EUROGRAPHICS 2014 / H. Carr, P. Rheingans, and H. Schumann
(Guest Editors)

Volume 33 (2014), Number 3

SimilarityExplorer: A Visual Inter-Comparison Tool for Multifaceted Climate Data

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Abstract

Inter-comparison and similarity analysis to gauge consensus among multiple simulation models is a critical visualization problem for understanding climate change patterns. Climate models, specifically, Terrestrial Biosphere Models (TBM) represent time and space variable ecosystem processes, like, simulations of photosynthesis and respiration, using algorithms and driving variables such as climate and land use. While it is widely accepted that interactive visualization can enable scientists to better explore model similarity from different perspectives and different granularity of space and time, currently there is a lack of such visualization tools.
In this paper we present three main contributions. First, we propose a domain characterization for the TBM community by systematically defining the domain-specific intents for analyzing model similarity and characterizing the different facets of the data. Second, we define a classification scheme for combining visualization tasks and multiple facets of climate model data in one integrated framework, which can be leveraged for translating the tasks into the visualization design. Finally, we present SimilarityExplorer, an exploratory visualization tool that facilitates similarity comparison tasks across both space and time through a set of coordinated multiple views. We present two case studies from three climate scientists, who used our tool for a month for gaining scientific insights into model similarity. Their experience and results validate the effectiveness of our tool.

1. Introduction

Inter-comparison of model simulations is a critical problem in the climate science domain for understanding climate change patterns. Consensus among model results is an important metric used for judging model performance. Analysis of model output similarity and dissimilarity is a complex problem because of the multiple *facets* involved in such comparisons: space, time, output variables, and model similarity. The goal of this work is to provide an interactive visualization tool that integrates space, time, and similarity, making it easier for climate scientists to explore model relationships from multiple perspectives.

The output of our work is a result of a six-month-long interaction between visualization researchers and climate scientists, including terrestrial biosphere modelers. Modelers generally perform their analyses by looking at spatial and temporal aspects in isolation, by running scripts, such as *MATLAB* and *R* on the data and by manually setting parameters. The first step during the iterative development of our tool was to provide the scientists with an interactive interface for selecting parameters and filtering the data. This was not sufficient as our interactions revealed that modelers needed a tool for analyzing both space and time within a single interface in order to judge multi-model similarity.

Existing visualization tools are only capable of integrating one or two facets as pointed out by Kehrer and Hauser [KH13]. Multifaceted data analysis is inherently challenging on two counts: i) preserving the mental model about the different facets, like space, time, and model similarity, necessitates an encoding strategy that preserves visual symmetry, and ii) exploring these facets at multiple levels of granularity and understanding their relationships necessitates a systematic interaction strategy.
To address these challenges, we developed the SimilarityExplorer tool which enables multi-faceted visual analysis of climate models, specifically, Terrestrial Biosphere Models (TBMs). Using our tool, climate scientists were able to get an overview of model similarity across space and time, and then drill down to further explore *where*, *when*, and by *how much* models were similar or different. A seamless integration and exploration of these facets in SimilarityExplorer

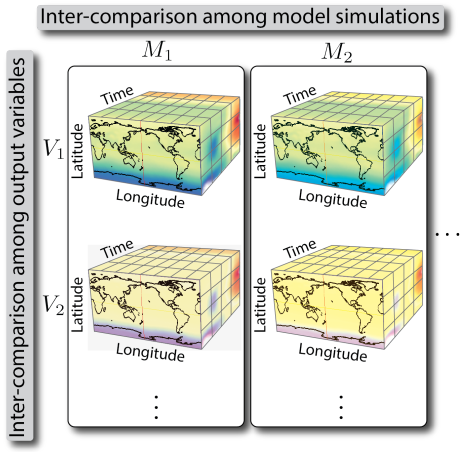

Figure 1: **Visualizing the complexity of multifaceted climate data** in terms of models, regions, time and variables.

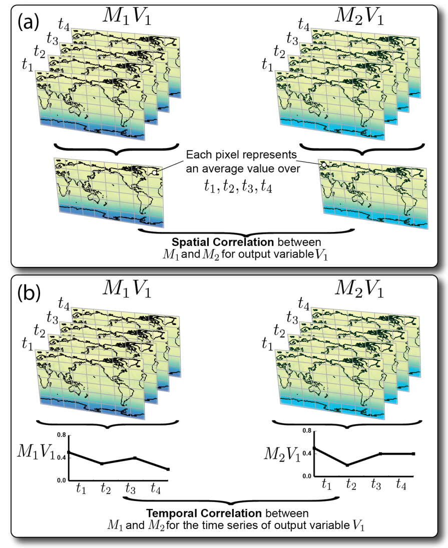

Figure 2: **Similarity computation**. Illustration of spatial and temporal correlations are computed between models M_1 and M_2 after aggregating the temporal information. The spatial granularity is preserved at the cost of temporal information, and vice versa.

let them generate and explore new hypotheses about model similarity which was not possible before.

