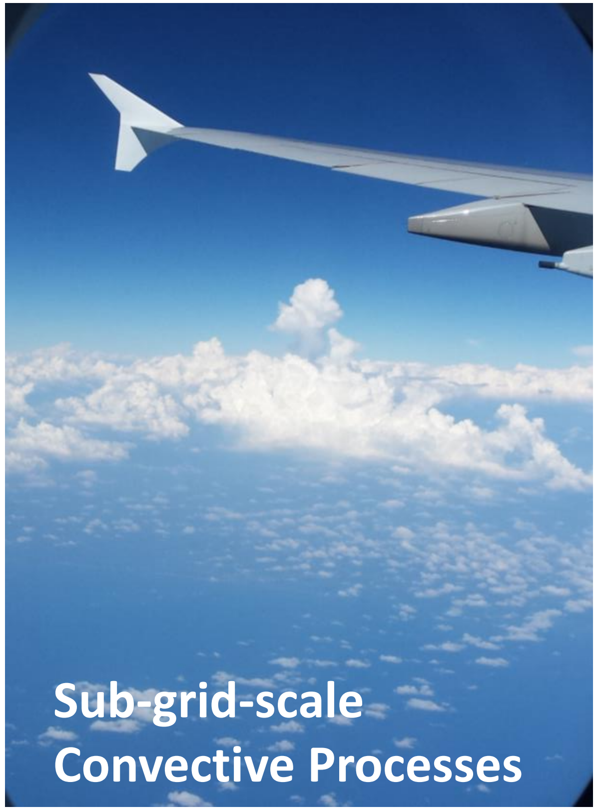
Non-Linear Dimensionality Reduction With a Variational Encoder Decoder (VED) to Understand Convective Processes in Climate Models

Gunnar Behrens [1,2], Tom Beucler [3], Pierre Gentine [2,4], Fernando Iglesias-Suarez[1],
Michael Pritchard [5] and Veronika Eyring [1,6]

1 Deutsches Zentrum für Luft- und Raumfahrt (DLR), Institut für Physik der Atmosphäre, Oberpfaffenhofen, Germany
2 Department of Earth and Environmental Engineering, Columbia University, New York, NY, USA
3 Institute of Earth Surface Dynamics, University of Lausanne, Lausanne, Switzerland
4 Earth Institute and Data Science Institute, Columbia University, New York, NY, USA
5 Department of Earth System Science, University of California Irvine, Irvine, CA, USA
6 University of Bremen, Institute of Environmental Physics (IUP), Bremen, Germany

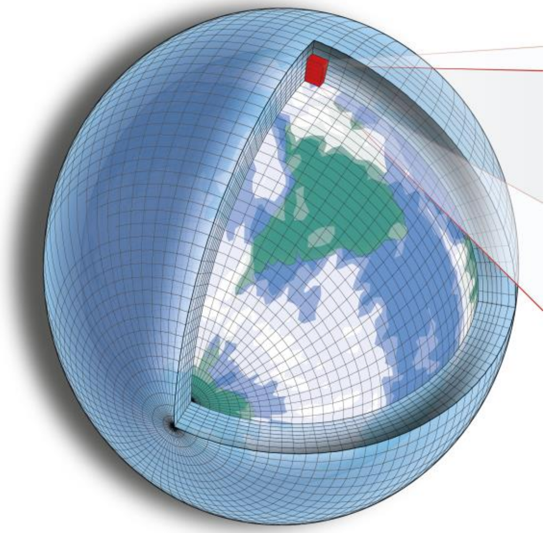
AGU 2022 / Deep Learning for Climate Science and Weather Prediction 12/12/2022

Convective Processes are complex, can we decode them?

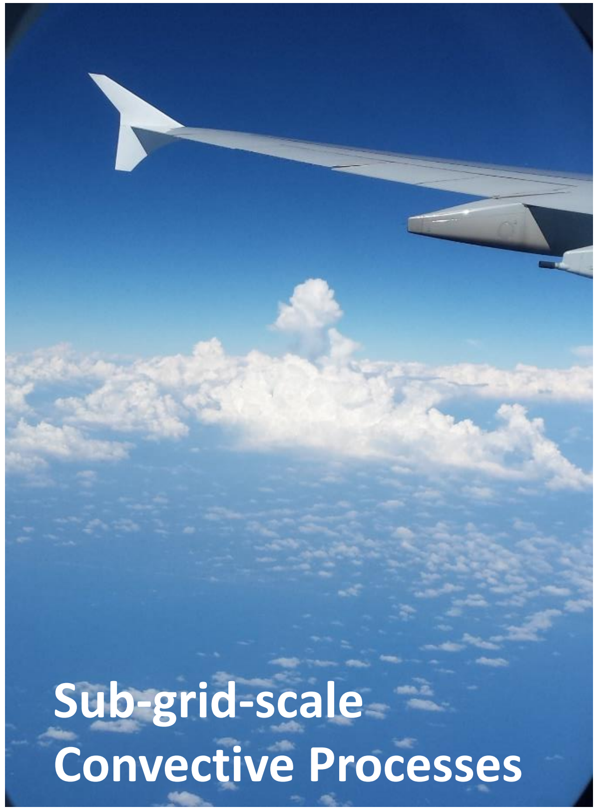


Convective Processes are complex, can we decode them?

Large-scale climate variables

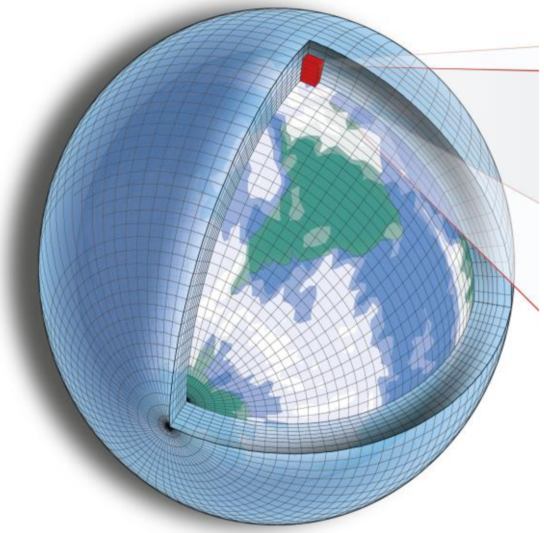


Schneider et al. (2017)



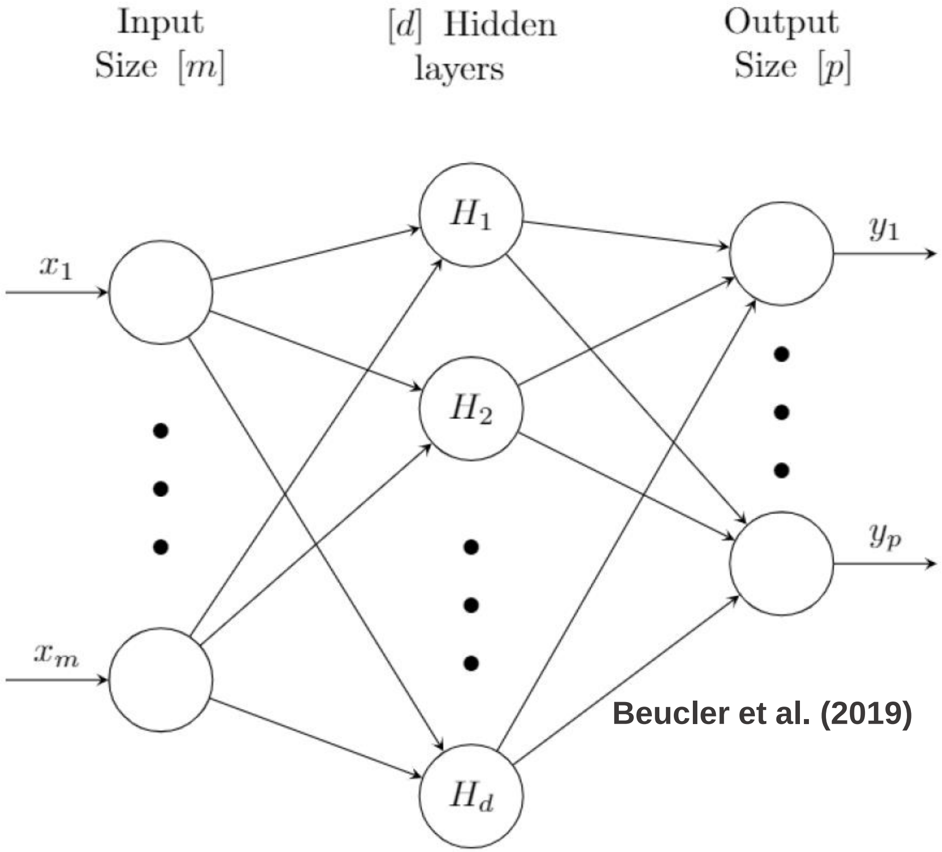
Convective Processes are complex, can we decode them? YES!

