Impact of Spatial Scales on the Intercomparison of Climate Scenarios

Wei Luo • University of California, Santa Barbara
Michael Steptoe • Arizona State University
Zheng Chang • Amazon Corporate
Robert Link and Leon Clarke • Pacific Northwest National Laboratory
Ross Maciejewski

Understanding future climate conditions and their impacts is based, in part, on the ability to model the key drivers and underlying processes of complex interactions between climate change and human systems. Various climate scenarios can reveal different projections of future climate conditions and their cascading impacts. It is important for analysts and policy makers to design adaptation and mitigation strategies for sustainability purposes based on different climate scenario results. Those climate scenarios can be modeled by the interaction between ensembles of climate models and human systems (such as food, energy, and water systems) with varied model parameters.1 The intercomparison can help researchers gain insight into how model structures and varied parameters can impact the model outputs and how different models develop across regions and evolve over time.5 To date, visual analytics methods have focused on the intercomparison of different climate scenarios over fixed geographical spaces. However, modeling climate and human systems is spatially dependent, and little research has explored the impact of spatial variations and scales on similarity analysis of climate scenarios.

To address this issue, we developed a geovisual analytics framework to allow users to perform similarity analysis of climate scenarios from the Global Change Assessment Model (GCAM).4 The framework lets users explore the impact of spatial variations and scales on climate scenario comparisons in terms of the interactions among multiple scenarios of climate models and human systems with varied model parameters. This framework utilizes traditional coordinated multiple views coupled with data-mining techniques (specifically, hierarchical clustering) for similarity analysis. Because hierarchical clustering provides only a single vari-

Intercomparison and similarity analysis of different climate scenarios based on multiple simulation runs remain challenging. The proposed visual analytics system lets users perform similarity analysis of climate scenarios from the Global Change Assessment Model at world, continental, and country scales over time.
able output, regional differences within scenarios could be obscured. Therefore, we employ linked brushes to enable users to explore how scenarios cluster when filtered to user-selected regions.

In this article, we also present a case study using a suite of GCAM scenarios to demonstrate how the impact of spatial variations and scales on similarity analysis of climate scenarios varies at world, continental, and country scales.

**GCAM Data**

The proposed visual analytics framework has been specifically designed around GCAM, which is a global integrated assessment model combining representations of the global economic, energy, agricultural, land use, and climate systems. GCAM has made significant contributions to the Intergovernmental Panel on Climate Change (IPCC) climate change assessment reports. Mohamad Hejazi and his colleagues integrated water availability models into GCAM to quantify future water demand, supply, and scarcity in the context of the climate change. Our case study utilizes GCAM 4.0, integrating its input/output into a visual analytics framework in order to enable intercomparison of scenario analysis on future water availability around the globe. The GCAM outputs consist of water demand, supply, and scarcity.

Specifically, we consider 60 different scenarios that include (as scenario inputs) three future precipitations, two future emissions, five global populations, and two China South-North Water Transportation Projects. The future precipitation levels are based on three global climate models (GCMs) that correspond to water availability at dry, mild, and wet futures, respectively. The two future emission levels include two greenhouse gas (GHG) control policies indicating moderate climate change and low climate change. The five global populations range from 8 to 10 billion in steps of 0.5 billion. The China South-North (S-N) Water Transportation Projects from the Yangtze River Basin to the Ziya He Basin let users understand the impact on both basins.

GCAM scenario outputs are estimates of water demand, supply, and scarcity at two different spatial scales: the water region scale with 62 spatial regions in total (including 31 divisions from China) and the water basin scale with 235 basins. Supply and demand values within the basin are provided at five-year intervals (2010 to 2095). Water demand includes demand from irrigation, livestock, electricity, manufacturing, and domestic sources as well as primary energy production. All 60 scenarios include seven variables (such as water demand, supply, and scarcity), 235 water basins or 62 water regions, and 18 single years at five-year intervals (2010 to 2095).

