Python and Machine Learning for Weather, Climate and Environment

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with contributions by Stefanie Hollborn, Jan Keller, Thomas Deppisch, Mareike Burba, Matthias Mages, Sarah Heibutzki, Marek Jacob, Florian Prill, Tobias Göcke, Nastaran Najari



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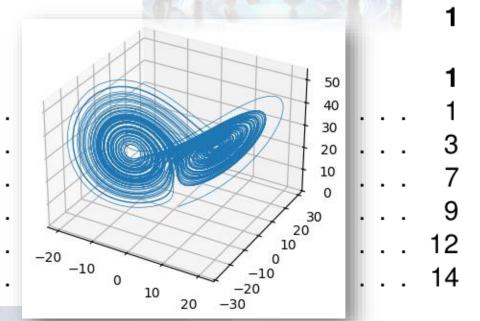
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Day 1: Python as Workhorse

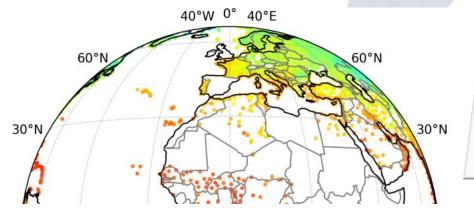
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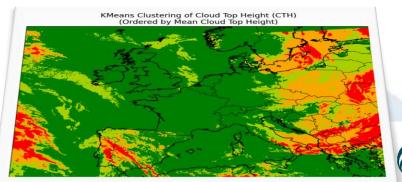
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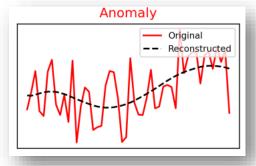
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Tutorial Philosopy

- 1) Learn to master things yourself
- 2) Work in small groups & help each other
- 3) Work from elementary understanding towards larger packages

4) Learn simple examples first

5) We need to understand the whole range of ML/Al techniques today in context



Building AI Expertise with Python and AI Workflows

To effectively integrate AI, we must ensure our teams are skilled in both AI methods and operational



- Establishing structured learning paths for key AI techniques relevant to weather and climate modeling.
- Using Python libraries such as numpy, eccodes, netcdf, and xarray for handling large meteorological datasets.
- Training teams in machine learning frameworks such as TensorFlow,
 PyTorch, and Hugging Face Transformers.
- Setting up end-to-end Al workflows in Jupyter-based environments, covering data ingestion, training, validation, and inference.
- Encouraging collaboration between meteorologists, model developers, and AI experts to foster cross-disciplinary innovation workflows.

Replacing and Hybridizing Forecasting Systems with Al

Some forecasting components will be fully replaced by AI, while others will integrate AI as a hybrid solution. Key shifts include:

- Al-Based Nowcasting: Al-driven short-term weather predictions using real-time observational data (e.g., satellite, radar, sensors), enhancing or replacing conventional nowcasting techniques.
- Neural Weather Models: Deep learning models trained on historical data can generate competitive forecasts at lower computational cost.
- Hybrid Al-NWP Models: Al enhances physics-based forecasting through bias correction, uncertainty quantification, and ensemble optimization.
- Machine Learning for Subgrid Processes: Al could improve or replace empirical parameterizations in turbulence, cloud physics, and convection models.
- Automated Impact Forecasting: Al-driven models provide direct risk assessments for extreme weather events, minimizing reliance on manual interpretation.



Al in Data Assimilation and Learning Directly from Observations

- Machine Learning for Observation Processing: Al-driven quality control of observational data, filling data gaps and detecting sensor anomalies.
- Al-Based Data Assimilation: Al improving assimilation processes by optimizing observation ingestion.
- Deep Learning for Data Assimilation: Al learning complex relationships between observations and model states, accelerating assimilation workflows.
- End-to-End Al Data Ingestion: Future Al models trained directly on observational datasets, potentially reducing reliance on classical assimilation techniques.
- Self-Learning Systems: Al dynamically adjusting to new data, improving continuously without manual recalibration.



Using Al for Code Refactoring and Model Development of the large of th

Al also modernizes modeling workflows, improving efficiency in research and development:

- Refactoring Legacy Code: Al-assisted tools improving Fortran, C++, and Python models for better maintainability and performance.
- Automated Model Optimization: Al tuning hyperparameters and optimizing computational 12 and optimizing computational 12 performance.
- Al-Assisted Scientific Discovery: Al identifying climate and weather patterns in large datasets.
- Al-Generated Documentation and Testing: Automating on fig. documentation and generating validation tests for USE mo_grid_ numerical models.

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Contact information: icon-model.org
  See AUTHORS.TXT for a list of authors
! See LICENSES/ for license information
 Diagnosis of physics after physics call
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MODULE mo_nwp_diagnosis

USE mo_kind,

#include "omp definitions.inc"

USE mo_impl_constants, ONLY: itccov, it USE mo_impl_constants_grf, ONLY: grf_bdywid USE mo_loopindices, ONLY: get_indice USE mo_exception, ONLY: message, m

USE_mo_model_domain, ONLY: iqv, iqc, igni, igg,

ONLY: wp

min_rlcell



Transforming Services and User Interaction with AI



All enables new ways to deliver weather and climate services, improving automation, personalization, and accessibility:

- Al-Generated Weather Reports: Natural language generation models translating raw data into meaningful insights for different user groups.
- Conversational Forecasting Assistants: All chatbots and voice assistants allowing users to interactively query weather and climate predictions.
- Real-Time Impact Forecasting: Al models directly linking weather forecasts to risks in agriculture, energy, transportation, and disaster management.
- Al-Powered Data Visualization: Interactive Al tools allowing users to explore, manipulate, and interpret complex weather datasets.



