MITRE | ADAPT™: Enhancing Adaptation Decision-Making with Streamlined Climate Model Data: A Robust Down-Selection Framework Using K-Medoids Clustering

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ADAPT

Underutilization and Complexity of Climate Models

Global climate models (GCMs) are powerful tools for evaluating potential climate responses to emission scenarios. However, the large number of GCMs (over 100 in the Coupled Model Intercomparison Project (CMIP) Phase 6) and the **large volume of data** they produce pose many challenges. One challenge is **computation**: the large volume of data increases the time and cost of data processing and modeling. Another challenge is **interpretation**: the large volume of data can leave decision makers overwhelmed, complicating actionable insights. A solution is necessary to reduce the complexity of computation and interpretation of GCMs for Climate Adaptation.

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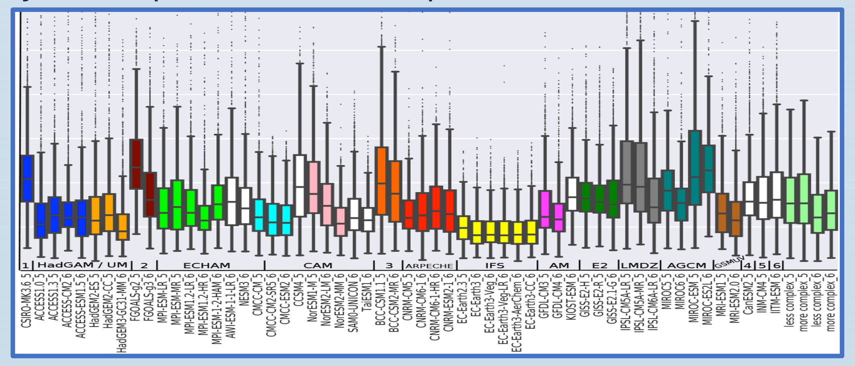


Complexity within Set of Coupled Climate Models from CMIP5-6 and their variability in Large Weather Type Frequences.
Source: *"A circulation-based performance atlas of the CMIP5 and 6 models for regional climate studies in the Northern Hemisphere mid-to-high latitudes", 2022*

Climate Model Selection for Regional Climate Adaptation

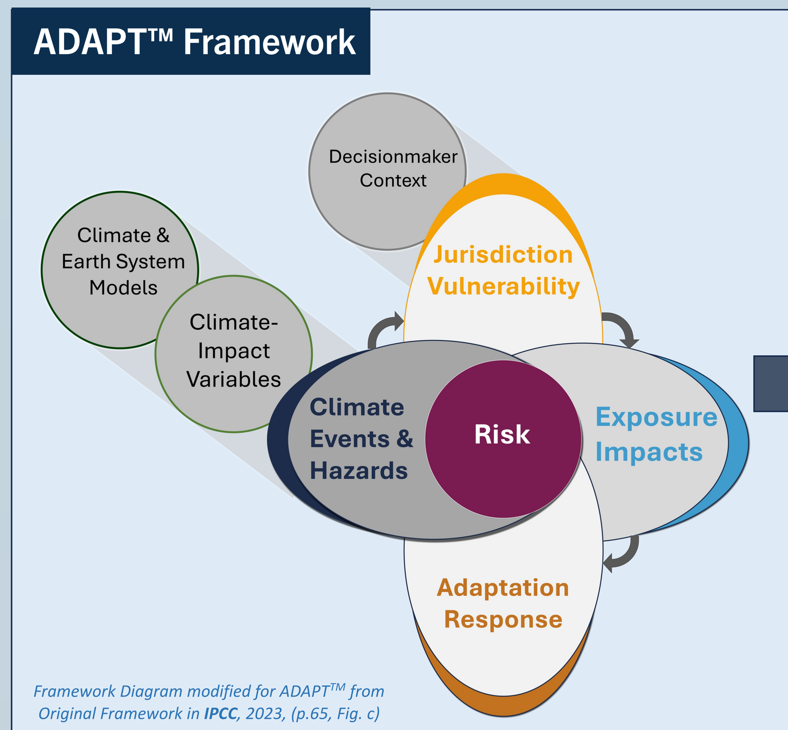
Our tailored K-Medoids Unsupervised Machine Learning down-selection framework in ADAPT address limitations from prior model selection methods addressing expansive robust model selection criterion: **Regional Relevance, Interpretability, Computational Efficiency, Ensemble Diversity, Ensemble Representation, Uncertainty Quantification, Error Propagation Analysis, and Extensibility.**

