



1 Background & Objective

Climate-data complexity

- Coupled climate system: atmosphere, ocean, land, cryosphere, biosphere
- Satellites, stations and buoys produce **petabyte-scale** data
- CMIP6 multi-model simulations; ERA5 reanalysis (0.25°, hourly)
- High-dimensional data challenge traditional linear methods

AI/ML opportunities

- Pattern recognition in multidimensional datasets
- Model emulation, downscaling, precipitation forecasting
- Drought monitoring and extreme-event detection
- Integration of heterogeneous data; rapid prediction

The scientific validation challenge

Black box
Neural networks resist physical interpretation

Generalization
Skill may fail under conditions unlike the training period

Physics inconsistency
Outputs may violate conservation laws or balances

High accuracy on a validation set does **not** guarantee correct climate physics.

Research objective

- Propose an **integrated AI/ML–ESMValTool methodology**
- Keep ML efficiency **and** scientific rigor and physical consistency
- Evaluate ML outputs with the same standardized framework used for climate models
- Focus on vulnerable regions, e.g. **East Africa**

2 Methodology & Key Findings

Six-stage framework **PROPOSED**

- Data integration & preprocessing**
Quality control, NetCDF, feature engineering
- ML model development**
Supervised, unsupervised, deep learning
- ESMValTool validation**
ML outputs evaluated like climate-model outputs
- Physical consistency assessment**
Energy, mass, momentum, thermodynamics
- Uncertainty quantification**
Bayesian, ensemble, dropout-based
- Climate analytics & decision support**
Forecasts, projections, risk indices

Data sources

CMIP6ERA5MERRA-2GPCPCERES

MODISTRMM/GPM SMAP

ESMValTool evaluation dimensions

Climatological meanVariability

TrendsSpatial patterns

Physical processesModel–observation agreement

Key findings (conceptual)

- Scientific bridge:** ESMValTool tests whether AI models capture meaningful climate relationships
- Shifts evaluation from network weights to **observable climate quantities**
- Systematic documentation supports **transparency & reproducibility**

Drought monitoring, East Africa

ILLUSTRATIVE

Inputs
NDVI (MODIS)
Precipitation (TRMM/GPM)
Soil moisture (SMAP)
ERA5 • seasonal forecasts

ML drought model
proposed lead time 1–3 months

ESMValTool checks
drought statistics, spatial patterns, duration & intensity, extremes

Proposed design shown for demonstration; no quantitative results are presented.

3 Implications & Conclusion

Transparency & reproducibility

- Document architecture, training data, metrics, procedures
- Enables community verification and cross-method comparison

Climate-model evaluation

- One standardized framework for process-based **and** ML-driven models
- Comparison with observations and physical principles

Climate resilience applications

- Early warning and probabilistic forecasts for risk-based decisions
- Global satellite data help where ground stations are sparse
- Evidence-based adaptation and environmental policy

Limitations

- Interpretability
- Generalization to novel climates
- Data and compute demands
- Physics vs. learned artifacts

Future directions

- Physics-informed neural networks
- Hybrid process–ML models
- Advanced uncertainty methods
- Explainable AI
- Real-time systems; equitable access

Conclusion

- ESMValTool evaluation offers an effective route to **validate AI-driven climate models**
- Rigor and transparency make AI/ML outputs **scientifically credible**
- Strategic adoption is a scalable pathway to **climate adaptation**, notably in developing regions

Selected references

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