A Clear Migration Strategy for Al Transformation

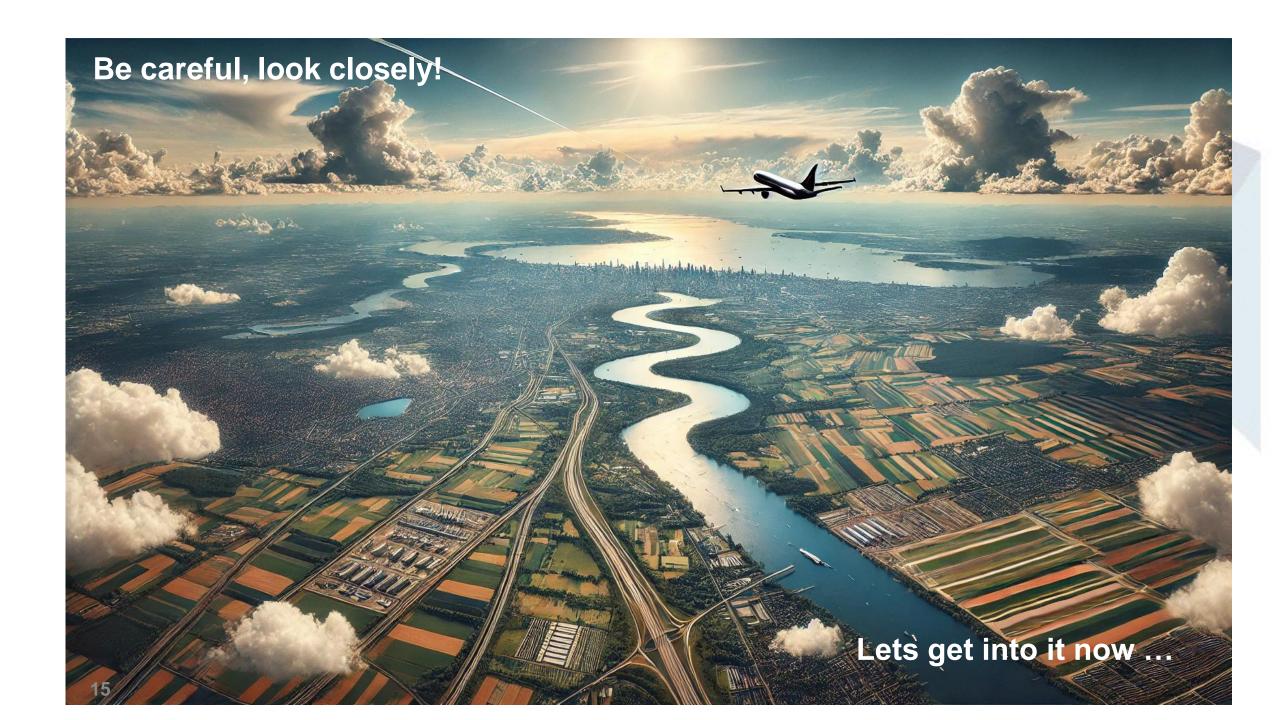
- 1. Al Readiness Assessment: Identify areas where Al provides the highest impact while ensuring compatibility with existing workflows.
- 2. Pilot Al Replacements: Test Al-based forecasting models in parallel with traditional methods before full adoption.
- 3. Hybrid Deployment Strategy: Introduce Al-driven improvements in stages, ensuring fallback options are in place.
- 4. Al Validation and Trust Building: Develop transparent evaluation metrics for Al models to ensure trust and reliability.
- 5. Workforce Training and Knowledge Transfer: Enable teams to transition smoothly from traditional methods to Al-driven solutions.
- 6. Continuous Al Governance: Establish guidelines for Al model retraining, performance monitoring, and ethical considerations.



Limitations and Responsible Use of Al

While AI offers transformative opportunities in forecasting, modeling, and service delivery, it is crucial to acknowledge its current limitations and apply it with scientific caution:

- Data Requirements: Most AI models rely on large, high-quality datasets and perform poorly in data-sparse or non-stationary environments.
- Lack of Physical Consistency: Al predictions may violate conservation laws or produce unrealistic results in rapidly evolving scenarios.
- Limited Interpretability: Unlike traditional models, many AI systems operate as black boxes, making it difficult to understand or trace their internal reasoning.
- Bias and Overfitting: Biased or unbalanced training data can lead to flawed predictions, while overfitting to historical data may reduce adaptability to changing climate conditions.
- Need for Rigorous Validation: Al models must be continuously monitored, validated, and benchmarked to ensure stability, fairness, and scientific reliability. Validation needs metrics and scores beyond traditional forecasting metrics.
- Complementary Role: All should be seen as an enhancement to—not a replacement for—physics-based modeling, supporting a hybrid approach for trustworthy innovation.



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