Climate Adaptation Robustness Criterion	Description	ADAPT K-Medoids Selection Framework	Prior Common Model Selection Frameworks from Literature					
			Representative T&P GCM Subsetting Approach	Reliability Ensemble Averaging (REA)	Minimum Redundancy Maximum Relevance (MRMR) Method	Performance-Based Validation & Selection	Climate Sensitivity Indices	Non-Medoid Clustering Methods
Regional Relevance	Represents variation at targeted spatio-temporal scales	**✓ Clustering can be performed on region-specific data to capture local patterns.**	✓ Specifically tailored to represent T&P signals relevant to the region.	✓ Weights can be regionally adjusted if reliability measures are region-specific.	✓ By selecting features relevant to a region, the subset can represent local conditions.	✓ Performance evaluation can be region-specific, improving regional relevance.	✗ Typically global indices, not inherently region-focused without additional steps.	✓ Clustering can be performed on region-specific data to capture local patterns.
Interpretability	Subset are actual models, not transformations	**✓ Identifies centroids as existing models in the ensemble.**	✓ Directly chooses actual GCMs from the original set.	✗ Produces a weighted average, not a direct model subset.	✓ Outputs a subset of real models chosen for relevance.	✓ Selected models are actual models (no composite transformations).	✓ Utilizes actual model outputs to derive sensitivity metrics and can select models.	✗ Identifies synthetic centroids rather than existing models in the ensemble.
Computational Efficiency	Efficient and not required for each new decision	**✓ K-Medoids is computationally efficient for large ensembles.**	✓ Straightforward subset selection reduces repeated heavy computations.	✓ Calculation of weights is relatively simple once baseline metrics are available.	(Varies)computationally moderate but generally efficient relative to large ensemble operations.	✓ Performance metrics can be computed once, enabling straightforward reuse of results.	(Varies) Computing sensitivity indices can be done once and reused.	✓ K-means is computationally efficient for large ensembles.
Ensemble Diversity	Capture full spread of projected futures	**✓ Leverages Proportion of Explained Variance to capture variability patterns of full ensemble**	✓ Ensures subset spans main T&P variability patterns.	✗ Focuses on weighting reliable models, not on full spread.	✓ Minimizes redundancy, ensuring a diverse subset.	✗ Focus on best performers may reduce ensemble diversity.	✗ Emphasizes sensitivity dimension, not overall diversity.	✗ Forms groups covering key patterns, but centroids may not be actual models.
Ensemble Representation	Reflect internal similarities/differences in original set models	**✓ Algorithm groups models into similar clusters, capturing internal structure**	(Partial) Selects models that represent distinct temperature/precipitation regimes.	✗ Produces a weighted mean, not explicitly representing internal structure.	(Partial) Selects models covering distinct feature dimensions.	✗ Selection based solely on skill may overlook structural ensemble patterns.	✗ Primarily ranks models by sensitivity rather than structural differences.	✓ Groups models into clusters, capturing internal structure but representatives are not actual models.
Uncertainty Quantification	Enables measurable uncertainty estimation	**✓ Framework expresses Uncertainty within both Ensemble Diversity and Representation**	✗ Primarily a selection approach, does not quantify uncertainty itself.	✓ Weights models based on performance and reliability, providing a sense of uncertainty range.	✗ Focuses on feature selection, not on quantifying uncertainty.	✗ Emphasizes performance criteria, not direct uncertainty metrics.	(Partial) While it highlights differences in sensitivity, it does not inherently quantify full uncertainty.	✗ Clustering alone does not provide formal uncertainty estimates.
Uncertainty Propagation Analysis	Tracks how uncertainty propagates in adaptation chain	**✓ Prior Uncertainty Metrics can be computed and tracked through each output**	✗ Does not incorporate downstream error propagation metrics.	✗ Averages outputs but does not inherently track error propagation.	✗ Feature selection approach lacks built-in error propagation analysis.	✗ Focuses on initial performance, not on downstream error propagation.	✗ Sensitivity indices do not directly link to propagation through adaptation models.	✗ Clustering is a structural grouping method, not an uncertainty propagation tool.
Extensibility	Reusable for varied applications	**✓ Clustering approach can be reapplied to new sets of models or regions.**	✓ Selecting models by T&P patterns can be reapplied to different contexts.	✓ REA weights can be recalculated or adjusted for new contexts.	✓ Selected diverse subset can be reused in various decision frameworks.	✓ Once top models are chosen by performance, they can be reused elsewhere.	✓ Sensitivity-based selection can inform multiple scenario analyses.	✓ Clustering approach can be reapplied to new sets of models or regions.

