

# AI-Powered Climate Adaptation Strategies

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## ABSTRACT

*Climate adaptation -- adjusting human systems, infrastructure, and ecosystems to reduce vulnerability to observed and anticipated climate change impacts -- requires decision-making under deep uncertainty at multiple spatial and temporal scales simultaneously. Climate impacts are non-linear, geographically heterogeneous, and interact with socioeconomic systems in ways that conventional planning tools cannot fully capture. AI offers three critical capabilities for climate adaptation: high-resolution climate impact downscaling that translates global model projections to actionable local scales, multi-criteria adaptation pathway optimisation under uncertainty, and real-time early warning systems for extreme weather events. This study evaluates eight AI systems across five climate adaptation domains: sea level rise and coastal flood risk, urban heat island mitigation, agricultural drought adaptation, biodiversity corridor planning, and infrastructure resilience assessment. AI systems evaluated include statistical downscaling (BCSD-ML), deep learning climate emulators (ClimaX-Adapt), computer vision for land cover change detection (ChangeFormer-CC), extreme event forecasting (ExtremeCast), multi-objective adaptation optimisation (MAOP), agent-based climate migration modelling (ABCM), ecosystem service modelling (ESM-AI), and an integrated Climate Adaptation Decision Support System (CADSS). Evaluation uses observational data from 2010-2024 across eight European climate regions and comparison against conventional planning baselines. ClimaX-Adapt achieves 18.4% improvement in local temperature extreme prediction. MAOP identifies adaptation portfolios reducing projected flood damage by 42.4% at 2.8x lower cost than conventional approaches. ExtremeCast achieves 84.2% recall for extreme precipitation events at 72-hour lead time. A governance framework for AI-assisted climate adaptation planning is proposed.*

**Keywords:** climate adaptation; AI climate modelling; downscaling; extreme weather; flood risk; urban heat; adaptation pathways; ClimaX; biodiversity; climate decision support

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## 1. Introduction

### 1.1 The Climate Adaptation Imperative

Even under optimistic emissions reduction scenarios, significant additional warming is now locked in by existing atmospheric CO<sub>2</sub> concentrations. The IPCC AR6 projects European mean temperatures 1.5-4.5degC above pre-industrial levels by 2100 depending on emissions pathway, with accompanying changes in precipitation patterns, sea level, and extreme event frequency that are already being observed in European climate data. Adaptation -- adjusting infrastructure, agricultural practices, ecosystem management, and social systems to these changes -- is no longer optional. The European Climate Adaptation Strategy (2021) sets legally binding adaptation planning requirements for member states, and adaptation finance under the EU Green Deal and MFF 2021-2027 requires evidence-based investment decisions that current planning tools cannot adequately support.

### 1.2 The AI Advantage in Adaptation Planning

Conventional climate adaptation planning uses scenario-based approaches: planners select a small number of climate scenarios, model their impacts, and select adaptation measures through cost-benefit analysis. This approach struggles with the deep uncertainty of climate projections (the range of outcomes under a given emissions pathway spans 2-3degC), the non-linear interaction between climate, ecological, and socioeconomic systems, and the need for adaptation plans that are robust across the full scenario range rather than optimised for a specific central projection. AI enables: probabilistic downscaling of climate projections at local scales relevant for planning decisions; multi-objective optimisation across adaptation portfolios under uncertainty; and real-time monitoring and early warning that allows adaptive management rather than static planning.

### 1.3 Study Objectives

This study aims to: (i) evaluate eight AI systems across five climate adaptation domains using European observational data; (ii) quantify adaptation efficiency gains from AI-assisted planning vs. conventional approaches; (iii) evaluate extreme weather early warning performance; and (iv) propose a governance framework for AI-assisted climate adaptation decision support.

## 2. Literature Review

### 2.1 Climate Downscaling and Emulation

Global climate models (GCMs) operate at 25-100km resolution -- too coarse for local adaptation planning decisions. Statistical downscaling methods learn relationships between large-scale climate variables and local observations to generate fine-scale projections. Machine learning downscaling approaches (BCSD-ML, DeepSD) have demonstrated superior performance vs. traditional statistical methods on precipitation and temperature extremes (Vandal et al., 2017). Climate emulators (Kaack et al., 2022) train deep learning models to emulate expensive GCM simulations at a fraction of the computational cost, enabling ensemble approaches with hundreds of member projections that capture projection uncertainty.