Large-scale climate variables

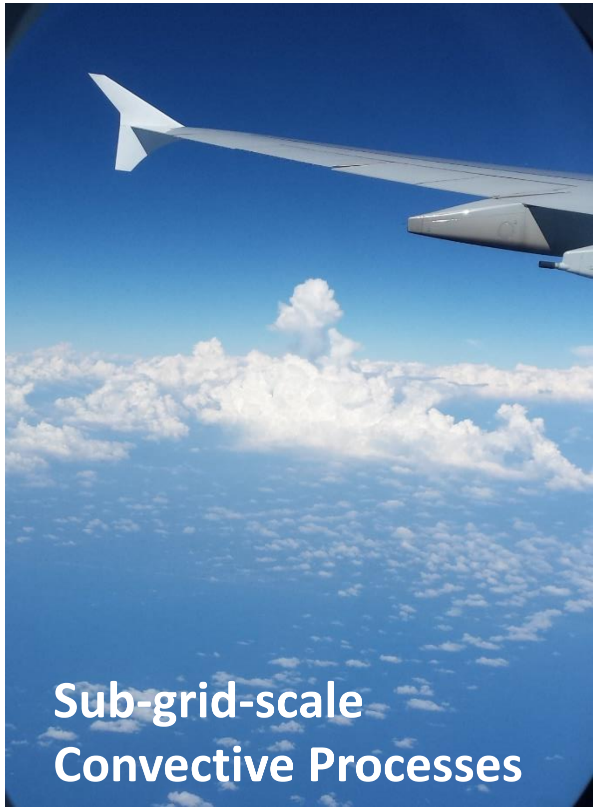


Schneider et al. (2017)

Fully connected Neural Net



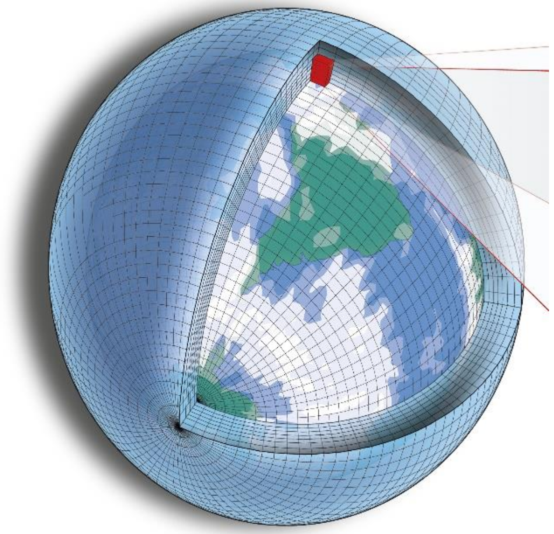
Beucler et al. (2019)



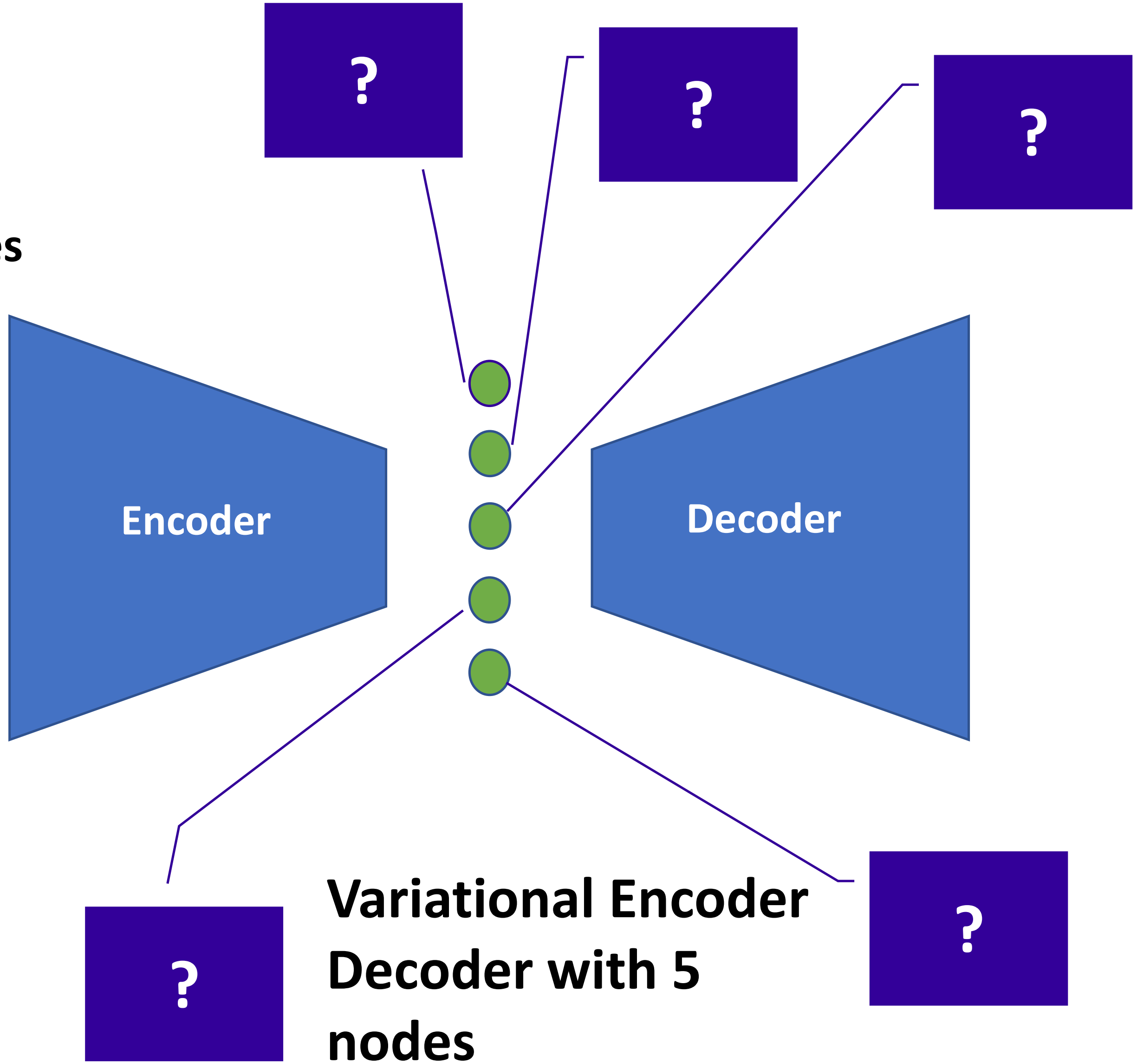
Rasp et al. 2018; Yuval et al. 2020; Brenowitz and Bretherton 2018; Mooers et al. 2021; Wang et al. 2022

Convective Processes are complex, can we encode them?

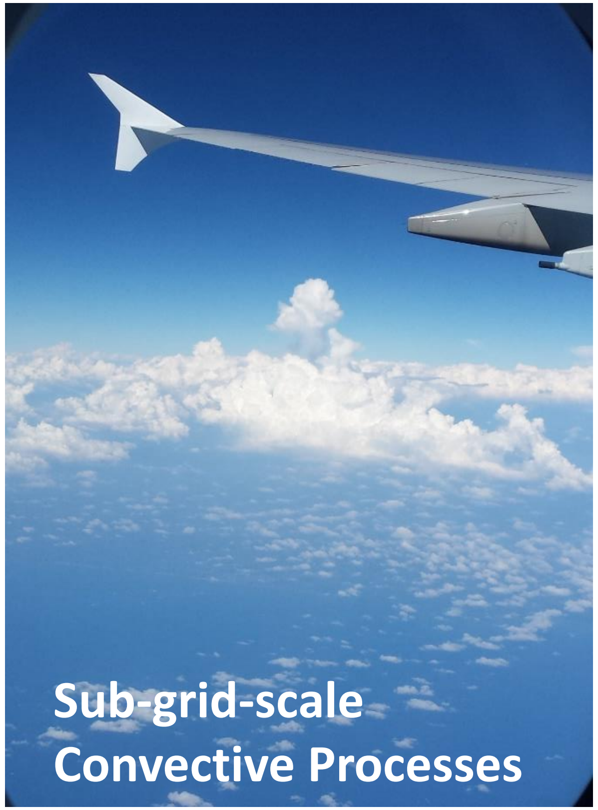
Large-scale climate variables



Schneider et al. (2017)