MITRE | ADAPT™ Solution

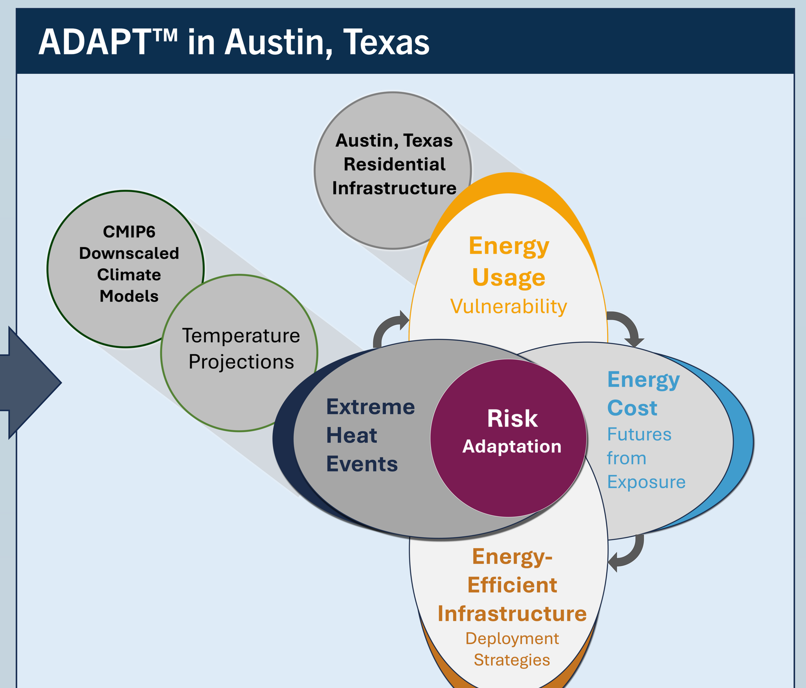
The MITRE ADAPT™ software is designed as an end-to-end decision support tool for users to efficiently integrate analyses of climate-change risks, impacts, and adaptation response option sets for Infrastructure Resilience. The ADAPT framework leverages climate sciences context with machine learning/big data analysis to provide actionable insights, supporting proactive climate adaptation tailored to stakeholder needs.

ADAPT™ Framework



Framework Diagram modified for ADAPT™ from Original Framework in IPCC, 2023, (p.65, Fig. c)