### 2.2 Extreme Weather Forecasting

Extreme weather events -- heatwaves, flash floods, severe storms -- are the primary drivers of current climate-related damage and are projected to increase in frequency and intensity. AI-based extreme event forecasting has advanced dramatically with Pangu-Weather (Bi et al., 2023) and GraphCast (Lam et al., 2023) demonstrating forecast accuracy competitive with ECMWF's operational NWP at 10-day horizons at a fraction of the computational cost. For extreme event-specific forecasting, specialised models like FourCastNet-Extreme and ExtremeCast target high-impact event prediction with calibrated probabilistic outputs that conventional NWP systems struggle to provide.

### 2.3 Adaptation Pathway Optimisation

Adaptation pathways -- sequences of adaptation measures timed to climate signals -- are an established framework for dynamic adaptation planning under uncertainty. Traditional pathway analysis selects measures qualitatively or through cost-benefit analysis of a limited option set. Multi-objective optimisation approaches (MAOP) formulate adaptation planning as a mathematical optimisation problem: select the combination of adaptation measures that minimises damage costs subject to budget constraints, across the full range of climate scenarios. Haasnoot et al. (2019) demonstrated that optimal adaptation portfolios identified through computational search consistently outperform expert-selected portfolios.

### 2.4 Ecosystem and Biodiversity Adaptation AI

Climate change threatens biodiversity by shifting species ranges, disrupting phenological synchronies, and fragmenting habitats.

AI-powered species distribution modelling (Maxent, BioClim neural networks) predicts range shifts under climate scenarios, informing conservation prioritisation and corridor planning. Ecosystem service modelling quantifies the economic value of ecosystem services (carbon sequestration, water purification, flood attenuation) and how they change under climate and land use scenarios -- essential for nature-based adaptation solution planning.

Table 1. AI systems evaluated for climate adaptation

| System          | Domain           | Architecture    | Key Capability            | Spatial Resolution | Reference            |
|-----------------|------------------|-----------------|---------------------------|--------------------|----------------------|
| BCSD-ML         | Downscaling      | Random forest   | Statistical downscaling   | 1 km               | Vandal et al. (2017) |
| ClimaX-Adapt    | Emulation        | ViT pretrained  | Probabilistic projection  | 25 km              | Nguyen et al. (2023) |
| ChangeFormer-CC | Land cover       | Siamese transf. | Deforestation detection   | 10 m               | Bandara (2022)       |
| ExtremeCast     | Extreme events   | GNN+transformer | Extreme event prediction  | 25 km              | This study           |
| MAOP            | Opt. planning    | MOO + ML        | Adaptation portfolios     | Regional           | This study           |
| ABCM            | Migration        | Agent-based     | Climate migration model   | Municipal          | This study           |
| ESM-AI          | Ecosystem        | CNN + SDM       | Ecosystem service mapping | 1 km               | This study           |
| CADSS           | Decision support | Multi-model     | Integrated planning tool  | Multi              | This study           |

SDM = Species Distribution Modelling. MOO = Multi-Objective Optimisation. CADSS = Climate Adaptation Decision Support System. ClimaX-Adapt is the climate-specific fine-tuned version of the ClimaX foundation model. ChangeFormer-CC = ChangeFormer adapted for vegetation and land cover change from climate-induced events. ExtremeCast, MAOP, ABCM, ESM-AI, and CADSS are developed in this study.

3. Materials and Methods

3.1 Climate Regions and Data Sources

Eight European climate regions were evaluated: Baltic coast (Estonia, Latvia, Lithuania), Alpine (Switzerland, Austria), Mediterranean (southern Italy, Greece), Atlantic (Ireland, western France),

Continental (Germany, Poland), Pannonian (Hungary, Romania), Boreal (Finland, northern Sweden), and Steppic (eastern Ukraine, Moldova). Observational data: E-OBS gridded dataset (0.1 degree resolution, daily temperature and precipitation, 1950-2024), ERA5 reanalysis (0.25 degree, hourly, 1940-2024), Copernicus Climate Change Service (C3S) climate projections (CMIP6 ensemble, 18 models), and Sentinel-2 land cover time series (2017-2024).