Our work consists of three key contributions: i) as part of the domain characterization [Mun09] of climate model inter-comparison, we present a systematic classification of the domain-specific intents of climate scientists, and that of the underlying data facets (Section 4), ii) we bridge the intents and facets with the visualization tasks and design through a classification scheme (Section 5); and iii) SimilarityExplorer is a tool that implements this classification. Our interactions with climate scientists were conducted before, during, and after the implementation phase for iterative refinement of the tool based on their feedback. In light of this, we present two case studies which helped elucidate and validate the benefits that scientists obtained when using SimilarityExplorer (Section 6).

2. Related Work

In this section we discuss the relevant related work with respect to spatiotemporal and multifaceted data visualization and tools available for climate data.

Simultaneous encoding of spatial and temporal relationships: Visualization of spatiotemporal data has witnessed a lot of research over the years. Peuquet [Peu94] had introduced the popular triad representation framework which is a general formalization of temporal dynamics in geographic information systems. In our tool we imbibe the concepts of *when*, *where*, and by *how much* models are similar. The need to integrate space and time through an exploratory analysis tool was also proposed by Andrienko et al. [AAD*10]. They devised a visual analytics [AA13] framework for exploring spatiotemporal data through spatially referenced time series. Similarly, visual analytics approaches for event detection [MME*12, MRH*10, MHR*11] have been proposed where spatial representation of the data is provided in conjunction with features for observing temporal trends and anomalies. While most of this work focused on direct encoding of the data, either spatially or temporally, Andrienko et al. applied self-organizing maps [AAB*10], for providing complementary perspectives on spatial and temporal relationships which is the guiding principle in SimilarityExplorer. The complexity in our work evolves from the fact that the scientists needed to understand the evolution of both spatial and temporal relationships simultaneously. This necessitated that the visualization provided an overview of spatial and temporal relationships, and then also allowed flexible interaction for exploring these relationships over both space and time.

Integration of spatial and non spatial data: There exists other approaches towards building visualizations for integrating spatial and non-spatial data [MMH*13]. Guo et al. [GCML06] proposed a generalizable visual analytics approach for integrating techniques from cartographic, visualization techniques and machine learning. That methodology is general and can be applied to spatiotemporal data. Most of the existing tools only integrate one or two different facets [KH13]. In the SimilarityExplorer we integrate four different facets: *space*, *time*, *multiple variables*, and *model similarity*, which are crucial for visual comparison of the different properties of models. Our technique is similar in principle with Kehrer et al.'s work on visual analysis of heterogeneous data, multi-model scientific data with examples from climate research data [KMD*11]. Kehrer et al. focus on providing multiple perspectives into statistical relationships between multi-run and spatially aggregated simulation data through different interactive views. In SimilarityExplorer, similar to multi-run data, we focus on multi-model data; and in addition to spatial relationships and patterns, we consider time, multiple variables and different visual approaches towards encoding similarity and facilitating visual comparison through the use of small multiples [Tuf83].

Visualization solutions for climate data: For addressing the needs of the climate research community, there has been some work on hypothesis generation [KLM*08], task characterization [SNHS13], and tool development [LSL*10]. Steed et al. introduced EDEN [SST*12], a tool based on visualizing correlations in an interactive parallel coordinates plot. Their focus is on a single model and analysis of the interdependence among variables. There also exists some general visualization tools such as Paraview [Kit], Visit [Law] and VisTrails [Vis] which offer some specialized climate visualizations but almost all of them only present the data without supporting any analysis. Those specialized packages were integrated in a provenance-enabled climate visualization tool UV-CDAT [WBD*13]. However, like most other tools, UV-CDAT does not support multi-model analysis. It also does not support multivariate analysis and dynamic linking between the views. This is crucial in the case of model inter-comparison as it requires a seamless transition among different facets facilitated by intuitive interaction methods, which is implemented in SimilarityExplorer. Through a closely-knit collaboration with climate scientists we were able to address the need for tools that emerge from genuine and interdisciplinary collaboration [OMBE11, MMDP10], for solving the problems with such complex data.

3. Background of Model Inter-Comparison Project

We collaborated with 3 climate scientists from the Oak Ridge National Lab as part of the Multi-Scale Synthesis and Terrestrial Model Inter-comparison Project (MsTMIP). Each of them have at least ten years of experience in climate modeling and model inter-comparison. MsTMIP is a formal multi-scale synthesis, with prescribed environmental and meteorological drivers shared among model teams, and simulations standardized to facilitate comparison with other model results and observations through an integrated evaluation framework [HSM*13].

3.1. Data

The data consist of simulations from 7 different TBMs for over 20 years at monthly temporal resolution, collected over a spatial resolution of 0.5 degree. Each produces multiple output variables, of which *three* are relevant for the analysis presented here. For segmenting the globe, the scientists use 11 different eco-regions. The temporal granularity of interest to them were annual, seasonal, and monthly. As shown in Figure 1 each model can be represented by a spatiotemporal volume over latitude, longitude, and time. Since each model is associated with multiple output variables, each model can be thought of as being a vector of such volumes. The basic goal of climate scientists is to efficiently subset this array of cubes along multiple dimensions, in order to understand model similarity based on multiple facets: *when* are models similar, with respect to seasons and months, *where* are models similar, with respect to regions, *why* are models similar, with respect to the output variables.