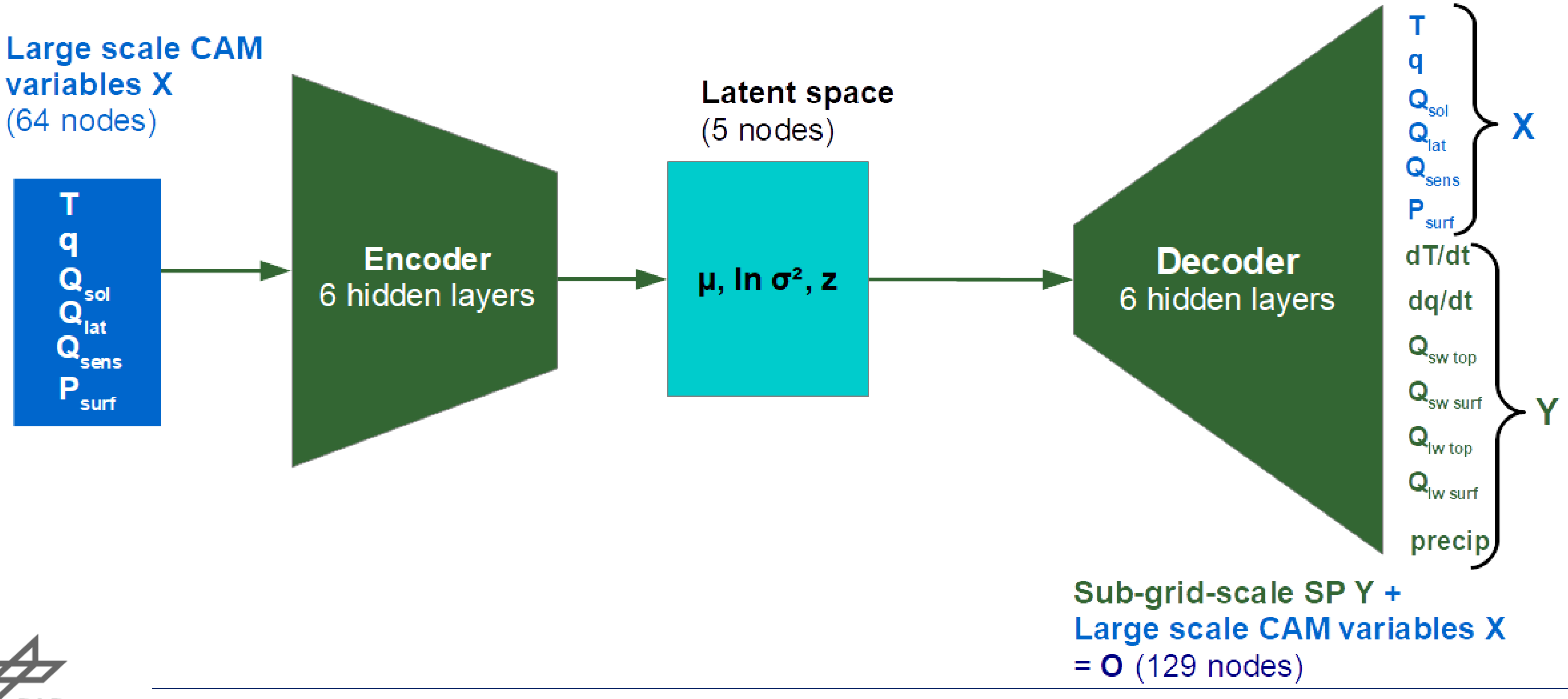
Variational Encoder Decoder with 5 nodes

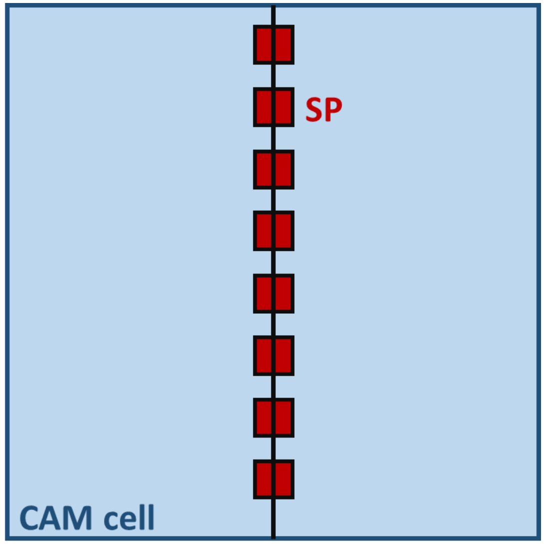


1. Variational Encoder Decoder (VED) architecture

- **VED** mirroring **superparametrisation (SP,** Grabowski (2001)**)** of **Community Atmosphere Model (CAM,** Collins et al. (2006)**) Version 3** with **aquaplanet setup**

- **VED :** Encoder + Decoder, Input variables: CAM, Output variables: CAM + SP

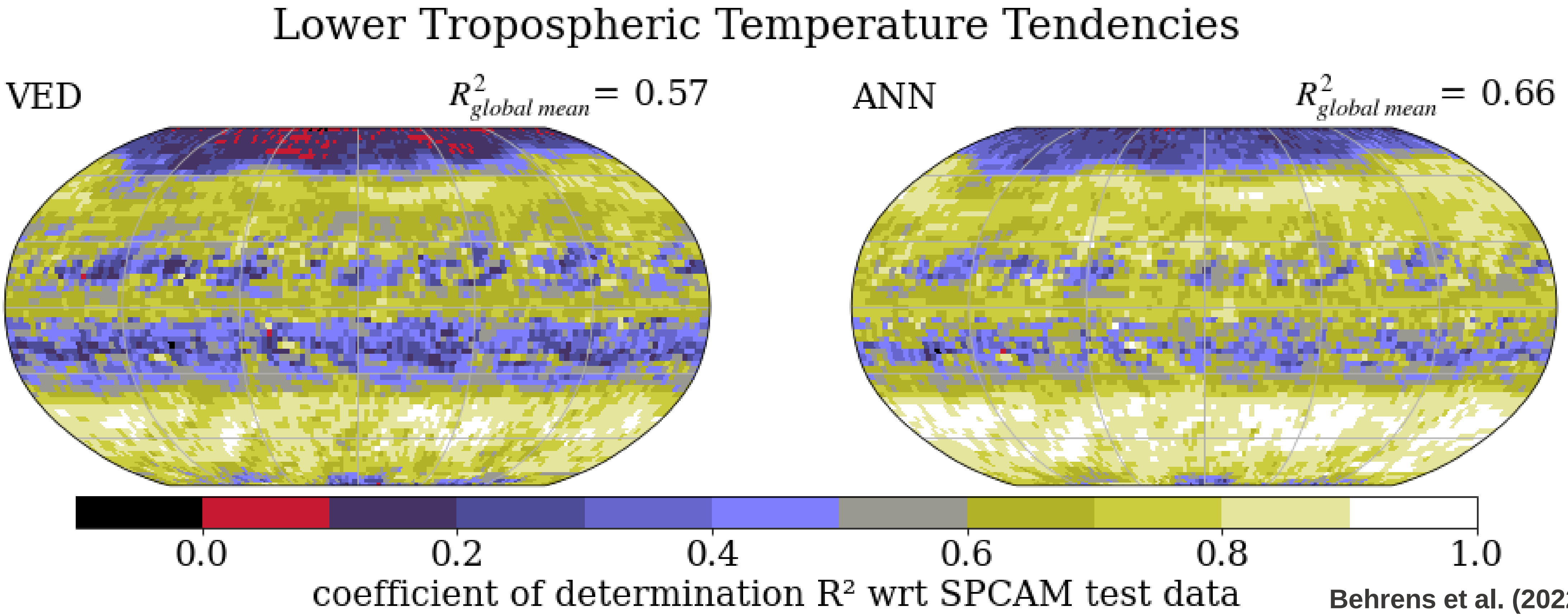




Behrens et al. (2022)