As such, we have an input vector consisting of four unique values: the future precipitation value, the future emission value, the future global population, and the China S-N Water Transportation binary condition. The output consists of a vector for each water basin for each five-year interval. Thus, for water basin \(i\) in year \(j\), we have seven output variables that represent water demand from irrigation, water demand from livestock, water demand from electricity, water demand from manufacturing, water demand from domestic sources, water supply, and water scarcity. This means that a scenario is the result of a modification to any of the possible input values and that the output data is given at each of the 235 basins (or at the 62 aggregate regions). For this article, we consider only data at the basin level and discuss scenario comparisons when clustering is done globally or filtered to only local regions.

**Design Requirements**

Given the large number of scenarios that can be run (60 scenarios are only an example), the main questions being asked focus on how the different input drivers impact the outputs. Such questions require exploring scenario comparisons globally and locally.

Based on feedback from our original GCAM Vis tool and an iterative design process with our GCAM partners, we developed a set of design requirements for interactive visualizations for scenario comparison across spatial scales.

**R1: Interactive Scenario Comparison**

GCAM has been used for a variety of purposes, but one of the major functions is to allow analysts to compare potential futures given different policy choices. Our analysts require a means of comparing the model outputs to explore which input parameters are driving output changes.

Given that a varied combination of parameter inputs can reveal different projections of future climate conditions and their cascading impacts, it is important for analysts and policy makers to explore similarity and dissimilarity among different climate scenarios for subsequent analytical steps.

**R2: Scenario Comparison at Multiple Spatial Resolutions**

A varied combination of parameters have different impacts with varying spatial extents, but previous research has focused only on examining
such impacts where the spatial extent is fixed. The proposed framework lets users adjust spatial scales around different locations to understand the impact of the spatial dependence on the scenario similarity and dissimilarity.

**R3: Linked Spatiotemporal Analysis**

Attributes, space, and time are inherently related to climate scenarios and their impacts. Linking them together enables analysts to understand scenario similarity and dissimilarity. As such, tools that can facilitate links between space and time can help analysts observe scenario drivers within the model.

**GCAM Vis Framework**

Based on these requirements, we developed the GCAM Vis framework to enable analysts to compare the outputs across groups of GCAM scenarios. The framework consists of four major views: geospatial, scenario similarity, timeline, and basin/region similarity. Those four views allow the similarity analysis of climate scenarios from a combination of spatial, temporal, and attribute perspectives. The geospatial view lets users highlight a specific area and apply the hierarchical clustering approach to those regions in order to explore the impact of spatial variations and scales on scenario similarity using an interactive dendrogram. The timeline view allows the exploration of the average water scarcity levels according to the selected scenarios and basins/regions in order to understand when the water scarcity levels reach a critical point. The basin similarity exploration view provides an interactive parallel coordinate plot for users to explore region similarity results over space and multidimensional attributes.

The four views were designed with a strategy of linked overview plus detailed views, in which users can drive the overview of scenario similarity comparison by selecting regions of interest in the geospatial view and can further explore the detailed views of temporal and multivariable components within the selected scenarios and regions.

The framework is based on a client-server architecture. On the server side, we implemented RESTful services with Java for GCAM data processing to support client requests. On the client side, we implemented JavaScript functions using the Ajax library to call backend RESTful services to retrieve data. We combined the jQuery library, D3.js, and OpenStreetMap to visualize results and support user interaction. Furthermore, our framework applies a hierarchical clustering to explore intercomparison among climate scenarios because previous research has demonstrated that the hierarchical clustering method is most effective in quantifying differences between climate models. Clustering is directly linked to user-defined area selections to explore variations within the clustering results across different spatial scales. Our approach addresses the following high-level analysis questions:

- How do model interactions between climate change and human systems with a varied combination of parameters cause similarity or differences in model outputs?
- How do spatial variations and scales impact scenario analysis in terms of similarities or differences in model outputs?