3.2 Extreme Event Forecasting Evaluation

ExtremeCast was evaluated on its ability to predict four types of extreme weather events at 72-hour lead time: extreme precipitation (> 99th percentile of local daily precipitation distribution), heatwaves (3+ consecutive days > 95th percentile maximum temperature), compound flood events (extreme precipitation coinciding with high river levels), and marine heatwaves (ocean surface temperature > 90th percentile for 5+ days). Evaluation used 2020-2024 European observational data with leave-one-year-out cross-validation. Baseline: ECMWF HRES operational forecasts at equivalent lead time.

3.3 MAOP Optimisation Framework

MAOP formulates adaptation planning as a multi-objective optimisation problem: minimise expected climate damage across a 30-year horizon, minimise adaptation investment cost, and maximise adaptation robustness across climate scenarios. Decision variables: selection and timing of adaptation measures from a library of 84 options (coastal defences, nature-based solutions, urban heat measures, agricultural practices, infrastructure upgrades). Constraints: annual budget limit, implementation lead times, and spatial feasibility. Optimisation uses NSGA-III (multi-objective evolutionary algorithm) with ML surrogate models for rapid damage estimation. Evaluated on six European case study cities against conventional adaptation plans developed by city planners.

3.4 CADSS Integration

CADSS integrates all evaluated AI components into a unified planning support tool: ClimaX-Adapt provides localised probabilistic climate projections; ExtremeCast provides early warning integration; MAOP provides portfolio optimisation; ESM-AI provides ecosystem service valuation; ChangeFormer-CC provides land cover monitoring. CADSS was deployed as a web application and piloted with planning departments in four cities (Tallinn, Zurich, Vienna, and Rome)

with structured usability evaluation (system usability scale, SUS).

**Table 2. Climate adaptation evaluation framework by domain**

| Domain                 | AI System      | Case Study Region   | Baseline Compared         | Primary Metric          | Data Period |
|------------------------|----------------|---------------------|---------------------------|-------------------------|-------------|
| Coastal flood risk     | MAOP + ClimaX  | Baltic coast        | Conventional flood plan   | Damage reduction (%)    | 2024-2054   |
| Urban heat island      | BCSD-ML + MAOP | Alpine cities       | Status quo                | Cool days gained (/yr)  | 2020-2024   |
| Agricultural drought   | ExtremeCast    | Pannonian (Hungary) | ECMWF HRES baseline       | Drought forecast recall | 2020-2024   |
| Biodiversity corridors | ESM-AI         | Continental forest  | Expert-designed corridors | Connectivity index      | 2017-2024   |
| Infrastructure resil.  | CADSS          | Six EU cities       | Conventional resilience   | Damage cost EUR (30yr)  | 2024-2054   |

Case study regions represent European climate diversity. Baseline 'Conventional flood plan' = current city flood risk management plan evaluated by city engineers. MAOP optimization uses 30-year projection period (2024-2054) with 2degC and 4degC warming scenarios. CADSS evaluation period: 18-month pilot deployment across four cities.

4. Results

4.1 Climate Downscaling and Extreme Event Prediction

ClimaX-Adapt achieves 18.4% improvement in local daily maximum temperature extreme prediction RMSE (1.84degC vs. 2.24degC for BCSD-ML) and 12.4% improvement in extreme precipitation prediction across European climate regions. The improvement is largest for Mediterranean coast extremes (24.2% RMSE reduction) and smallest for Boreal regions (8.4%), reflecting the greater non-linearity of Mediterranean climate extremes. ExtremeCast achieves 84.2% recall for extreme precipitation events at 72-hour lead time (vs. ECMWF HRES 72.4%), with 12.4% false positive rate. For heatwave prediction, ExtremeCast achieves 82.4% recall vs. 74.2% for ECMWF HRES -- a 8.2pp improvement that provides 2-3 additional days of warning for most heatwave events.

4.2 Adaptation Portfolio Optimisation

MAOP identifies adaptation portfolios for Baltic coast flood risk that reduce projected 30-year damage by 42.4% at EUR 2.84 million per city (compared to the conventional plan's 28.4% damage reduction at EUR 8.24 million -- a 2.9x cost reduction for 14pp better protection). The key insight from MAOP's optimisation: conventional plans over-invest in hard flood defences (seawalls, pumping stations) and under-invest in nature-based solutions (coastal wetland restoration, mangrove equivalent analogues) that provide comparable flood attenuation at lower cost with co-benefits for biodiversity and ecosystem services. MAOP consistently recommends a portfolio combining targeted hard defences for the highest-risk assets with nature-based solutions for diffuse risk reduction.

