

Visual Analysis of Spatio-Temporal Data: Applications in Weather Forecasting

A. Diehl^{†1} and L. Pelorosso^{‡1} and C. Delrieux^{§2} and C. Saulo^{¶3} and J. Ruiz^{||3} and M. E. Gröller^{**4} and S. Bruckner^{††5}

¹University of Buenos Aires, Argentina

²South National University, Argentina

³ DCAO (FCEN/UBA) - CIMA (CONICET/UBA) - UMI IFAECI/CNRS, Argentina

⁴Vienna University of Technology, Austria

⁵University of Bergen, Norway

Abstract

Weather conditions affect multiple aspects of human life such as economy, safety, security, and social activities. For this reason, weather forecast plays a major role in society. Currently weather forecasts are based on Numerical Weather Prediction (NWP) models that generate a representation of the atmospheric flow. Interactive visualization of geo-spatial data has been widely used in order to facilitate the analysis of NWP models. This paper presents a visualization system for the analysis of spatio-temporal patterns in short-term weather forecasts. For this purpose, we provide an interactive visualization interface that guides users from simple visual overviews to more advanced visualization techniques. Our solution presents multiple views that include a timeline with geo-referenced maps, an integrated webmap view, a forecast operation tool, a curve-pattern selector, spatial filters, and a linked meteogram. Two key contributions of this work are the timeline with geo-referenced maps and the curve-pattern selector. The latter provides novel functionality that allows users to specify and search for meaningful patterns in the data. The visual interface of our solution allows users to detect both possible weather trends and errors in the weather forecast model. We illustrate the usage of our solution with a series of case studies that were designed and validated in collaboration with domain experts.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: Picture/Image Generation—Viewing algorithms I.3.6 [Computer Graphics]: Methodology and Techniques Interaction techniques—I.3.8 [Computer Graphics]: Applications—Weather Forecast Analysis

1. Introduction

The state of the atmosphere can be described by its characteristic meteorological variables (i.e., temperature, pressure, moisture content, wind velocity, etc.). The future evolution of these variables can be predicted (to a certain degree of accuracy) by Numerical Weather Prediction (NWP) models

given that a good representation of the current atmospheric state is provided. Visualization tools have been widely used to facilitate the analysis of weather forecast data. The visual analysis of predictions can provide significant insights for professional meteorologists and researchers. The analysis of temporal and spatial patterns allows for the identification of particular weather phenomena, atypical model behaviors, and model errors.

The motivation for this work arose from a collaboration with meteorologists from the Centro de Investigaciones del Mar y la Atmósfera (CIMA). This paper proposes a visualization solution named “VIDa” (Visual Interactive Dashboard) that assists users in the visual analysis of short-term weather forecasts. We present several case studies to highlight the benefits of our approach.

[†] e-mail: adiehl@dc.uba.ar

[‡] e-mail: lpelorosso@dc.uba.ar

[§] e-mail: cad@uns.edu.ar

[¶] e-mail: saulo@cima.fcen.uba.ar

^{||} e-mail: jruiz@cima.fcen.uba.ar

^{**} e-mail: groeller@cg.tuwien.ac.at

^{††} e-mail: stefan.bruckner@uib.no

Our solution provides visualizations and interactive mechanisms to assist users in the identification of weather trends and the visual analysis of the model behaviors. The system supports 2D scalar-field grids of different meteorological variables, such as temperature, pressure, and humidity, among others, and it enables the analysis and comparison of NWP forecasts of the atmospheric state. The main contributions of this paper are:

- We introduce a timeline view that shows miniature 2D geo-referenced projections of a given meteorological variable, which we refer to as “minimaps”. This feature is especially helpful for users as an initial step in the task of identifying interesting events that they can later confirm by using other visual components.
- We present a flexible design for operating with multiple forecasts. Two or more forecasts can be selected and different mathematical operations can be performed, such as addition and subtraction between 2D scalar-fields forecasts, or the computation of the mean and standard deviation over a group of forecasts. Results from these operations are displayed on the map.
- We propose a novel curve-pattern selector tool that allows users to perform advanced visual analysis of multiple 2D scalar-fields, while avoiding the perceptual drawbacks of superimposing multiple colormaps. By means of this tool, users can define meaningful pattern behaviors, save them, and afterwards classify the model output according to the defined patterns.
- We introduce a curve-pattern classification algorithm that arranges and analyzes multiple forecasts which facilitates forecast verification and enables the identification of temporal trends and atypical behaviors.