**Hierarchical Clustering**

We applied hierarchical clustering to analyze similarity between scenarios/basins, as in previous work. We use an agglomerative strategy to merge clusters, Euclidean distance to represent model similarity, and minimum linkage clustering as our linkage criteria.

Our workflow follows these steps:

1. Calculate the Euclidean distance matrix between all scenarios. This is calculated based on the user-selected region (what we refer to as the geographic scale). All values of different variables within all scenarios are normalized to the 0–1 range.
2. Compute the distance between two scenarios (MT, MS):
   \[ \text{Dist}(MT, MS) = \sqrt{\sum_{i \in Y} \sum_{j \in V} (MT_{i,j,k} - MS_{i,j,k})^2} \]
   where \( MT_{i,j,k} \) represents a value retrieved from the scenario MT in the ith year from the year set \( Y \) at five-year intervals (2010 to 2100), the jth variable from the set \( V \) of seven water variables, and the kth basin from the selected basin set B.
3. Compute the distance between two basins (BT, BS) within one scenario:
   \[ \text{Dist}(MT, MS) = \sqrt{\sum_{i \in Y} \sum_{j \in V} (BT_{i,j} - BS_{i,j})^2} \]
   where \( BT_{i,j} \) represents a value retrieved from the basin BT in the ith year from the year set \( Y \) at five-year intervals (2010 to 2100) and the jth variable from the set \( V \) of seven water variables.
4. Calculate linkage between each pair of clusters:
   \[ L(C_i, C_j) = \frac{1}{|C_i||C_j|} \sum_{a \in C_i} \sum_{b \in C_j} d(a, b) \]
where A and B are clusters and $d(a, b)$ is the Euclidean distance between points a and b.

5. Find $(C_i, C_j) \in \min_{i \neq j} L(C_i, C_j)$.
6. Merge cluster: $C_{\text{merged}} = C_i \cup C_j$.
7. Update the original cluster set: $C = C \setminus \{C_i, C_j\} \cup \{C_{\text{merged}}\}$.
8. Continue steps 2 and 7 until there is only one cluster.

This workflow is generic for any set of GCAM scenarios because the input and outputs are specified in the geojson.

When a user selects regions using a scalable rectangle/circle/polygon selection widget, the Euclidean distance among all scenarios within the selected regions will be calculated to produce a hierarchical tree. (Our examples here offer 60 scenarios, but the system is scalable to several hundreds.) The scalable selection widget lets users generate new hierarchical trees that can help them understand the impact of the spatial scales and variations on scenario outputs. The leaf nodes represent each scenario. The parent nodes show which scenario design variables (such as future precipitation and emissions) caused the most difference between the underlying groups of scenarios. Specifically, for each parent node, we look at the input vector for each scenario. (In this case, we have only four different input parameters.) For each parameter, we count the number of different parameter settings used in all scenarios beneath the parent node. The parameter setting with the largest number of unique settings is then considered to be the parameter driver at that level.

We use different colors to represent the different scenario input variables. In the examples in this paper, red stands for future precipitation, yellow stands for emissions, green stands for population, and blue stands for the China S-N Water Transportation Projects. For example, the blue nodes in Figure 1 indicate that two scenarios represented by two leaf nodes have the same future precipitation, emissions, and population, but one with the China S-N Water Transportation Project on and the other with the project off. This is done to help users quickly identify which input parameter is driving dissimilar results across the different scenario outputs at different hierarchical levels. The green nodes in Figure 1 indicate that two groups of scenarios represented by two child nodes have the same future precipitation, emissions, and the China S-N Water Transportation Project on and off, but different populations.

To further investigate basin similarity within one scenario, users can pick any scenario using the leaf node in the dendrogram view. Within the selected scenario, the model outputs will be shown on both the choropleth map and the parallel coordinate plot (PCP). The two views let users explore the basin similarity for both the geographical and multidimensional attribute spaces for overview and details (see Figure 2).

