substantially
- · Some Predictors have less to no resolving power with respect to the target values

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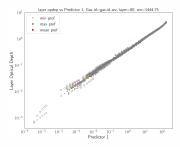
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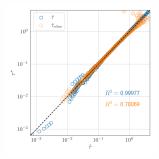


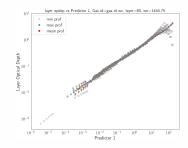
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- Predictors are overally strongly correlated
- That is one of the reasons we need preconditioning (normalization, whitening...)

Coefficients estimation - How does the fit look in the layer optical depth space?

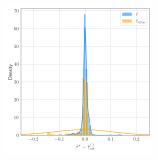


Fit with new coefficients.

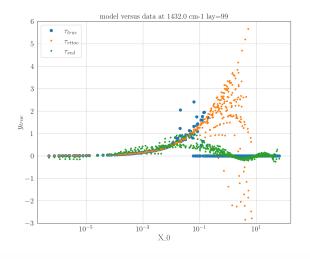




Fit with RTTOV coefficients.



A notorious problem of RTTOV – breakdown of the linear model



The model is predicting negative optical depth

Take home messages

- This is still an ongoing study which raises more questions than it answers yet!
- Our current inverse problem is strongly ill-conditioned
 → Mostly because of colinear features
- Is their room for improvement without changing the philosophy of the gas absorption parametrization?
 → I strongly believe so
- Machine learning approach are probably flexible enough to fit the observed layer optical depth