3.2. Model Similarity

As a first step in our design study [SMM12], we discussed with the climate scientists about their existing approaches for understanding model similarity. To reduce complexity of the data, they are used to compressing space and time. It emerged that, from a temporal aspect they are mostly interested in comparing model behavior for seasons or months aggregated across all years. In this context, they perform two distinct operations on the data for analyzing similarity from the spatial and temporal perspectives. These operations are sketched in Figure 2 and described below:

a) Spatial Correlation: For this step, as shown in Figure 2a the data is pre-processed in such a way that temporal information is aggregated but spatial granularity is preserved. For each point on the map, the average value for a time period is computed. Temporal granularity can range from *long-term mean* (value at one point is the average for all months and all years within the time period), *long-term monthly mean* (12 monthly maps, with each map representing an average month for the time period), and *seasonal* mean (four maps with each map representing an average season for the time period). Next, correlation between maps of two models is computed using the Pearson correlation coefficient.

b) Temporal Correlation: In this case, the data preprocessing helps aggregate spatial information but preserves temporal granularity (Figure 2b). For the map at each time step, a spatially averaged or summed value is computed. Next we compute a time series, which varies based on the temporal granularity: one value for *long-term mean*, 12 values for *long-term monthly mean* and four for *seasonal mean*. At the end the models are represented by their time-series signatures. While there are multiple ways for comparing time-series signatures of two models, in discussion with the scientists, we chose correlation as the measure for temporal similarity.

4. Domain Characterization

The initial discussion about the data characteristics was followed by an analysis of the domain-specific intents through face-to-face interactions and conference calls. In this section, we present the first contribution of our work, which is a characterization of the domain-specific intents of the climate scientists and the underlying data facets.

4.1. Domain Specific Intents

We identified four major intents of the climate scientists in the context of model inter-comparison, which are as follows:

Q_1: In general, modelers would like to know the degree of spatial and temporal correlation of models with respect to any output variable.

Questions	Tasks	Facets				Visualization Design	
		Space	Time	Variables	Similarity	Views	Comparison method
Q₁	*identify*(p) *identify*(t) *identify*(p,t)	g/r	$a/s/m$	single	pairwise pairwise multi-way	matrix (maps) matrix (area graph) projection	explicit encoding
Q₂	*compare*(p,v) *compare*(t,v)	g,r	a,s,m	multiple	pairwise	matrices (map) *smlt*: maps matrices (area graph) *smlt*: area graph	juxtaposition
Q₃	*associate*(p) *associate*(t)	r	s,m	single	multi-way, pairwise pair-wise	parcoords, matrix time-series, matrix	juxtaposition superposition
Q₄	*distribution*(p,v) *distribution*(t,v)	r	s,m	multiple	multi-way, pairwise pairwise	parcoords time-series	juxtaposition superposition

p: Space *t*: Time *v*: Variables *g*: global *r*: regional *a*: annual *s*: seasonal *m*: monthly *smlt*: small multiples

Table 1: **Translating tasks into visualization design through a classification scheme**. The visualization design is based on the different views and comparison methods required for reflecting the tasks that can be performed on the multifaceted data. Note that space and time have different levels of granularity. The symbol '/' reflects an *OR* operation and ',' reflects an *AND* operation.

$\mathbf{Q_2}$: With multiple models, they would additionally like to know which models are similar, and when, where, and why they are similar.
$\mathbf{Q_3}$: They would want to understand if different sub-regions agree or disagree with the global temporal or spatial correlations, or with the same for other sub-regions.
$\mathbf{Q_4}$: Scientists do not always trust the level of abstraction at which similarity is deduced, as there can always be anomalies that are not captured. Thus they wanted to look at the original distribution of the data to verify their hypotheses and validate their findings.

4.2. Facets: Space, Time, Variables, Similarity

The inherent complexity involving inter-comparison of climate models stems from the multifaceted data underlying the climate models. The facets [KH13] relevant for the climate model data are space, time, variables, and similarity as shown in Table 1. *Space* and *time* also involve different levels of granularity. The different levels granularity for spatial data are global (g) and regional (r) and that for temporal data are annual (a), seasonal(s), and monthly (m), as shown in Table 1. Additionally, there are three output variables for each model. *Similarity* among models is the other facet which can be classified based on the following perspectives: i) pairwise: in this case scientists are interested in observing similarity between each pair of models and ii) multi-way: in this case scientists are interested in observing similarity among all models taken together, and iii) one-to-many: in this case scientists might choose one model as a reference. Our collaborators revealed that the third option is rarely used in comparison of TBMs, since no model is known a priori to be any better as a "reference" than any other. As a result we did not implement this option in the tool.

5. Visualization Tasks and Design

The next step in our study was to connect the intents and facets though concrete visualization tasks and subsequently translate the tasks to visualization design. This led to our second contribution: a classification scheme for integrating tasks, facets, and design (Table 1).