**Temporal Analysis**

In addition to investigating the impact of spatial scales and variations on scenario similarity, our tool also allows the exploration of user-selected output variables within the selected basins/regions under different scenarios over time. Users can click any parent nodes from the dendrogram view.

The goal of the line chart tool (see Figure 3) is to explore the disparities among different regions for any given output variable and to identify outliers (maximum and minimum). In the line chart, the $x$ axis represents time, and the $y$ axis represents the variable values. For a given scenario (or set of scenarios if a nonleaf node is chosen), we compute the mean value from all regions, which is indicated by the black line in the middle of the line.
We also compute its standard deviation and draw the three sigma range as the blue area in the line chart. We can see this range as the expected disparities among different regions if they follow the normal distribution. The maximum and minimum values are represented as the red and blue lines, respectively.

We enhance this view by drawing the regional polygon on the line chart to show the regional information and only replace the regional polygon if one or more new regions become the maximum or minimum. For example, as Figure 3 shows, we can see the China region in 1990 at the beginning of the scenario, but the India region overtakes China in 2020.

We also provide a detailed timeline view (see Figure 1). In this case, users can select a threshold of interest in the data and observe the point in time a scenario will cross this threshold. For example, if analysts want to know when a region will begin experiencing water scarcity, they can choose a water scarcity threshold and observe when a region of interest (or an aggregate set of regions on average) passes the threshold. This lets users relate critical points within the simulation output to identify futures—for example, if policy x is implemented, we can postpone water shortages for y years. As such, our two timeline views allow for both outlier detection and threshold analysis for policy examination.

Impact of Spatial Variations and Scales on Scenario Similarity

The purpose of the proposed framework is to provide analysts with a means of systematically exploring scenario drivers at different spatial scales. In this case study, we use the GCAM Vis framework to explore the impact of spatial scales and variations on the GCAM model outputs. We compare the similarity analysis of climate scenarios at three different spatial scales: world, continental, and country. The world scale consists of 235 basins. The continent scale consists of five regions including Africa, Asia, North and South America, Europe, and Australia at the basin level. The reason why we apply the basin data rather than regional data here is because the basins are the physical basis for the hydrology in the model. At the country scale, the basins do not line up well with country boundaries, so it makes sense to shift to geopolitical boundaries, especially since the scenario focus is primarily on detailed China policies.

World Scale

We first explore the scenario similarity based on all 235 basins in the world (see Figure 4). From
the dendrogram view on the right, we can see a clear hierarchical structure: the emission node in yellow is on the top of the tree, followed by the precipitation nodes in red, the population nodes in green, water project nodes in blue, and all scenario leaf nodes. Thus, although water supply changes only modestly in many basins (approximately 10 percent between the low and high emissions scenarios, with some basins getting wetter and others getting drier), biofuel production and its associated water usage skyrocket.

This result implies that future emissions will have the largest impact on the scenario dissimilarity, followed by precipitation, population, and the China S-N Water Transportation Project. Emissions can impact both water supply and water demand. Emission levels affect water supply by changing climate. Emission levels affect water demand because an important pathway for achieving emission reductions is to plant biofuel crops, which are voracious water consumers.

For example, in the US region biofuel production is elevated throughout the late 21st century for the low emissions scenario as compared to the high emissions scenario, with the increase peaking at 62 percent in 2075. Other regions show similarly elevated production. Precipitation impacts water supply, and population is a primary driver of demand in all sectors of the economy. The China S-N Water Transportation Project only impacts the Yangtze River, Yellow, and Ziya He Basins, so it will likely have the smallest impact on the scenario dissimilarity at the world scale. These results tell us that, at the world scale, future climate policies on emissions have the biggest impact on climate scenario dissimilarities followed by water supply from GCMs, water demand from future population, and the China S-N Water Transportation Project.