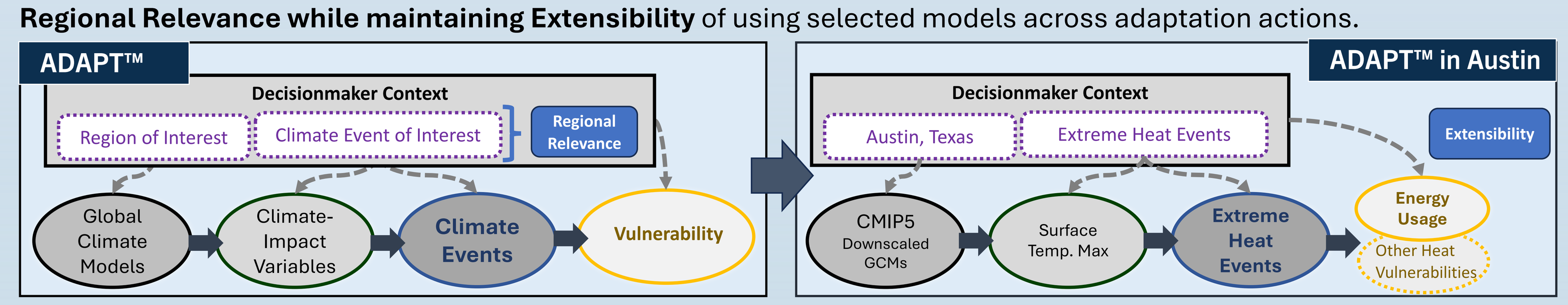
ADAPT™ in Austin, Texas



ADAPT™ Robust Down-Selection Methodology

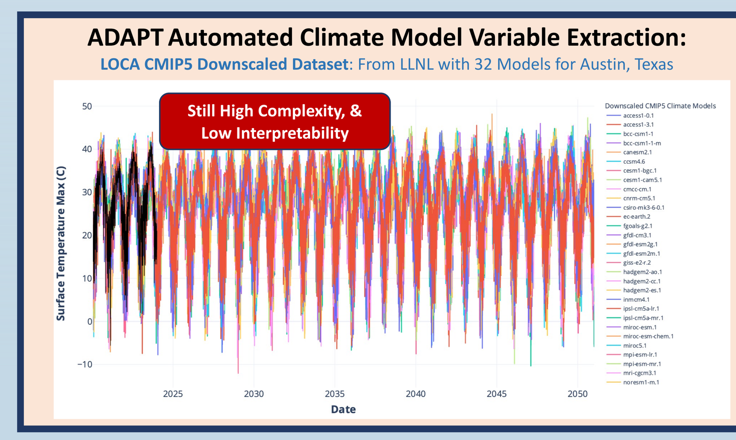
Incorporating Decisionmaker Context within Down-Selection

ADAPT tailored down-selection leverages **decisionmaker context** within model selection on the climate event of interest projected within the target region of interest from the GCMs. This approach **optimizes Computational Efficiency and Regional Relevance while maintaining Extensibility** of using selected models across adaptation actions.