5.1. Tasks

For identifying the tasks, we took inspiration from Zhou and Feiner's taxonomy [ZF98], among which *identify*, *compare*, *associate*, and *distribution* are relevant here. Notably, the transition from Q_1 to Q_4 also indicates increasing complexity of the visualization tasks, which we describe below. In table 1 the abbreviation after task name indicates the facet they operate upon.
Identify: The intent Q_1, that is understanding model-model similarity is reflected in SimilarityExplorer by three variants of the identification tasks: finding the degree of spatial correlations among models (*identify*(p)), finding the degree of temporal correlation among them (*identify*(t)), and also finding the degree of overall spatiotemporal correlation (*identify*(p,t)). While the first two tasks reflect pairwise similarity, the last one expresses multi-way similarity. In Table 1, the symbol / reflects an *OR* operation. So in case of the identification tasks any granularity of space (g/r) and time (a/m/s) can be selected using different filters.
Compare: The intent Q_2, that is understanding output-output similarity is reflected in SimilarityExplorer by the comparison tasks: comparing the degree of spatial correlation (*compare*(p,v)) and temporal correlation (*compare*(t,v)) among multiple output variables. These tasks can involve multiple selections of granularity of space and time indicating an *AND* operation as shown by the *comma* (g,r and a,s,m). For example, global correlation of models with respect to one output variable can be compared with the regional correlation.
Associate: The intent Q_3 involves combining the understanding of similarity by analyzing the region-wise anomalies and trends for the models. This task applies to both spatial (*associate*(p)) and temporal correlation (*associate*(t)) for which different views are instantiated. These involve mainly drill-down and brushing operations and are per-

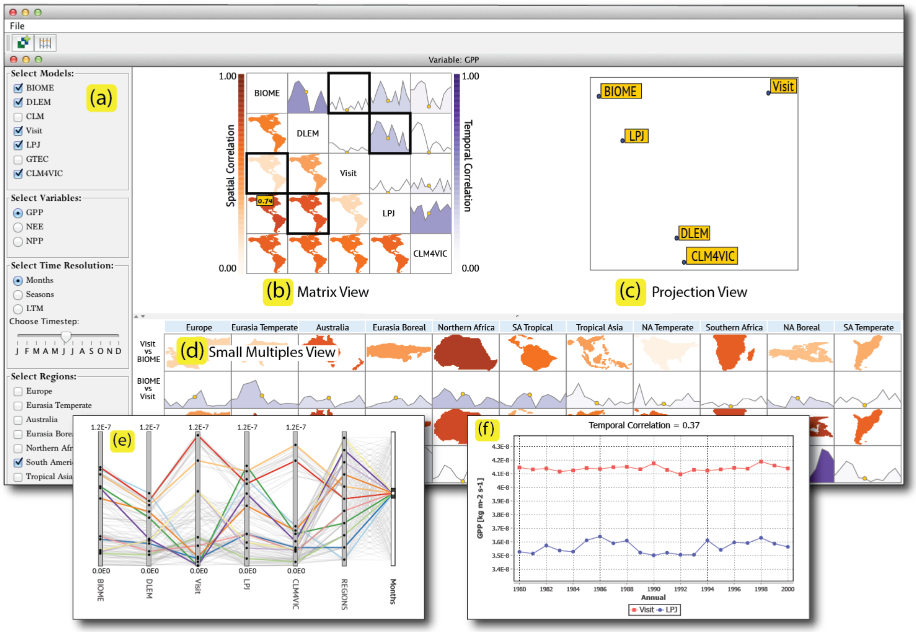

Figure 3: **SimilarityExplorer is composed of a set of filters (a), similarity views (b, c, d) and data views (e, f)**. The *similarity views* are b) a matrix view for showing pairwise similarity, c) a projection view for showing multi-way similarity, and d) a small multiples view for showing region-wise spatiotemporal similarity. The *data views* are: e) a parallel coordinates view for showing multi-model distribution of each variable, and f) a time series for showing temporal distribution of any pair of models.

formed at the regional granularity of space and monthly or seasonal granularity of time.

Distribution: The intent Q_4 is reflected by the distribution task that helps provide a multi-way perspective on behavior of regions with respect to multiple models ($distribution(p,v)$), and on pairwise model-model relationships for all regions. Scientists could also get additional information about outlying regions and models using this task, which allows exploration at a greater level of detail than the other tasks. This task also involves drilling down to the temporal distribution of a pair of models ($associate(t,v)$).