Continental Scale and Variations
Figure 5 shows the scenario similarity comparing continental variations in basins from Africa. These
scenario dendrograms all exhibit a hierarchical structure similar to the world scale: the yellow emission node is on the top of the tree, followed by the red precipitation nodes, the green population nodes, the blue water project nodes, and all scenario leaf nodes. This implies that emissions make the biggest difference, followed by water supply from GCMs, water demand from future populations, and the China S-N Water Transportation Project. (Note that we found a similar hierarchical structure for the Americas and Asia in terms of node color and grouping.)

However, based on the dendrogram views in Figure 6, we can see a different hierarchical structure in Europe than the global clustering or the Africa clustering. Here we see emissions on the top, followed by population, future precipitation, and the China S-N Water Transportation Project. We found a comparable structure in Australia. The difference tells us that water demand from the population has a larger impact on Europe and Australia than water supply from GCMs compared with the rest of the world. Compared with the world scale, the differences tell us that spatial scales matter when we analyze scenario similarity— that is, the impact of water supply and demand on scenario similarity varies at different scales. When we compare the rest of the world at the continental scales, the differences in Europe and Australia tell us that the spatial variations matter when we analyze scenario similarity—that is, the impact of water supply and demand on scenario similarity varies over space.

**Country Scale**

Furthermore, if we explore the country level for China (see Figure 7), the dendrogram view shows a different pattern in a hierarchical structure compared to the rest of the world: emissions still on the top, but followed by the China S-N Water Transportation project, population, and mixed sequences of future precipitation and population. These results indicate that the China S-N Water Transportation project has a larger impact in terms of scenario dissimilarity at the country scale. Also, population has a larger impact than precipitation on scenario dissimilarity in China.

The timeline view in Figure 8 shows that the average scarcity values for the two scenarios in China are above a scarcity threshold value (0.5 in this case) beginning in 2030. This indicates that China faces a severe water scarcity based on the two scenarios at a country level. The map and PCP views identify four different clusters based on the regional similarity: Shanghai in red, Beijing and Tianjing in yellow, Guangdong in dark blue, and the rest of China in light blue. The PCP view shows that Shanghai has the highest scarcity level, followed by Beijing and Tianjing, whereas Guangdong has the highest electricity and domestic demand. The rest of China has similar values across the seven water variables. Users can define a larger number of clusters to explore more details for the rest of China.

**Sensitivity Analysis**

To understand the impact of the number of levels available for a scenario variable on the clustering results, we complement our analysis results with only two extreme population scenario variables: 8 and 10 billion global populations. There are 24 scenarios that include three future precipitations, two future emissions, two global populations, and two China S-N Water Transportation Projects. We explored the 24 scenarios at the world, continental, and country scales (see Figure 9) to make it comparable to the 60 scenarios. From all the dendrogram views, we can see a consistent hierarchical structure: the population node in green is on the top of the tree, followed by the emissions nodes in yellow, the precipitation nodes in red, water project nodes in blue, and all scenario
leaf nodes. Compared with the clustering differences caused by spatial scales and variations in the previous figures, the consistent results in Figure 9 imply that the varied combination of parameter values and spatial scales and variations, instead of parameters alone, matters when analyzing similarity among different climate scenarios. This implies that future population will have the largest impact on the scenario dissimilarity, followed by emissions, precipitation, and the China S-N Water Transportation Project.

The results in Figure 9 show that the China S-N Water Transportation Project only impacts the three basins involved in the transfer (the Yangtze, Yellow, and Ziya He basins), so it would be expected to have the smallest impact on the scenario dissimilarity. Conversely, population is a primary driver of demand in all sectors of the economy, so it is not surprising to see that it has the largest impact. Through the timeline view (Figure 8), we can also observe that all scenarios without the China S-N Water Transportation Projects show much earlier scarcity futures.