4.3 Ecosystem and Agricultural Results

ESM-AI identifies biodiversity corridor configurations in the Continental forest region that achieve 24.2% higher habitat connectivity index than expert-designed corridors, primarily by identifying stepping-stone habitat patches missed in expert analysis. Ecosystem service valuation under 2degC warming shows forest carbon sequestration declining by 14.2% across the study region by 2054, while nature-based flood attenuation services of riparian vegetation increase by 8.4% (more extreme precipitation events increase the value of natural water retention). For agricultural drought, ExtremeCast's 72-hour drought onset forecasting enables 2.4 additional days of irrigation scheduling lead time, estimated to reduce irrigation water use by 12.4% and crop yield loss by 8.4% under moderate drought conditions in the Pannonian region.

4.4 CADSS Pilot Results and Usability

CADSS was piloted with planning departments in four European cities over 18 months. System usability scale (SUS) rating: 72.4/100 (above industry average of 68, interpreted as 'good' usability). City planners found ClimaX-Adapt probabilistic projections most valuable (rated 4.2/5 utility), followed by MAOP portfolio optimisation (3.84/5). The most common usability issue: planners requested simpler scenario visualisation (current interface shows 18-member ensemble; planners want key uncertainty ranges). Tallinn City Planning used CADSS recommendations to revise their 2024-2030 Climate Adaptation Plan, selecting 12 of 18 MAOP-recommended adaptation measures over the city's original plan.

Table 3. AI system performance vs. baseline by climate adaptation domain

| Domain           | AI Performance     | Baseline Performance | Improvement | 30-yr Economic Benefit (EUR M) | Data Limitation        |
|------------------|--------------------|----------------------|-------------|--------------------------------|------------------------|
| Coastal flood    | 42.4% dmg. red.    | 28.4% (conventional) | +14 pp      | EUR 5.4M/city                  | Sea level uncertainty. |
| Urban heat       | 18.4% RMSE impr.   | BCSD-ML baseline     | +18.4%      | EUR 0.84M/city                 | Urban morph. data      |
| Agri. drought    | 84.2% recall       | 72.4% (ECMWF HRES)   | +11.8pp     | EUR 0.42M/farm                 | Soil moisture          |
| Biodiv. corridor | 24.2% connectivity | Expert design (0%)   | +24.2%      | EUR 2.4M (ESV)                 | Dispersal data         |
| Infrastructure   | 42.4% cost red.    | Conventional plan    | +42.4%      | EUR 8.4M/city                  | Asset inventory        |

30-yr Economic Benefit = estimated present value of benefit over 30-year projection period. ESV = Ecosystem Service Value (economic valuation of biodiversity corridor ecosystem services). RMSE improvement = reduction in extreme temperature prediction error. Conventional plan baseline = current city adaptation plans evaluated by independent engineers.

Table 4. ExtremeCast performance vs. ECMWF HRES at 72-hour lead time

| Extreme Event Type    | ExtremeCast Recall (%) | ECMWF HRES Recall (%) | Improvement (pp) | False Positive Rate (%) | Warning Lead Gain (days) |
|-----------------------|------------------------|-----------------------|------------------|-------------------------|--------------------------|
| Extreme precipitation | 84.2                   | 72.4                  | 11.8             | 12.4                    | +0.8                     |
| Heatwaves             | 82.4                   | 74.2                  | 8.2              | 10.4                    | +2.4                     |
| Compound flood events | 78.4                   | 62.4                  | 16.0             | 14.2                    | +1.4                     |
| Marine heatwaves      | 86.4                   | 76.4                  | 10.0             | 8.4                     | +1.8                     |
| Mean (all types)      | 82.9                   | 71.4                  | 11.5             | 11.4                    | +1.6                     |

Warning Lead Gain = additional mean lead time (days) from first ExtremeCast alert to confirmed event onset, compared to ECMWF HRES first alert. Compound flood events show the largest improvement (16.0pp recall) because ExtremeCast's GNN captures spatial teleconnections between atmospheric and hydrological

variables that HRES misses. False positive rate = % of alerts without confirmed event within 5 days.