5.2. Visual Encoding Challenges

The challenges in translating the tasks to different aspects of visual encoding were met by integrating the iterative feedback from the scientists' on our intermediate prototypes. We justify our key design choices with respect to the following aspects.

i) Separating space and time: The tasks described above required us to separate as much as possible, the facets of space and time, although in the final analysis, they are inextricably linked. A climate scientist remarked that he wanted *no time* in his analysis, but wanted to see only space. Upon reflection, we realized that what this user really wanted was more like *all time*, i.e., spatial correlations which had been composited over the entire time interval, with no temporal subsetting. In this sense, then, the spatial correlations shown are composited over time, and the temporal correlations are composited over space. This had to be reflected in the visual representation by having a separation between spatial and temporal encodings.

ii) Facilitating systematic interaction: Both spatial and temporal relationships could vary over space (e.g., regions) and time (e.g., seasons). This decomposition needed to be reflected through brushing over space and time and selections of regions and time-steps. These operations also had to be associative: any spatial operation could adapt the temporal similarity to reflect the selected region and any temporal operation could adapt the spatial side to represent the correlation for a particular time step. Another role of interaction was to allow scientists explore different granularity of space and time. This was facilitated by interaction operations such as filtering and drill-down to additional views showing different levels-of-detail.

iii) Preserving the mental model: This was a critical design issue due to the interplay between space and time, and the need to *associate* them in a holistic view [AAB*10]. Both geographical maps and time-series could be used to represent variation of either the spatial or temporal correlation. In one of the interactive sessions we presented mock-ups that used time-series to represent the variation of both spatial and temporal correlation. But without consistent visual cues linking the representation to space or time, they were confused: "I like this but I have to wrap my head around what the visualization is telling me: is it space or is it time? It will be much better if I don't have to process this in my mind"

We resolved this issue by collectively taking a design decision: for temporal correlation we would display the variation

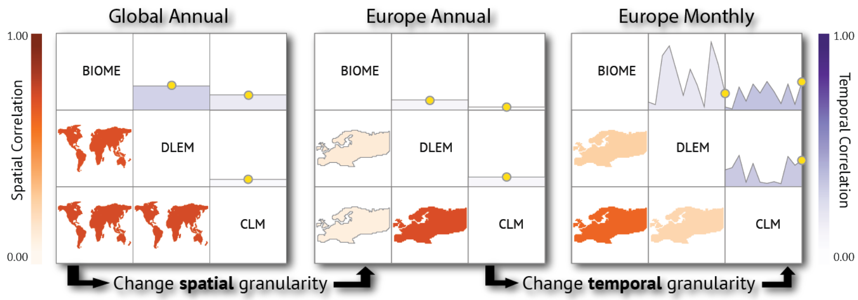

Figure 4: **Preserving the mental model and symmetry about spatial and temporal similarity** through use of *maps* for representing space and use of *area graphs* for representing time, and by reflecting the change in granularity on both sides.

of the correlation over time by displaying a time-series that adapts to the temporal granularity (annual, months, seasons). On the spatial side, we would display maps showing spatial correlation for the selected time step. Thus we use consistent spatial cues in the form of maps and temporal cues in the form of time series (Figure 3b,d). By brushing over time, we would see the change in spatial correlation as the displayed map adapts to the selected time step.

iv) Retaining symmetry while drilling down: Preserving a symmetrical relationship among the different granularity of space and time through consistent visual representation was essential for scientists to keep track of any change that occurred. The change of spatial granularity is reflected by transforming the maps to represent the selected regions. The change of temporal granularity is reflected by transforming the number of steps in a time series (Figure 4).

5.3. Comparison methods

Facilitating visual comparison among the models and output variables is one of the main goals of this work. We followed Gleicher et al.'s taxonomy [GAW*11] of visual comparison methods for guiding the representation of the different aspects of similarity and the eventual placement of the different views. As shown in Table 1, the three comparison methods that are used are explicit encoding, juxtaposition and superposition. Explicit encoding is used to encode the degree of similarity among the different views with the help of correlation metrics. For comparison tasks multiple views are juxtaposed next to each other. We represent multiple time series by superposing them in the same view (Figure 3f). Different interaction mechanisms like filtering, brushing, linking, and drilling-down allow scientists to browse through the multiple perspectives of similarity.

6. SimilarityExplorer

Our third contribution is the design of the SimilarityExplorer, an exploratory visualization tool for analyzing multi-faceted, multi-granularity, climate model similarity. This design was guided by: the domain characterization presented in Section 4, and the classification scheme described in Section 5. The scientists' analysis needs motivated our design decision of using multiple linked views [Rob07], a visualization approach that is appropriate for flexible analysis of multifaceted data. There is an implicit hierarchy [Shn96] in the type of views in SimilarityExplorer, which are *similarity views* and *data views*.

6.1. Similarity Views

With the help of similarity views, we explicitly encoded spatial and temporal correlation between models, based on the computation we had described in Section 3.2. The different similarity views are described below:

Matrix View: A model is a primary unit of comparison. Our collaborators needed a view that would show both spatial and temporal correlation for the models in one integrated view, that would be flexible enough to adapt to different granularity of space and time. We took inspiration from the multi-form matrix [MXH*03] designed by MacEachren et al. and designed a matrix view that reflects pairwise similarity between models (Figure 4). In keeping with the idea of preserving the mental model about space and time, it is divided into two halves across the diagonal: the cells in the lower triangle represent the pairwise spatial correlation through color-coded maps and the cells in the upper triangle represents the temporal correlation between two models. The color coding uses a continuous color map([HB03]) and reflects the degree of correlation, with orange for correlations on the spatial side and purple for correlations on the temporal side. The color map adapts to the range of correlation values: if there are negative correlations, a divergent color map is used.