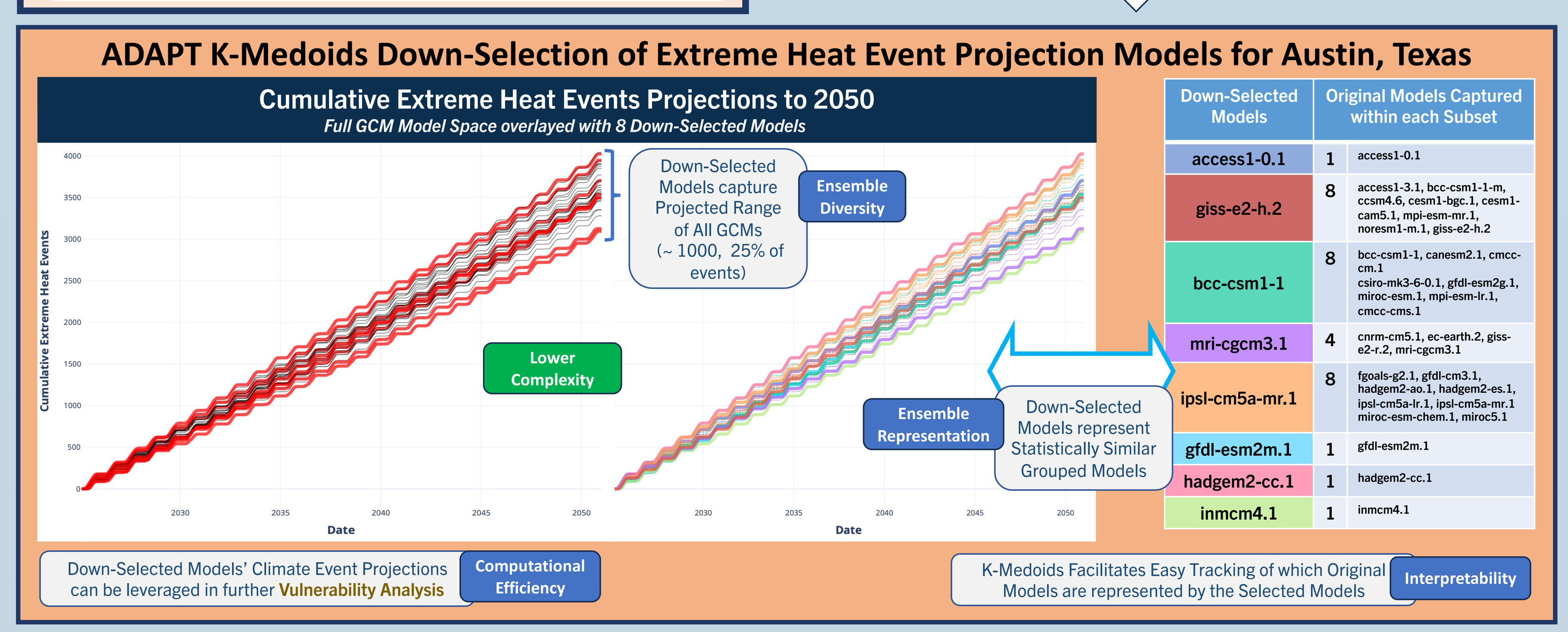
ADAPT™ Tailored K-Medoids Down-Selection for Austin Climate Adaptation

The ADAPT tailored down-selection with K-Medoids is performed for Austin, Texas for Extreme Heat Events. The Figures below show how this framework **reduces the complexity** of the original global climate models and facilitates **ensemble diversity, ensemble representation, interpretability, and computational efficiency**.



ADAPT Climate Event Projection Transformation

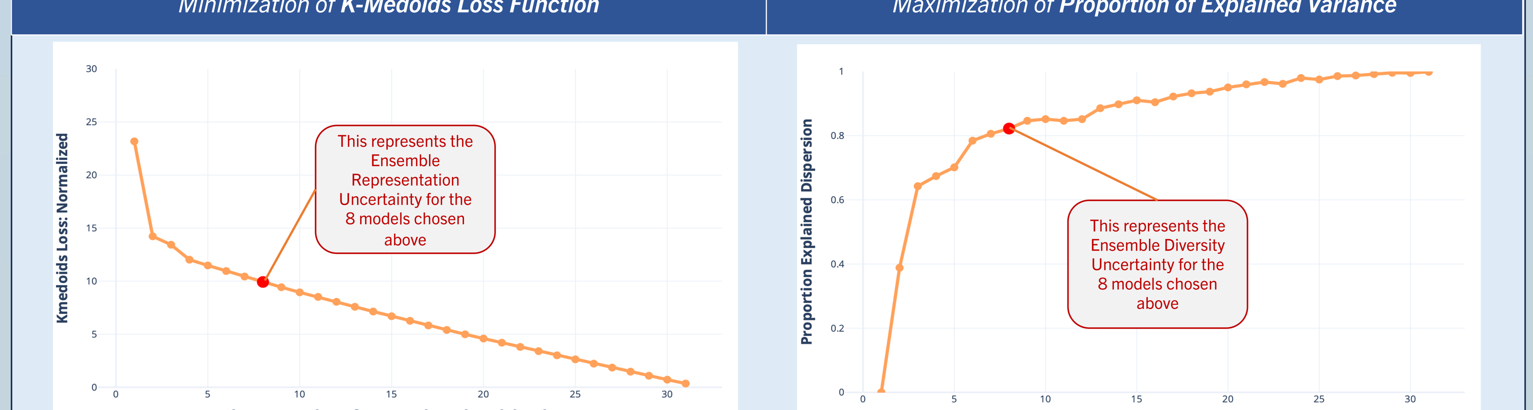
$$Extreme\ Heat\ Events_{month} = \sum_{i=0}^{days_{month}} \left(\prod_{j=0}^{days_{event}-1} \mathbb{1}(T_{tasmax,i+j} > Threshold_{event}) \right)$$