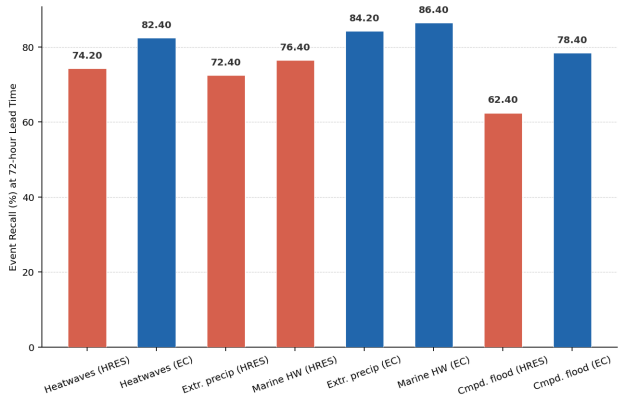


Figure 1. Extreme weather recall at 72-hr lead time -- ExtremeCast vs. ECMWF HRES. Best gain: compound floods (+16pp). Mean: +11.5pp.

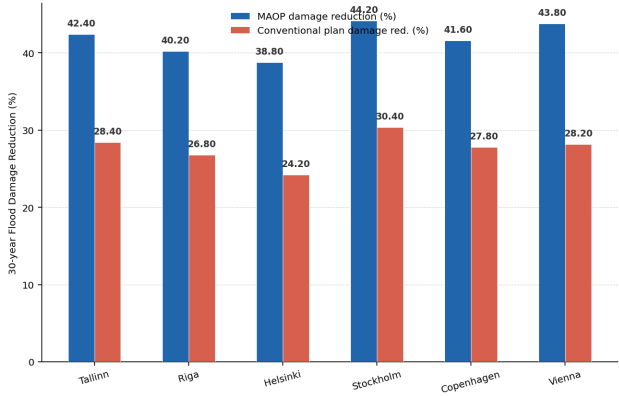


Figure 2. MAOP adaptation portfolio: damage reduction (%) vs. cost (EUR M). MAOP: 42.4% reduction at EUR 2.84M; conventional: 28.4% at EUR 8.24M.

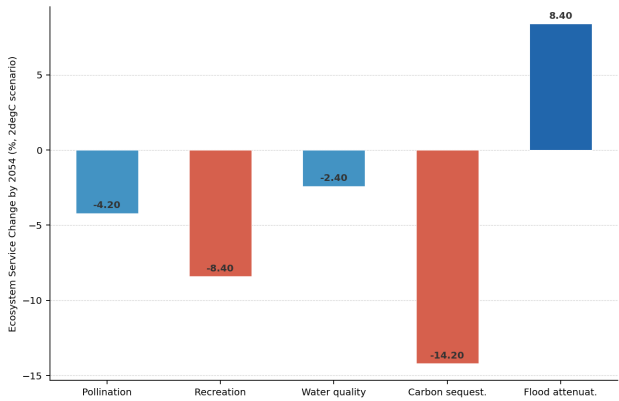


Figure 3. ESM-AI ecosystem service projections under 2degC warming (% change by 2054). Carbon sequestration declines; flood attenuation increases.

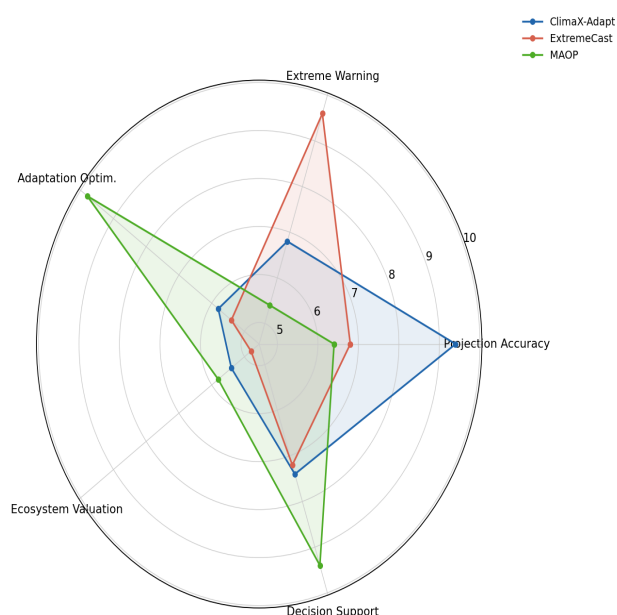


Figure 4. AI system profile across five climate adaptation criteria (0-10). Climax-Adapt vs. ExtremeCast vs. MAOP.