2. Realistic reproduction of Convective Processes

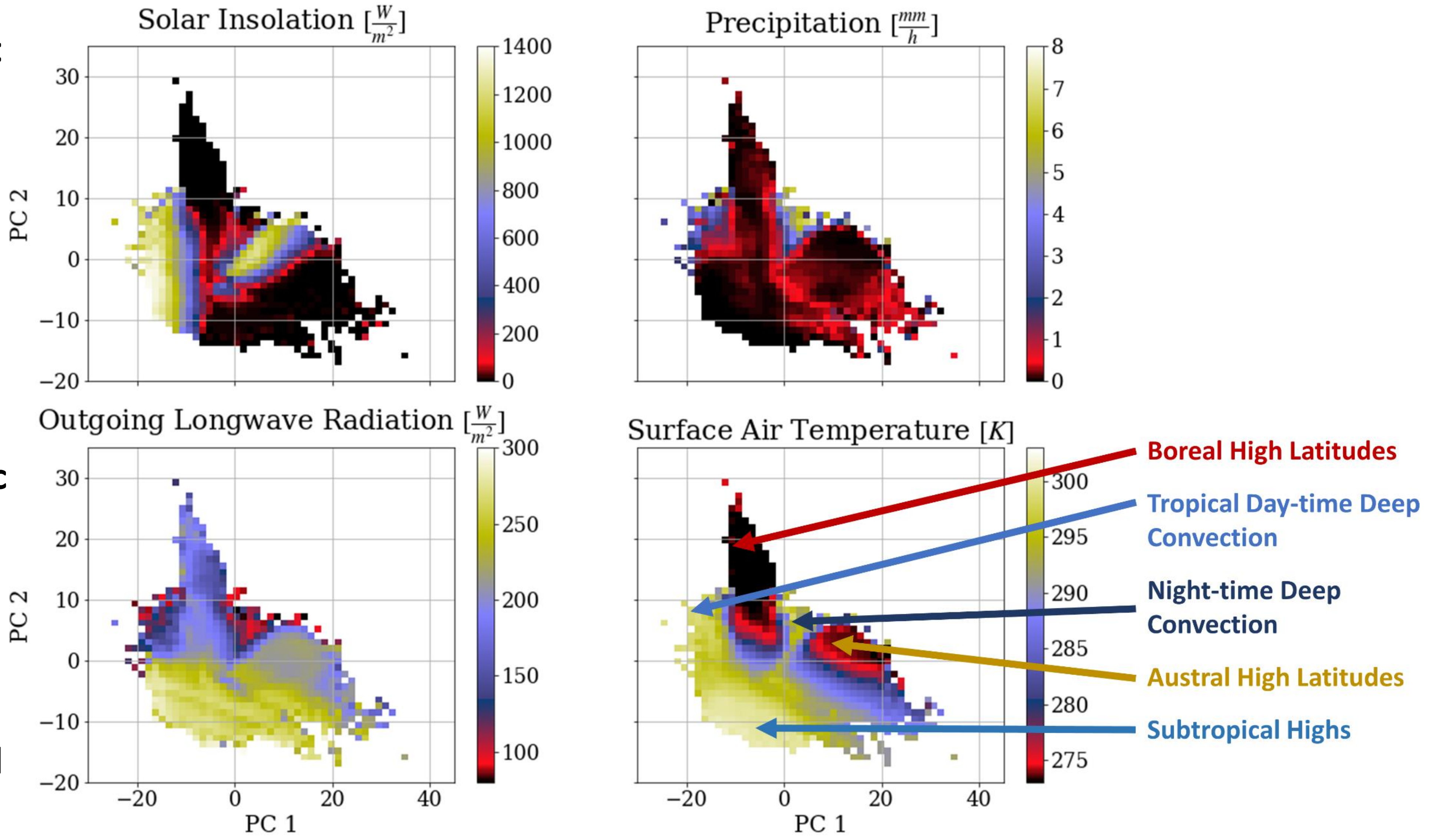
- Compare against Artificial Neural Net (ANN) of Rasp et al. (2018) for R^2 of dT/dt on 700 hPa
- Good reproduction of VED in mid latitudes and near InterTropical Convergence Zone (ITCZ)
- Weaker performance around Subtropical Highs (~ 20° N/S)
- Slightly decreased performance with respect to ANN (5 nodes in latent space vs. 256 nodes per layer)



Behrens et al. (2022)

3. Physically Meaningful Latent Space

- **2D Principal Component Analysis (PCA) compression of VED latent space:**
  - Compute conditional averages of convection related variables
- **Discriminate geographic origin of samples in latent space of VED**
- **enhanced interpretability compared to traditional input PCA**



Behrens et al. (2022)

4. Convective Processes Predictability

- **Example: Latent Node 4**

  – Translation along one latent dimension, while keeping the others fixed to their median values

  – Feed resulting $z_{translation}$ array into Decoder

$$z_{translation\ Node\ 4} = [median(z_1), median(z_2), median(z_3), perc(z_4), median(z_5)]$$

vertical profile or 2D variable

Increasing percentiles

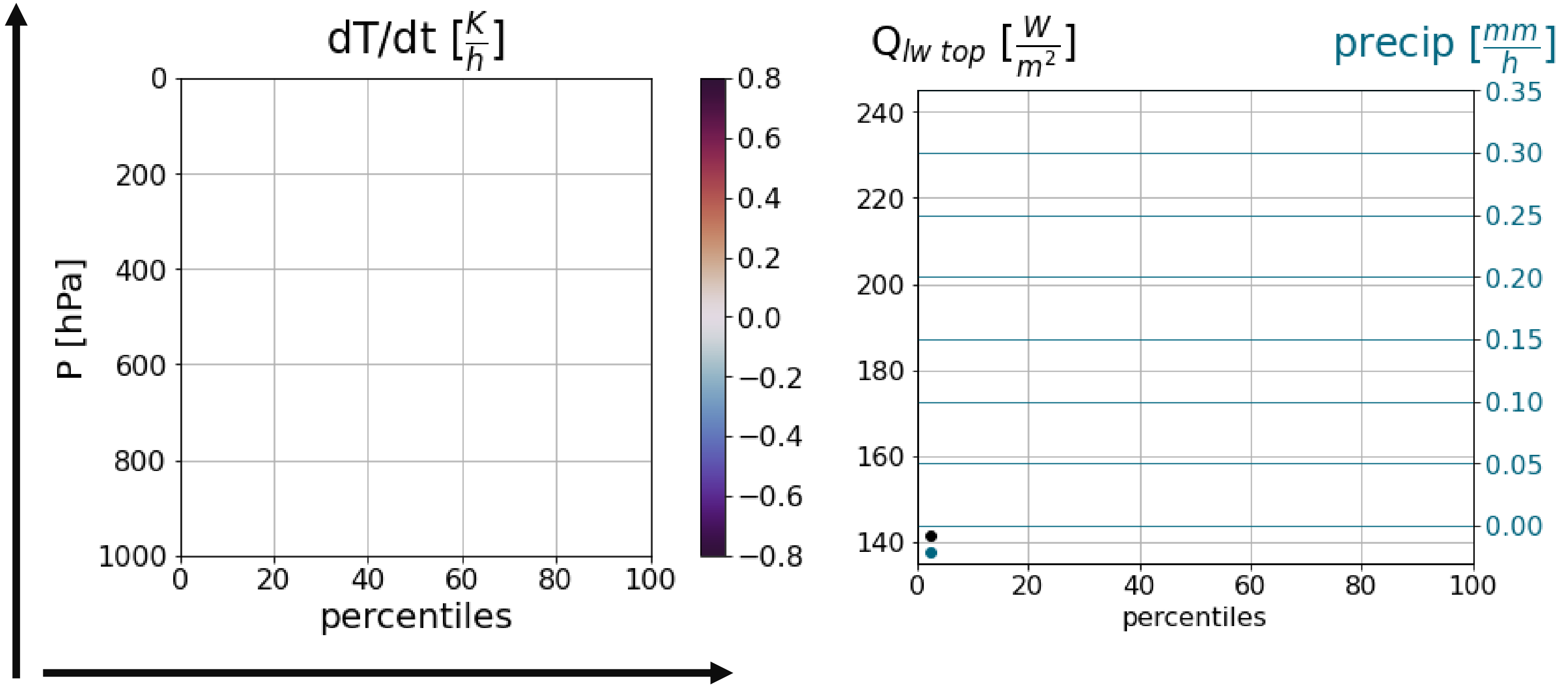
Behrens et al. (2022)

4. Convective Processes Predictability

- **Example: Latent Node 4**
  – Translation along one latent dimension, while keeping the others fixed to their median values
  – Feed resulting $z_{translation}$ array into Decoder

$$z_{translation\ Node\ 4} = [median(z_1), median(z_2), median(z_3), perc(z_4), median(z_5)]$$