ADAPT™ Tailored K-Medoids Model Selection through Uncertainty Optimization

The ADAPT tailored down-selection with K-Medoids allows users to choose their number of down-selected models through **balancing and optimization** of the **Uncertainty Quantification** for both the **Ensemble Diversity** and the **Ensemble Representation**.

Down-Selection Uncertainty Quantification for each Number of Down-Selected Climate Models for Austin



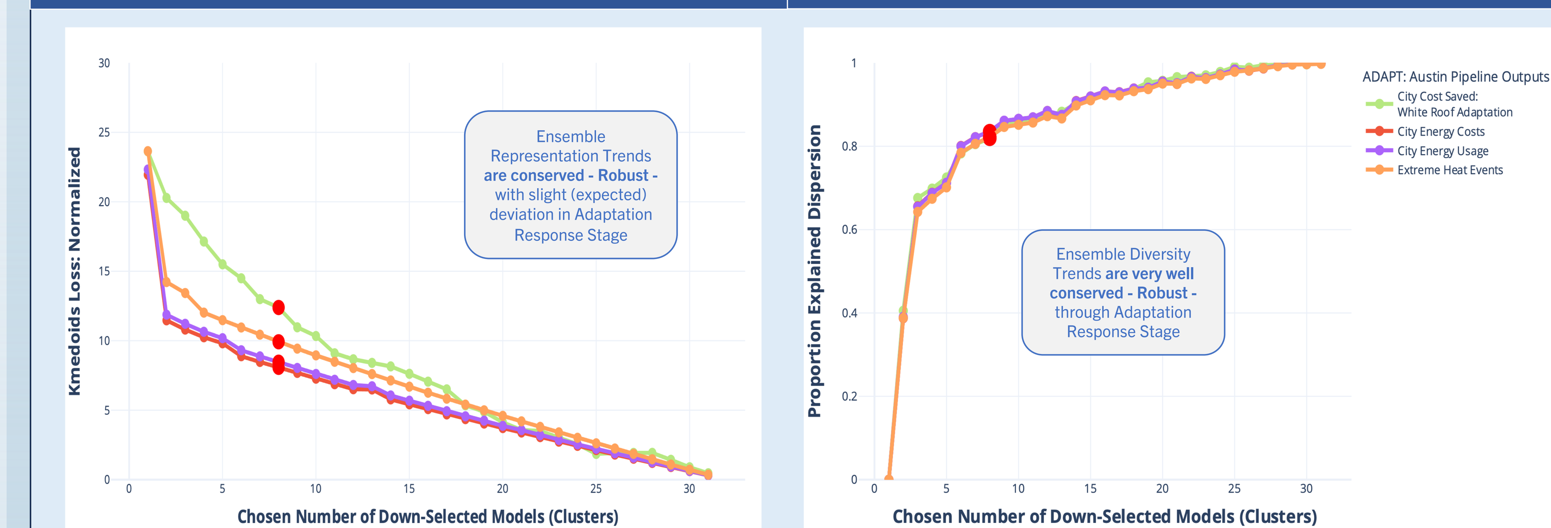
This graph represents K-Medoids Loss over the Normalized Climate Event Model Projections for each potential number of Down-Selected Models. The K-Medoids Loss Function represents the total amount of distance found between each down-selected model and the models clustered within it's subset. This allows the **K-Medoids Loss to be used as a measure of Uncertainty** for the internal similarities between each down-selected model and it's representation of the original climate models i.e **Ensemble Representation**.