Scientists can perform the following tasks using the matrix as shown in Table 1: i) *identification* tasks by filtering the view by different regions or time and ii) comparison tasks launching multiple matrices of different variables (Figure 6). For the latter case, we could have encoded a derived statistic that would explicitly encode the average correlation based on multiple variables, in a single matrix. However, the scientists were interested in analyzing the high or low correlations for the individual variables. Thus we use the option of juxtaposing multiple matrices for the different variables.

The effect of changing spatial and temporal granularity are shown in Figure 4. The initial view is for showing global, annual correlation. On selection of a sub-region, i.e., Europe, maps for Europe are shown on the spatial side, while

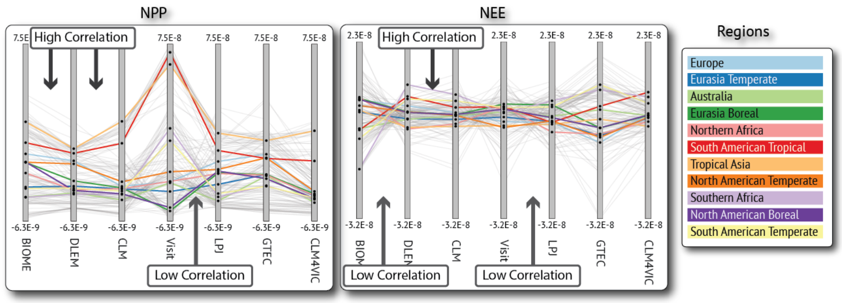

Figure 5: **Data View: Parallel Coordinates**. The ability to examine the region-wise range and distribution of variables enables climate scientists to relate the meta views to the patterns in the data view, i.e., parallel coordinates, and additionally, find clusters and outliers. For NPP, we can see a cluster of polylines for the regions South American Tropical and Tropical Asia for all models, indicating multi-model similarity for those regions.

the temporal side gets updated to show the annual average correlation for Europe. On selection of seasonal granularity, the area graph gets updated to a time-series representing the four seasons and shows the maps for the selected season. Thus spatial and temporal operations are symmetrical: they affect both sides of the matrix and the color-coding reflects the correlation for the selected time step.

Projection View: After presenting the matrix view to our collaborators, they felt the need for representation which gave a high-level overview of *all* models with respect to each other. This prompted us to design the projection view (Figure 3c) that shows multi-way similarity among models. Thus, it overcomes the limitation of the matrix view, which is only able to show pairwise patterns. As mentioned in Table 1, the projection view is used to mainly *identify* which models are more similar, triggering the subsequent analysis steps for exploring the reason for similarity. The projection view is generated by using the spatial or temporal correlation between models as the distance metric and then using multidimensional scaling (MDS) for mapping the data points onto a two-dimensional scatter plot. The physical proximity of models encodes their overall similarity. Initially, some of our collaborators were confused by the projection view but on seeing the merits of getting a multi-way overview of similarity they became more appreciative of its utility. One of them commented: "*The axes have no meaning here and we are not used to seeing this, but I really like the all-way comparison we can perform which we could not do before*". This view adapts to different selections of time steps or regions.

Small Multiples View: The small multiples ([VDEVW13], [Tuf83] view as shown in Figure 3d supports drilling down into the correlation patterns for each individual region. The drill down operation can be initiated from both the spatial and temporal sides of the matrix: drill down from the spatial side shows a map representing spatial correlation for a region and a selected time step; and that from the temporal side shows time series representing variation of temporal correlation for a region. One of the design options was to show a global map for the spatial drill down, with individual regions being color-coded based on spatial correlation between two models. However, this would not have been symmetrical with the temporal side, as there would be a map for each time-step and it is visually complex to represent so many maps, and still preserve the mental model about the relationships. Using this small multiples view, scientists can perform several comparisons: i) by selecting a cell within a matrix the region-wise spatial and temporal correlation for that pair is shown, which lets them compare anomalies between global and regional patterns, ii) by comparing across space and time, scientists can understand the cause of anomalies , and iii) by comparing these small multiples for different variables, scientists can hypothesize about which output variables affect similarity of models across different regions.