vertical profile or 2D variable



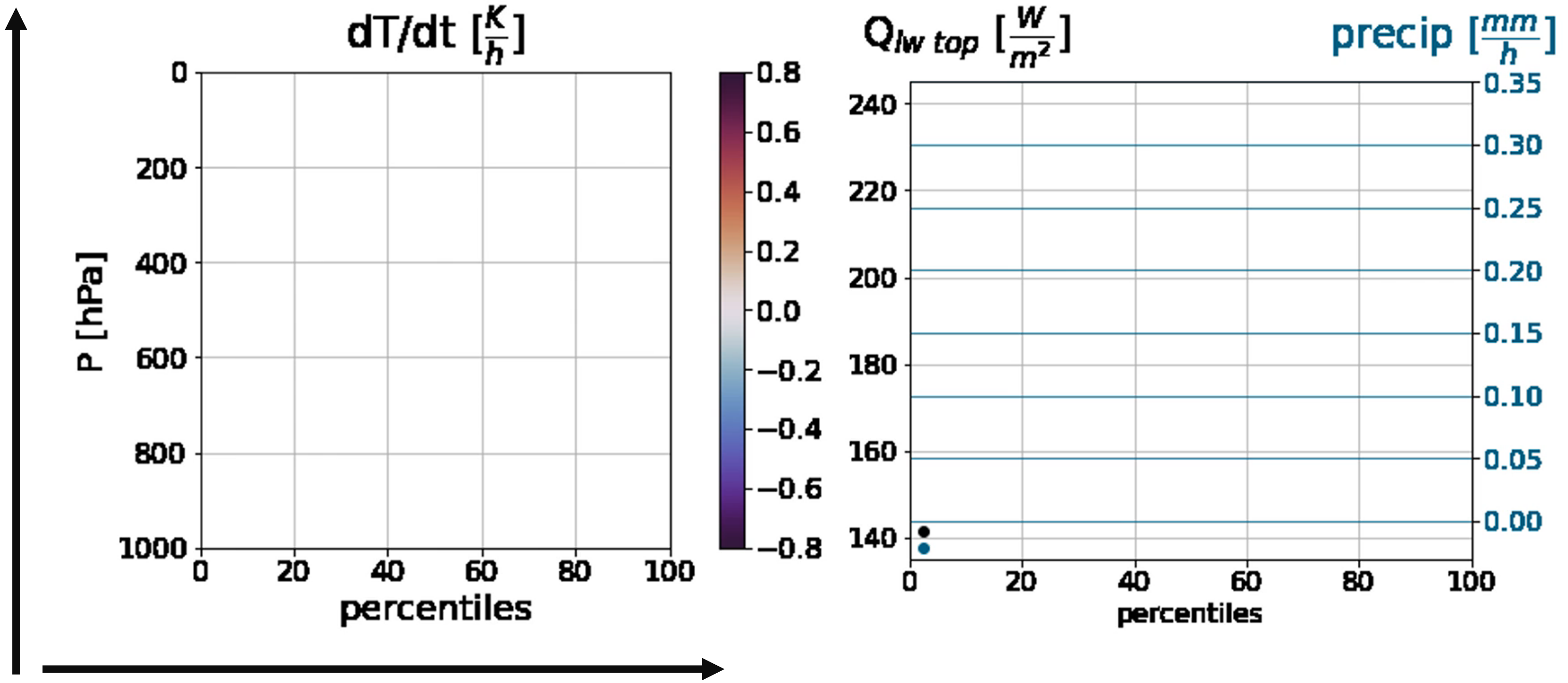
Increasing percentiles

4. Convective Processes Predictability

- **Example: Latent Node 4**
  - Translation along one latent dimension, while keeping the others fixed to their median values
  - Feed resulting $z_{translation}$ array into Decoder

$$z_{translation\ Node\ 4} = [median(z_1), median(z_2), median(z_3), perc(z_4), median(z_5)]$$

vertical profile or 2D variable



Increasing percentiles

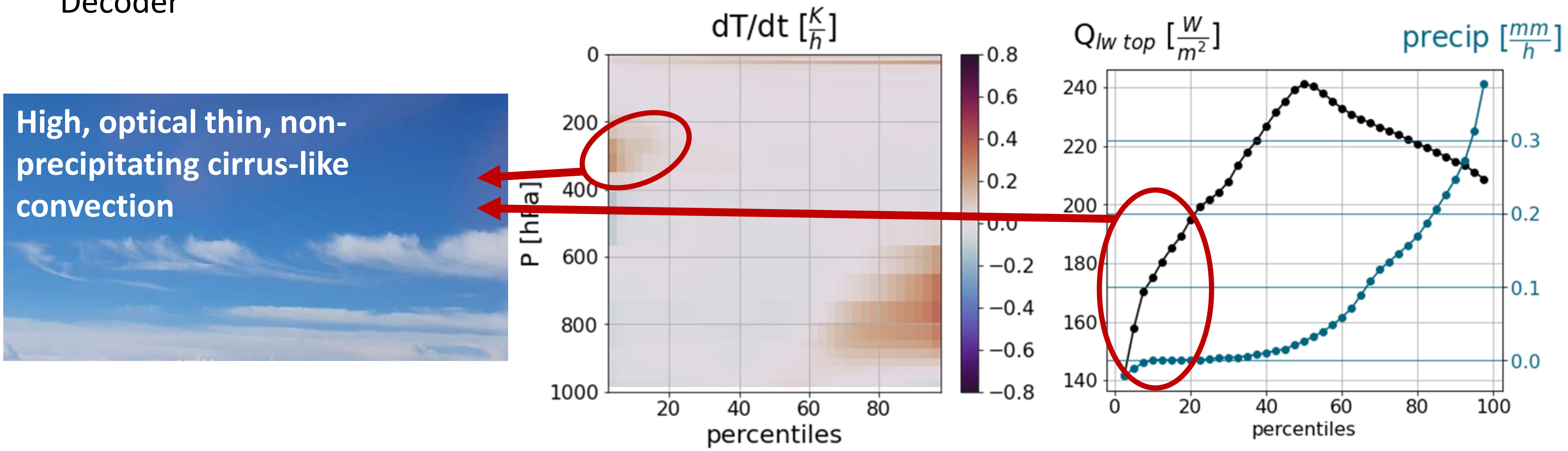
Behrens et al. (2022)

4. Convective Processes Predictability

- **Example: Latent Node 4**

– Translation along one latent dimension, while keeping the others fixed to their median values

– Feed resulting $z_{translation}$ array into Decoder

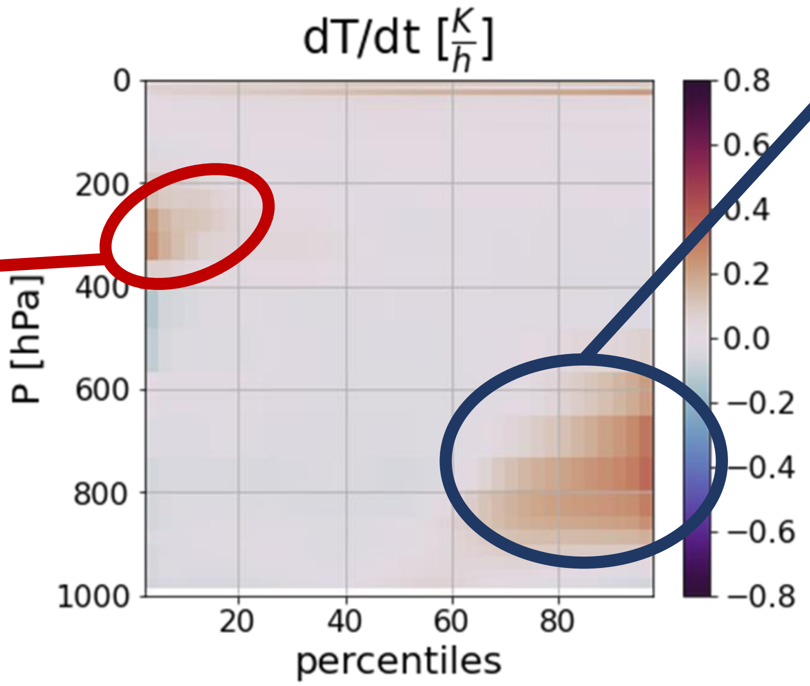


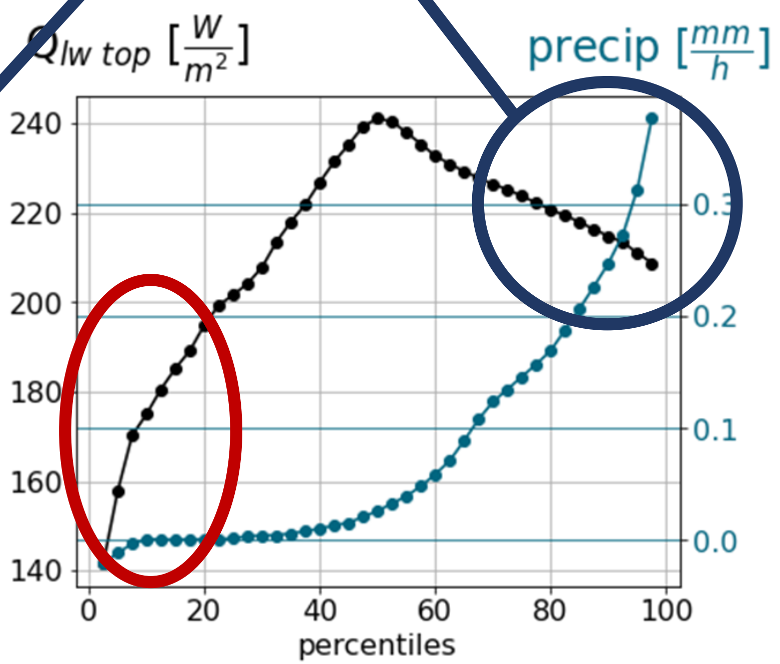
4. Conv. Processes Predict./ Node 4: Mid latitude storm tracks

- **Example: Latent Node 4**

– Translation along one latent dimension, while keeping the others fixed to their median values