This graph represents Proportion of Explained Variance over the Normalized Climate Event Model Projections for each potential number of Down-Selected Models. The Proportion of Explained Variance represents proportion of the total variance in the original GCMs that is explained by the down-selected models (inter-cluster variance). This allows the **Proportion of Explained Variance to be used as a measure of Uncertainty** for how much the down-selected models capture the full spread of the original climate models i.e **Ensemble Diversity**.

ADAPT™ Robust Uncertainty Propagation in Adaptation Pipeline

The ADAPT down-selection framework facilitates Uncertainty Quantification on each further output within the ADAPT pipeline to test the **robustness** of Ensemble Representation and Ensemble Diversity **Uncertainty Propagation** - How well the initial uncertainties from the selected climate models are conserved for each further Vulnerability, Exposure Impact, and Adaptation Response output modeled using the down-selected climate models.

Uncertainty Quantification for each output in ADAPT: Austin Pipeline

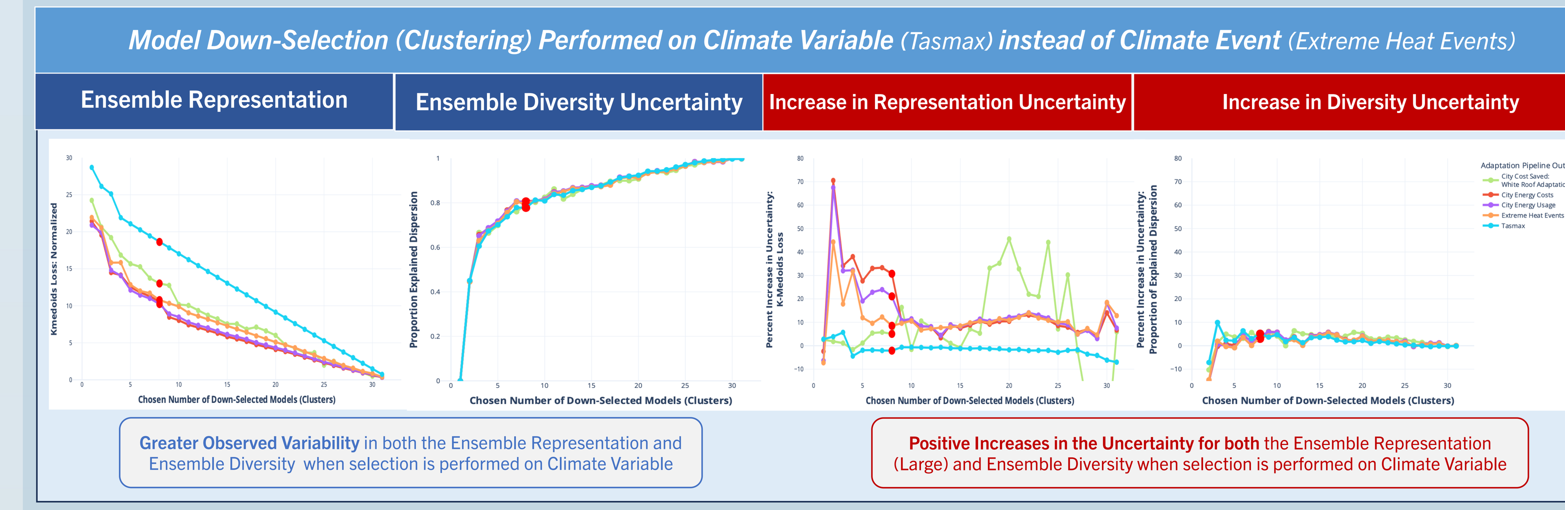


The ADAPT: Austin Case Study leverages the Down-Selected Climate Models to then model Vulnerability: Projected Austin Energy Usage (Auto-Arima ML), Exposure Impact: Projected Austin Energy Costs, and Adaptation Responses: Optimal Austin City Costs Saved through White Roofing Subsidies (Multi-Objective Optimization). **Despite the non-linear transformation**s that occur between each stage, our results show that the **down-selected climate model**s from the Extreme Heat Events **maintained very similar trend analysis of explaining the Ensemble Representation and Ensemble Diversity through of modeled outputs in each further stage of the ADAPT pipeline**.