6.2. Data Views

Using the data view scientists can drill down to the distributions of different variables and gain information about outliers which the similarity views might not show. Below we describe the data views:

Parallel Coordinates: For each output variable, we use parallel coordinates (Figure 5) for enabling scientists to analyze the multi-model similarity based on the region-wise distribution of the variable. In discussion with the scientists, we found that multivariate relationships among the different output variables are not of interest in their analysis. Instead of modeling parallel coordinates conventionally, where variables are mapped on to the vertical axes and data objects are mapped to polylines, we use one parallel coordinates plot per variable. We use each vertical axis to represent a model and a polyline connecting the different axes represents the value of a variable for a given region. We compute a global scale across all models, for mapping the values so that they are comparable. The regions are represented by a categorical color scale. The number of data points, that is the number of polylines, depends on the temporal granularity selected. For annual correlation, there is only one polyline per region, for seasons there are four, and in the case of the lowest level of temporal granularity, months, there are twelve polylines for each region. Brushing by time and region allows the scien-

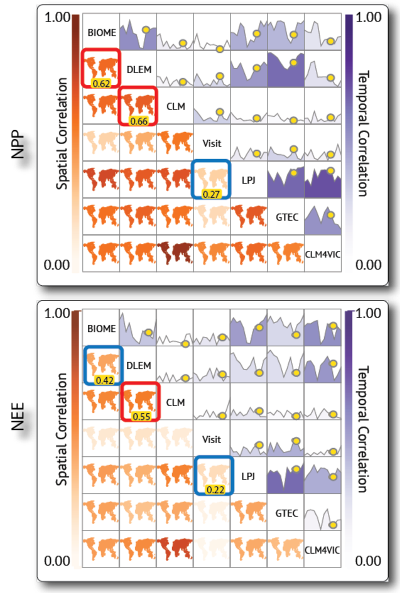

Figure 6: **Comparing multiple output variables** for different months and analyzing their distribution (Q2, Q4).

tists to look at only specific instants of time, a few regions, or both. By observing the trajectory of polylines, scientists could perform a multiway comparison of region-wise distribution across models. By linking the parallel coordinates with the matrix view, they can also *associate* the degree of correlation among models with the data distribution across the different regions. In case of comparison of multiple variables, multiple parallel coordinates plots can be instantiated.

Time Series: The temporal correlation represented by the area graph in the matrix is based on a pair of time-series for each time-step. Since correlation is just one of the ways of representing the relationship between two time-series, the scientists were also interested in looking at the original time-series to find any additional information, like the high or low temporal distribution, or any anomalies. Based on this requirement, we designed a time series view that shows the temporal distribution of any variable for a pair of models. The view is instantiated when any cell on the temporal side of the matrix is selected (Figure 3f).

7. Case Study

We describe the features of the SimilarityExplorer with two different scenarios that our climate scientist collaborators used for analyzing model similarity.

7.1. Understanding Output-Output Similarity (Q_2,Q_4)

The climate scientists wanted to compare how models behave with respect to two output variables: Net Primary Productivity (`NPP`) and Net Ecosystem Exchange (`NEE`) for the month of September. Considered to be two of the most important “vital statistics” of ecosystems, `NPP` represents the amount of productivity that is available for growth, while `NEE` reflects the input/output balance of carbon to and from the ecosystem. Both output variables are critical for understanding the atmospheric carbon cycle. As shown in Figure 6, all the models seemed to be more spatially correlated with respect to `NPP` (on the top) than `NEE` (on the bottom). This prompted the scientists to look at the region-wise distribution of the variables for confirming this. The parallel coordinates plot for `NPP` (Figure 5, on the left) showed a high number of parallel lines between highly correlated models like `BIOME-DLEM` and `DLEM-CLM`. But the high correlation for `BIOME-DLEM` is absent for `NEE` (Figure 5, on the right), where lines are more scattered in different directions, reflecting the different input/output balance points for carbon across ecosystems in different regions. By using parallel coordinates plot, the scientists found that `NPP` (Figure 5, on the left) shows higher spread among the values than `NEE` (Figure 5, on the right). The high spread and high values of `NPP` for the `Visit` model appear to be outliers. The scientists concluded that these outlying regions were causing the `Visit` model to be quite different from the rest. This can also be seen in the matrix plots, by the consistently low spatial correlation between `Visit` and most of the other models, for both variables. However, for `NEE`, the distribution for `Visit` is identical to the distribution for the other models: in this case the lack of correlation causes `Visit` to be different from the rest. The outlier regions, `Tropical Asia` and `South American Tropical`, appeared to be similar for all the models, as shown by the clustered polylines for `NPP`. The scientists confirmed that this was an expected pattern for tropical regions for NPP; such a pattern was expected to be absent for `NEE`, which was also confirmed by observing the parallel coordinates plot.

By using SimilarityExplorer the climate scientists were thus able to discover that the models had better agreement for tropical areas where there is little seasonality in growing conditions, like temperature. The models had lower agreement for temperate and boreal ecosystems that have distinct and more variability in growing conditions. One of our collaborators commented that “*this would allow them to develop hypotheses on performing additional experiments*" and that "the free-style nature of the exploration lends well to shift from one variable to another and support root-cause analysis”.