– Feed resulting $z_{translation}$ array into Decoder

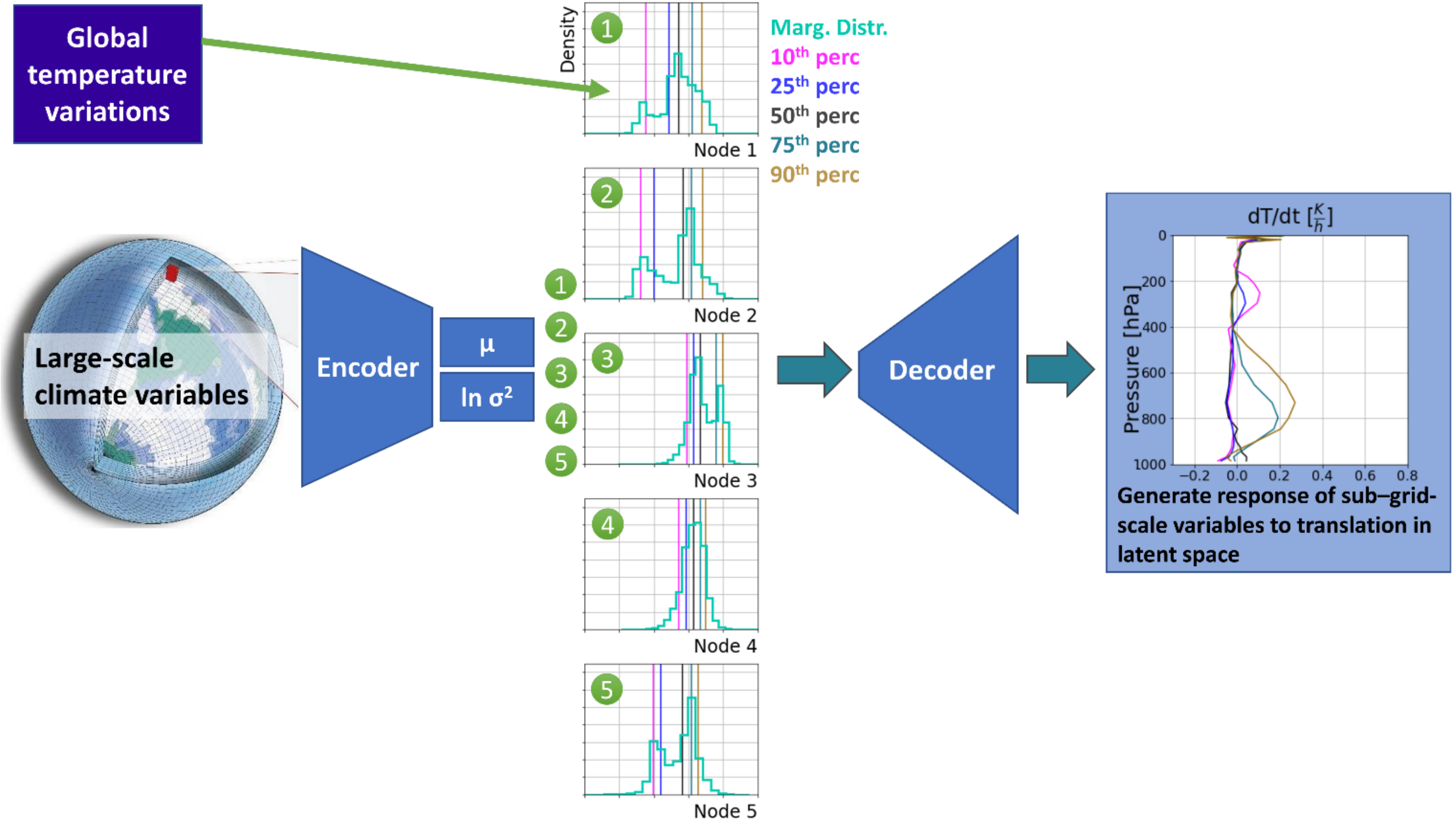




Separation of two mid lat. Convective Regimes along latent dimension

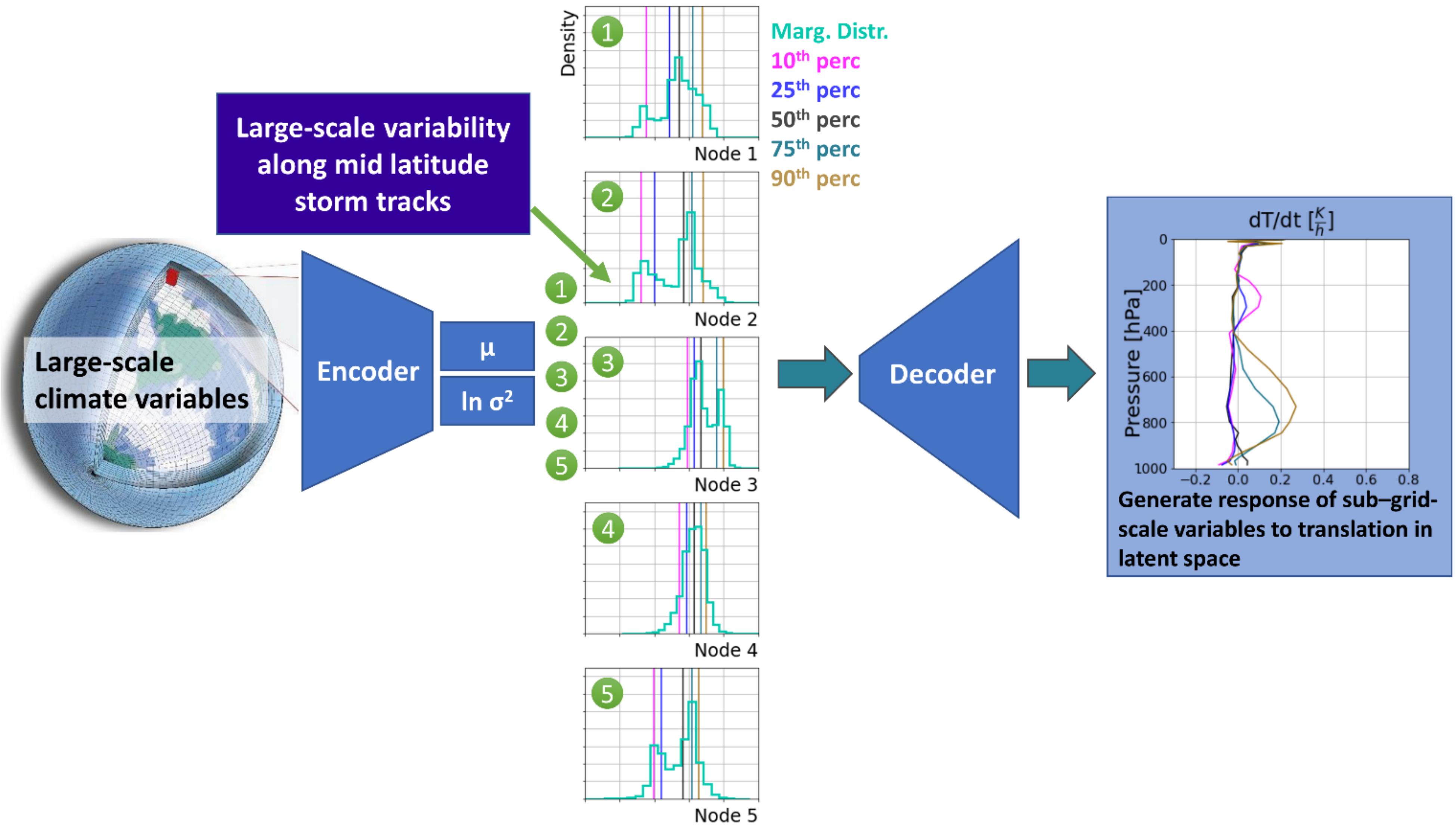
Behrens et al. (2022)

5. Understand Convective Processes in Climate Model with VED



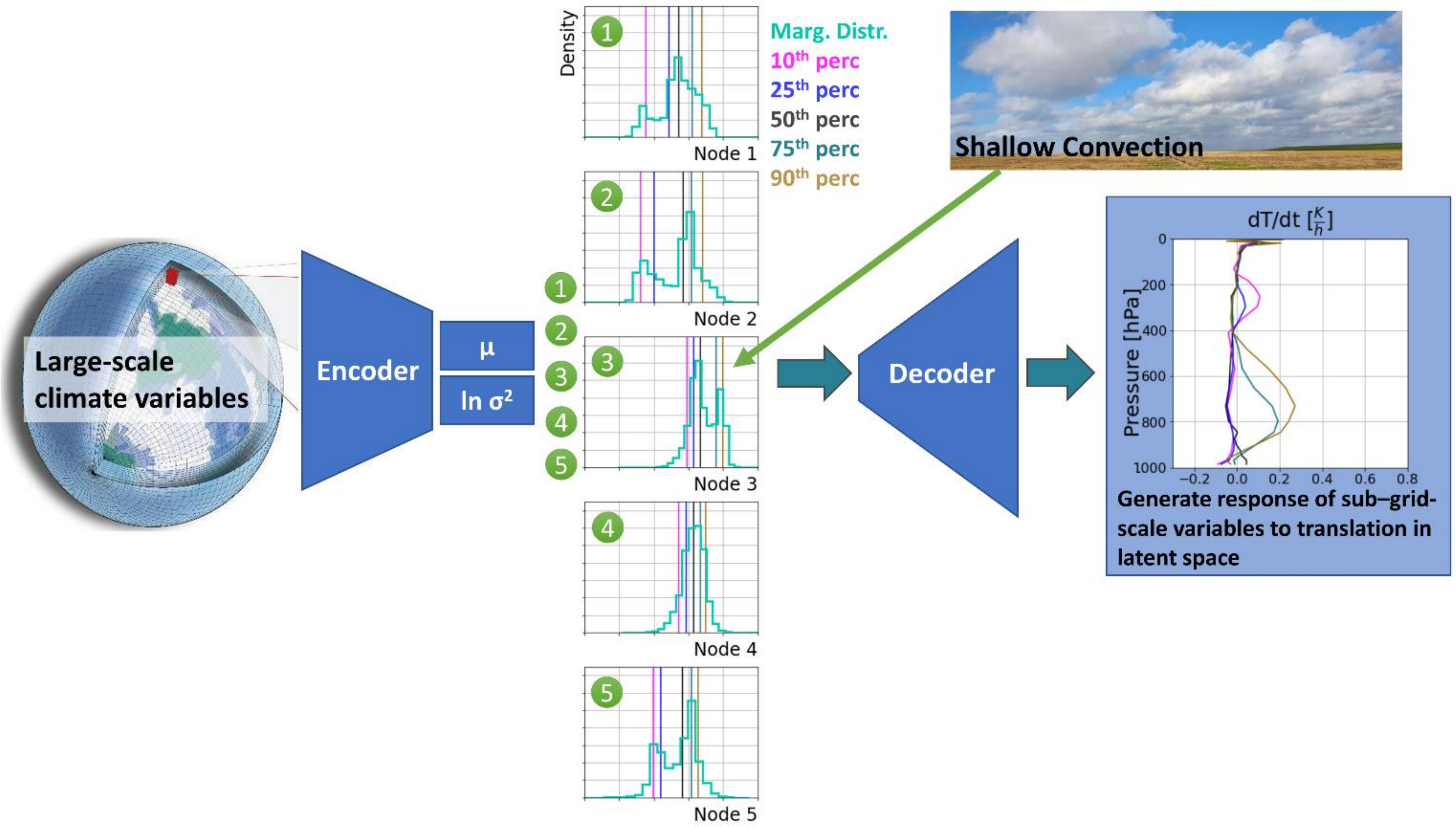
Behrens et al. (2022)