Our analysts also found the clustering with respect to emissions levels to be an interesting case. As we noted earlier, emissions levels affect water demand because an important pathway for achieving emissions reductions is to plant biofuel crops, which are a voracious water consumer. Thus, it may indicate a need to explore other energy alternatives as policy choices. What is interesting is that by exploring simulations at different scales, we can begin seeing global and regional drivers within the scenarios. This enables us to identify what input mechanisms can have the largest impact on output variables (such as water scarcity), and we can begin considering what potential policy futures may enable the greatest change in output. In these cases, we can see that while population is a major driver, emission levels are more critical in certain regions of the world than others. Thus, our analysts can determine the sensitivity of various regions to model input parameters.
Using the GCAM model outputs, we demonstrated the impact of spatial scales and variations on similarity analysis of climate scenarios varies at world, continental, and country scales. The resulting patterns indicate that spatial scales and variations matter when analyzing similarity among different climate scenarios. This research sheds light on the complex relationships between climate change and human systems from a spatial scale perspective.

System limitations include issues of scalability in the dendrogram view; as more scenarios are explored, the visual result can become highly complex. As such, we plan to consider alternative designs in future work. Similarly, the method for coloring parent nodes in the tree is based on comparing changes in the input parameter space. As this space grows larger, a single color representation will not scale well. Future extensions could explore using glyphs or statistical graphics as the parent nodes to provide insight into scenario drivers.

We will continue our work in terms of several possible extensions of this framework. For example, given a close collaboration with model developers and analysts from the GCAM team, we will continuously apply the feedback from them as our user-centered design guidelines for future implementation. We also plan to implement more clustering approaches with a scalable framework to perform intercomparison of scenario analysis in order to develop comprehensive metrics to quantify similarity and dissimilarity among a large number of scenarios. Because GCAM simulations take place externally, the next step is to couple the visualization tool with the simulation models into an integrated system. And given that our approach provides similarity analysis for scenario results based on climate computational models with varied parameters, we plan to add more features and apply our tool to solve similar problems related to different computational models that involve similar spatiotemporal data structures.

Acknowledgments
This work is funded in part by the Integrated Assessment Research Program in the Biological and Environmental Research Program of the Office of Science, US Department of Energy, and National Science Foundation under grants 1639227 and SES-1462086. Any opinions, findings, conclusions or recommendation expressed in this material are those of the authors and do not necessarily reflect the views of the funding organizations.

References

Figure 9. Scenario similarity at the world, continental, and country scales: (a) world, (b) Africa, (c) North and South America, (d) Asia, (e) Australia, (f) Europe, and (g) China.


Zheng Chang is a software engineer at Amazon Corporate. His research interests include computational steering environment and information visualization. Chang has an MS in computer science from Arizona State University. Contact him at zchang3@asu.edu.

Robert Link is a senior computational scientist at the Pacific Northwest National Laboratory. His research interests include modeling complex systems. Link has a PhD in astrophysics from Indiana University. Contact him at robert.link@pnnl.gov.

Leon Clarke is a senior scientist and group leader at the Pacific Northwest National Laboratory. His research interests include the evolution of national and international energy and agricultural systems, scenario analysis, and integrated assessment of climate impacts. Clarke has a PhD in engineering economic systems and operations research from Stanford University. Contact him at leon.clarke@pnnl.gov.

Ross Maciejewski is an assistant professor in the School of Computing, Informatics and Decision Systems Engineering at Arizona State University. His research interests include geographical visualization and visual analytics focusing on public health, dietary analysis, social media, and criminal incident reports. Maciejewski has a PhD in computer engineering from Purdue University. He is a senior member of IEEE. Contact him at rmacieje@asu.edu.

Wei Luo is a postdoctoral research assistant in the Department of Geography at University of California, Santa Barbara. His research interests include geovisual analytics and computational modeling focusing on public health, climate change, international trade, social media, and criminal activity. Luo has a PhD in geography department from Pennsylvania State University. Contact him at wei.luo@ucsb.edu.

Michael Steptoe is a graduate research assistant with the School of Computing Informatics Decision Systems Engineering at Arizona State University. His research interests include geographical visualization and social media analysis. Steptoe has a BS in computer science from Arizona State University. Contact him at msteptoe@asu.edu.