7.2. Exploring Model-Model similarity (Q_1, Q_3)

Gross Primary Productivity (`GPP`) is arguably the most important ecosystem variable, indicating the total amount of energy that is fixed from sunlight, before respiration and decomposition. Climate scientists need to understand patterns of `GPP` in order to predict rates of carbon dioxide increases and changes in atmospheric temperature. The motivation for this scenario was to compare multiple models with respect to `GPP` by exploring model similarity for the `Europe` and `Eurasia` sub-regions; for the summer and winter seasons, and compare those trends with the correlations for tropical and temperate regions.. As shown in the summer view in Figure 7, the model pairs of `CLM-CLM4VIC` and `BIOME-`

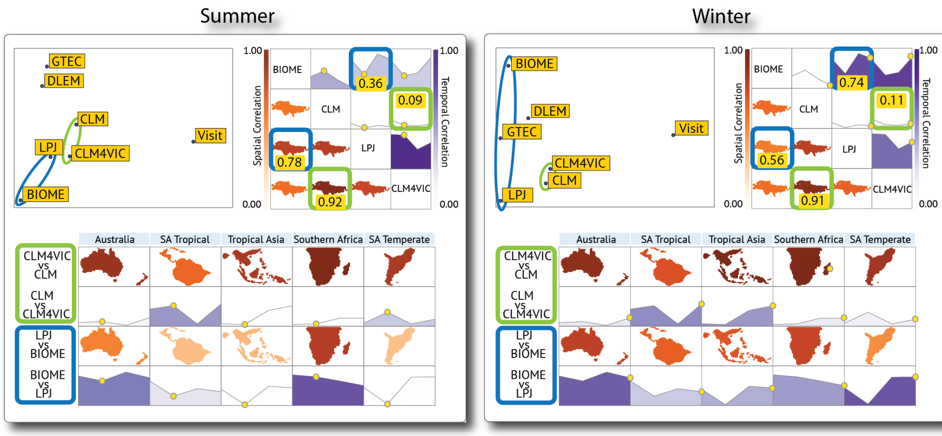

Figure 7: **Comparing model similarity for GPP and analyzing spatiotemporal anomalies for winter and summer (Q1, Q3)**. Using the projection view, scientists were able to select similar models; using the matrix view they could compare spatial and temporal correlation (indicated by the numbers); and identify anomalies using the small multiples view.

`LPJ` appear to be similar, based on their relative proximity in the projection view. They selected these models and instantiated the matrix view (Figure 7). This showed high spatial correlation but low temporal correlation for the `CLM-CLM4VIC` model pair for summer, as well as for winter season. For comparing the trends with the temperate and tropical regions, they used the small multiples view. The notable deviations were i) `SA tropical` which showed higher temporal correlation across summer and winter for this model pair, and ii) `Tropical Asia` which showed higher temporal correlation than `Europe` and `Eurasia` sub-regions for the winter season. For the `BIOME-LPJ` pair, the models appeared to be more similar during summer than winter based on the projection view. The drop in spatial correlation during winter was confirmed by the matrix views. However, the temporal correlation was higher in winter than during summer. From the small multiples view, the scientists found that during summer the `SA Tropical`, `Tropical Asia` and `SA Temperate` regions had lower spatial correlation than `Europe` and `Eurasia` sub-regions; while `Tropical Asia` and `SA Temperate` had lower temporal correlation compared to the same. Both spatial and temporal correlation for this model pair seemed to increase for the winter season for the `SA Tropical`, `Tropical Asia` and `SA temperate` region. This trend was contrary to the pattern for the `Europe-Eurasia` region.

By using SimilarityExplorer the climate scientists were able to visualize the interdependency between seasonality, region, and model. The fact that the SimilarityExplorer made their analysis more streamlined and efficient was validated from one of their comments: "*Without this tool scientists would literally print hundreds of plots and pin them on the wall, this tool solves this problem*". They also appreciated the fact that "*the tool can be easily extended for more models, the benefit is being able to do this with* 20 *models*".

8. Conclusion and Future Work

In this paper, we have presented SimilarityExplorer, a visual analysis tool for comparison of multifaceted climate models. Climate scientists are naturally more familiar and comfortable working in one of the two facets of space and time than the other. Most of their exploratory thinking, tools and analyses tend to be biased toward one of them, at the expense of investigations into the other. Because of the relative ease with which users can 'cross the diagonal' from one realm of analysis to the other, the scientists found that "*the SimilarityExplorer offset such natural prejudices and facilitated commensurate symmetry, resulting in more complete exploration and understanding*". A drawback of SimilarityExplorer is that the data pre-processing takes place externally, thereby restricting the flexibility of the tool. We are working on integrating pre-processing capabilities and additional metrics so that the tool is more flexible in adapting the visualization to the analysis needs of the scientists. Our approach of providing multiple perspectives on occurrence and causality of similarity is generalizable to other domains that involve spatiotemporal data, like urban data. We are looking forward to add more features to, and apply SimilarityExplorer for solving problems related to such different domains.

9. Acknowledgement

This work was supported by the DataONE project sponsored by the NSF Grant number OCI-0830944, and by NSF CNS-1229185, NASA ROSES 10-BIOCLIM10-0067, and DOE Office of Science Biological and Environmental Research (BER). The data was acquired through the MAST-DC (NASA Grant NNH10AN68I) and MsTMIP (NASA Grant NNH10AN68I) projects funded by NASA's Terrestrial Ecology Program. We also extend our gratitude to all members of the Scientific Exploration, Visualization, and Analysis working group (EVA) for their feedback and support.

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