5. Understand Convective Processes in Climate Model with VED



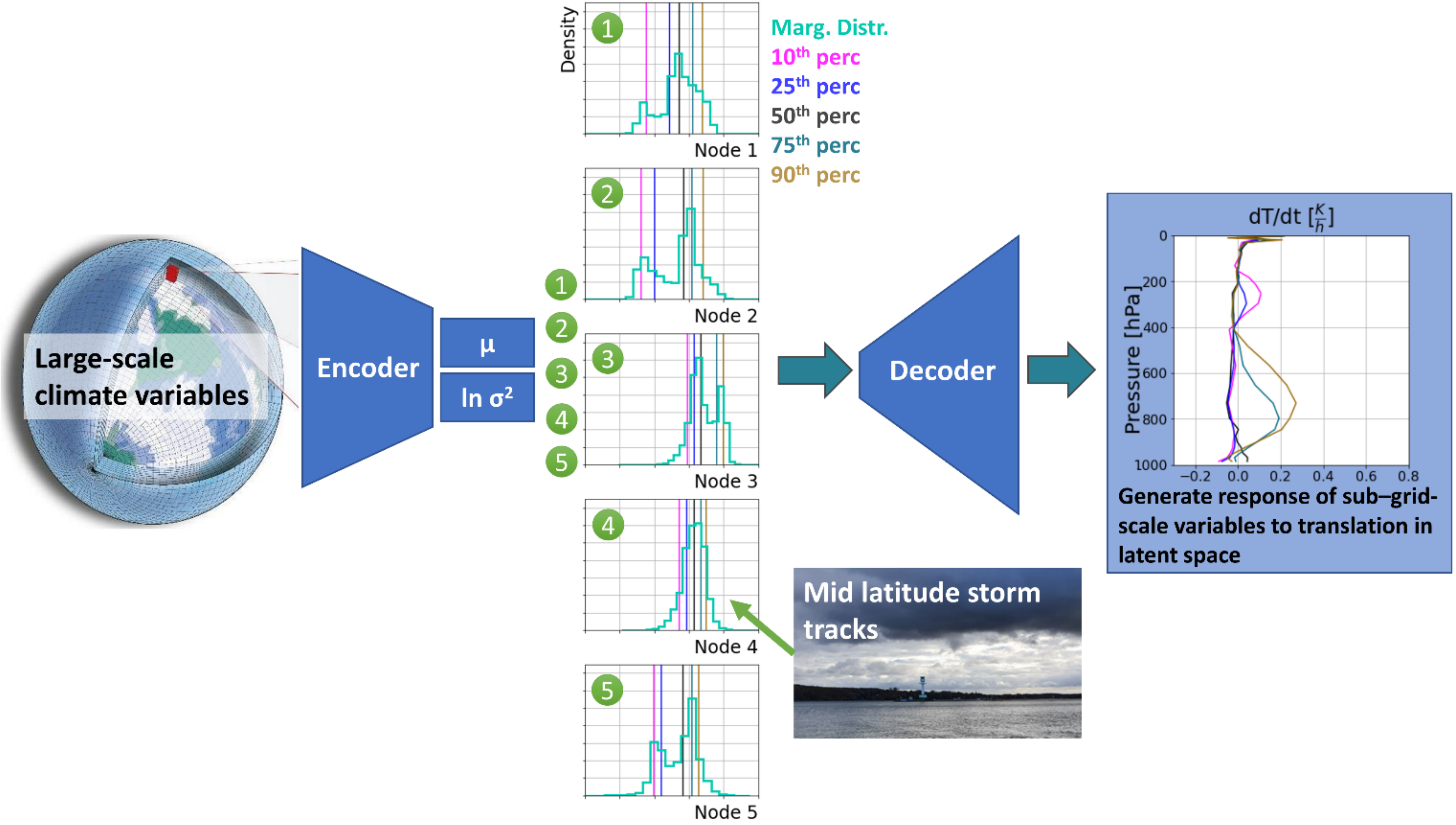
Behrens et al. (2022)

5. Understand Convective Processes in Climate Model with VED



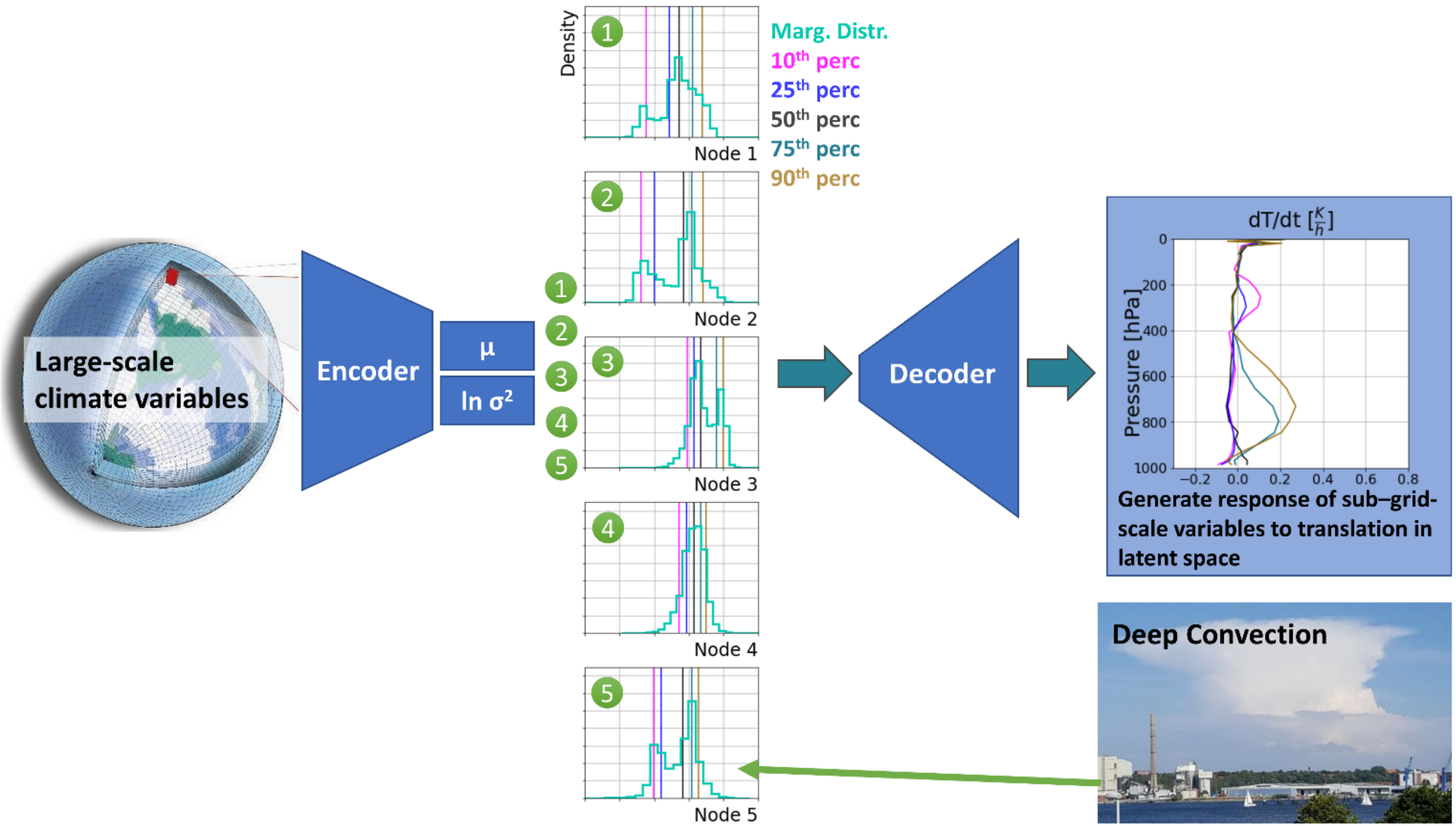
Behrens et al. (2022)