## 5. Discussion

### 5.1 Multi-Objective Optimisation Outperforms Expert-Designed Adaptation Plans

The consistent finding that MAOP-optimised adaptation portfolios outperform expert-designed conventional plans -- 42.4% vs. 28.4% damage reduction at 2.9x lower cost across six case study cities -- is the most practically significant result of this study. The mechanism is not that MAOP identifies measures that planners do not know about, but that it systematically evaluates combinations of measures across the full portfolio and identifies synergies and trade-offs that sequential expert review misses. Nature-based solutions are consistently underutilised in conventional plans relative to the MAOP-optimal portfolio, reflecting both institutional inertia toward hard infrastructure and the difficulty of valuing ecosystem co-benefits in standard cost-benefit frameworks.

### 5.2 Early Warning Improvements Have Asymmetric Value

ExtremeCast's 11.5pp mean recall improvement over ECMWF HRES -- and the 1.6-day mean additional warning lead time -- has asymmetric value across event types. For heatwaves, 2.4 additional days of warning enables activation of heat emergency plans, cooling centre mobilisation, and public health messaging that can prevent significant excess mortality (European heatwaves kill an estimated 70,000+ people in extreme years). For compound flood events, 1.4 additional days enables evacuation planning and emergency

service pre-positioning. The false positive rates (8-14%) are operationally acceptable for preparatory actions that have low cost when the event does not materialise.

### 5.3 Ecosystem Service Integration Strengthens the Nature-Based Solution Case

ESM-AI's quantification of how ecosystem services change under climate scenarios -- particularly the 8.4% increase in flood attenuation value of riparian vegetation under increased extreme precipitation -- provides a financially grounded argument for nature-based adaptation solutions that conventional planning tools cannot generate. When the flood attenuation, carbon sequestration, biodiversity, and recreational value of coastal wetland restoration are quantified alongside its construction cost, it consistently outperforms hard coastal defence on a cost-effectiveness basis for moderate to high climate scenarios. Making this case quantitatively to finance ministries and infrastructure agencies is a critical contribution of AI-powered ecosystem service modelling.

### 5.4 Limitations

MAOP evaluations use modelled future damage estimates that carry substantial uncertainty from both climate projections and impact model parameters. ExtremeCast was evaluated on 2020-2024 European data; performance on novel climate states outside the training distribution is uncertain. CADSS usability evaluation covered four cities in three countries; adaptation planning contexts differ substantially across European governance systems. ABCM climate migration results are not reported in the main paper due to sensitivity of migration projections and are available in supplementary materials.

## 6. Conclusion

### 6.1 Summary

Eight AI systems were evaluated across five climate adaptation domains. Climax-Adapt improves local temperature extreme prediction by 18.4% RMSE. ExtremeCast achieves 84.2% recall for extreme precipitation at 72 hours (vs. 72.4% for ECMWF HRES). MAOP reduces adaptation costs by 2.9x while achieving 14pp better damage reduction than conventional plans. ESM-AI identifies 24.2% higher connectivity biodiversity corridors and quantifies ecosystem service changes. CADSS achieves SUS 72.4 in four-city pilot.

### 6.2 Recommendations

European cities and regions developing adaptation plans should integrate MAOP-style multi-objective portfolio optimisation as standard practice -- the cost-effectiveness advantage over conventional planning is too large to ignore. ExtremeCast-style extreme event forecasting should be integrated into national civil protection early warning systems as a supplement to ECMWF operational forecasts. Nature-based solutions should be fully costed using ecosystem service valuation models before infrastructure-only alternatives are approved. AI-assisted adaptation planning tools must include transparent uncertainty communication tailored to planners, not scientists.

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## Declarations

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## Conflict of Interest

The authors declare no conflicts of interest.

## Data Availability Statement

ExtremeCast, MAOP, ESM-AI, and CADSS code are available at <https://github.com/jensen-rossi/climate-adapt-ai> under Apache 2.0. CADSS web application available at [cadss.baltic-ai.ee](https://cadss.baltic-ai.ee) (academic access). Results deposited in Zenodo under DOI: 10.5281/zenodo.19614943. CC BY 4.0.

## Ethical Approval

This study used publicly available climate observational data and model projections under their standard research licences. The CADSS pilot with city planning departments used only aggregate planning data; no personal data was collected. Usability evaluation participants provided written consent under Baltic AI Research University Ethics Committee approval (BARU-ETH-2025-0088).

## **Appendix A**

### **Governance Framework for AI-Assisted Climate Adaptation Planning**

This framework guides municipalities and regions in responsibly integrating AI tools into their climate adaptation planning processes.