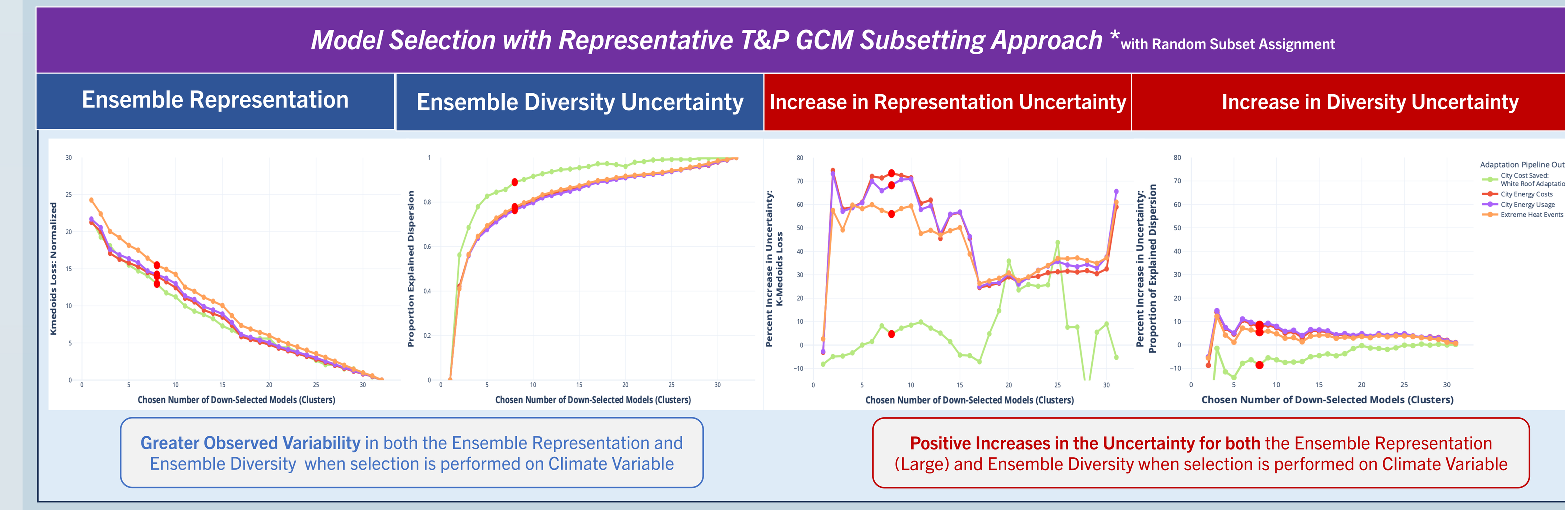
ADAPT™ Comparison with Alternate Selection Methods

The ADAPT tailored down-selection framework for Austin was compared to alternate model selection and model clustering methods. Generalized results **demonstrated overall greater variability in adaptation output uncertainties with higher increases in uncertainty across alternate methods tested.** Two results are shown below.

Model Down-Selection (Clustering) Performed on Climate Variable (Tasmax) instead of Climate Event (Extreme Heat Events)



*Model Selection with Representative T&P GCM Subsetting Approach *with Random Subset Assignment*



Next Steps

Further ADAPT Case Studies: Test robustness of tailored K-Medoids down-selection framework across varied spatiotemporal scales , climate events/hazards, and adaptation needs.

Enhance Model Selection Clustering Algorithms: Test customized algorithms that incorporate medoid based modeling into existing methods (ex. Hierarchical or Bayesian Clustering), incorporate climate sensitivities within clustering data, and modify loss functions to optimize for balances in ensemble representation & ensemble diversity across pipeline.