5. Understand Convective Processes in Climate Model with VED



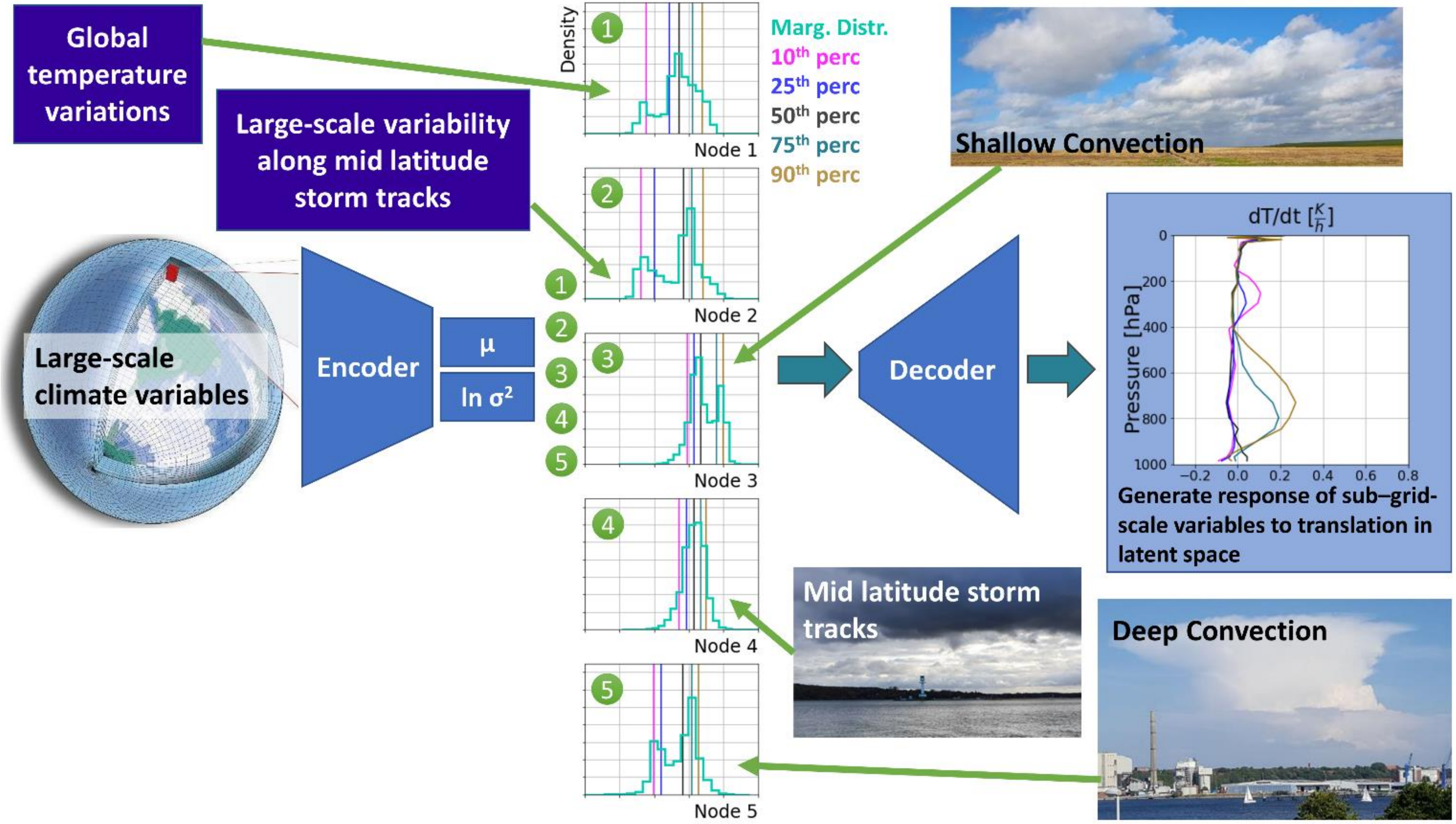
Behrens et al. (2022)

5. Understand Convective Processes in Climate Model with VED



Behrens et al. (2022)

5. Understand Convective Processes in Climate Model with VED



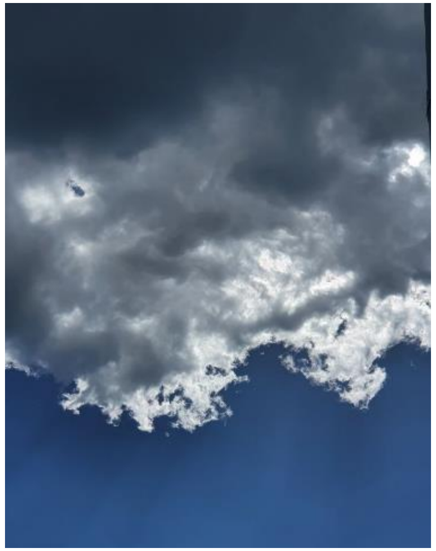
Behrens et al. (2022)

Outlook

- VED for cross-validation of existing Convective Regimes based on observations or simulations

- VED for identification of clusters / regimes based on GCM runs for Dynamics, Convection and other complex processes

- VED for development of regime-oriented parametrisations in Earth System Models



Thank you for your attention!

References

Behrens, G., Beucler, T., Gentine, P., Iglesias-Suarez, F., Pritchard, M., & Eyring, V. (2022). Non-Linear Dimensionality Reduction With a Variational Encoder Decoder to Understand Convective Processes in Climate Models. Journal of Advances in Modeling Earth Systems, 14(8), e2022MS003130.

Beucler, T., Rasp, S., Pritchard, M., & Gentine, P. (2019). Achieving conservation of energy in neural network emulators for climate modeling. arXiv(1), 2-5.

Brenowitz, N. D., & Bretherton, C. S. (2018). Prognostic Validation of a Neural Network United Physics Parameterization. Geophysical Research Letters, 45 (12), 6289-6298

Clare, M. C. A., Sonnewald, M., Lguensat, R., Deshayes, J., & Balaji, V. (2022). Explainable artificial intelligence for Bayesian Neural Networks: Toward trustworthy predictions of ocean dynamics. Journal of Advances in Modeling Earth Systems, 14, e2022MS003162. https://doi.org/10.1029/2022MS003162

Collins, W. D., Rasch, P. J., Boville, B. A., Hack, J. J., McCaa, J. R., Williamson, D. L., . . . Zhang, M. (2006). The dynamical simulation of the Community Atmosphere Model version 3 (CAM3). Journal of Climate, 19 (11), 2162-2183

Grabowski, W. W. (2001). Coupling cloud processes with the large-scale dynamics using the clouds-resolving convection parameterization (CRCP). Journal of the Atmospheric Sciences, 58 (9), 978-997

Huaman, L., & Schumacher, C. (2018). Assessing the vertical latent heating structure of the east Pacific ITCZ using the CloudSat CPR and TRMM PR. Journal of Climate, 31(7), 2563-2577.

References

Mooers, G., Pritchard, M., Beucler, T., Ott, J., Yacalis, G., Baldi, P. & Gentine, P. (2021). Assessing the Potential of Deep Learning for Emulating Cloud Superparameterization in Climate Models With Real-Geography Boundary Conditions. Journal of Advances in Modeling Earth Systems.

Mooers, G., Pritchard, M., Beucler, T., Srivastava, P., Mangipudi, H., Peng, L., ... & Mandt, S. (2022). Comparing Storm Resolving Models and Climates via Unsupervised Machine Learning. *arXiv preprint arXiv:2208.11843*.

Rasp, S., Pritchard, M. S., & Gentine, P. (2018). Deep learning to represent sub grid processes in climate models. Proceedings of the National Academy of Sciences of the United States of America, 115 (39), 9684-9689

Schneider, T., Teixeira, J., Bretherton, C. S., Brient, F., Pressel, K. G., Schär, C., & Siebesma, A. P. (2017). Climate goals and computing the future of clouds. Nature Climate Change, 7(1), 3-5.

Wang, X., Han, Y., Xue, W., Yang, G., and Zhang, G. J.: Stable climate simulations using a realistic general circulation model with neural network parameterizations for atmospheric moist physics and radiation processes, Geosci. Model Dev., 15, 3923–3940, https://doi.org/10.5194/gmd-15-3923-2022, 2022.

Yuval, J., & O'Gorman, P. A. (2020). Stable machine-learning parameterization of sub grid processes for climate modeling at a range of resolutions. Nature Communications, 11 (1), 1-10.