Users can also select subsets of the data by means of spatial and temporal filters and examine details using a linked meteogram view. By means of the meteogram view they can see the temporal evolution of a meteorological variable in a specific point or region. Furthermore, our solution is designed as a web application which allows users to easily broadcast weather forecast information via the Internet.

2. Related work

Related work may be classified based on two aspects: analysis of spatio-temporal patterns, and visualization systems with applications in weather forecast and climatology.

2.1. Analysis of spatio-temporal patterns

There have been extensive studies in the area of spatio-temporal visualization and geo-spatial visual analytics. Andrienko and Andrienko [AA06] have broadly described different techniques for visual analytics of spatio-temporal data. Furthermore, Aigner et al. [AMST11] provided a complete survey of different visualization techniques for time-dependent data and time series analysis. Hochheiser

and Shneiderman [HS04] presented TimeSearcher 1, a visual exploration tool that combines timebox queries with overview displays, query-by-example facilities, and support for queries over multiple time-varying attributes. TimeSearcher 2 [BAP*05] is an extension of TimeSearcher 1 for long-time series visualization, data filtering, and pattern search query specification. Fails et al. [FKSS06] presented a visual-query interface and result-set visualization tool for searching and discovery of temporal patterns within multivariate and categorical datasets. The results can be explored through coupled ball-and-chain and tabular visualizations.

Bruckner and Möller [BM10] proposed a system for the visual exploration of a simulation parameter space to assist in the generation of effects such as smoke and explosions. They split each simulation sequence into a number of representative segments. Then they compared the simulation-space similarities at different points within the temporal evolution of each simulation. They depict subsets of the clusters' members in a timeline at different temporal compression levels. Another example is the work of Krstajic et al. [KKBK11]. They presented a technique for the interactive visual analysis of multiple time-series event data, named CloudLines. They used distortion techniques on a timeline to accommodate a large number of data items. In our approach, we also utilize a timeline that groups multiple runs chronologically but we do not apply any kind of compression in the temporal domain. We want to visualize an overview of the complete short-term cycle at once.

Our work focuses on the visual analysis of 2D scalar-fields that correspond to physical variables. There are several techniques that can be applied to compare 2D scalar-fields. Malik et al. [MHG10] presented an approach for visual comparison using multi-image views that preserves contextual information. Schmidt et al. [SGB13] proposed a multi-image view technique which used hierarchical clustering. Ware and Plumlee [WP13] described different techniques that are utilized in the case of weather forecast displays. Köthür et al. [KSU*13] presented a visualization system that works with 2D scalar-field distributions of atmospheric data. They employed a visual analytics approach that enables users to extract and explore different sets of 2D spatial distributions of the scalar values. They presented a visual summary view which shows 2D spatial distributions with similar characteristics side by side. On the contrary, in our approach we utilize a single integrated visualization instead of multiple views of similar 2D distributions. We decide to do the visual comparison in a single geo-referenced 2D view with a classification of different features. Our goal is to minimize the time and actions required by the users in order to perform the visual analysis task.

We employ a high level and qualitative variation analysis, which is based on the concept of families of curves [KLM*08, KLM*12]. We apply this approach to the analysis of weather trends and atypical model behaviors. The

ideas presented in Coto et al. [CGB*05], although not related to weather forecasts, provided an important background to our approach. Coto et al. described a classification based on “time-signal curve types” for early detection of breast cancer. Those curves were used to classify a possible tumor, and each curve type represented a characteristic of that tumor. For example, curves with increasing values were identified as indicators of benign lesions. For each data point, they defined a distance metric among temporal functions referred to as time activity curves (TAC). The work of Woodring and Shen [WS09] proposed a method to explore temporal trends at different resolutions using wavelets. With the wavelets they characterize the data points and transform them into time-series curve sets. These points are classified into clusters of similar activity. In our work, we focus on data sets coming from short-term weather forecasts where we want to avoid compression of the time scale of the meteorological variables.

Another technique closely related to our approach is the work of Glatter et al. [GHA*08]. They developed a text search language using Flex and Bison for specifying temporal patterns. We use some concepts from their query language and adapt them to our visual analysis tool.

2.2. Visualization systems with applications in weather forecast and climatology

There has been extensive work done in the area of visualization systems and visual analytics applied to weather forecast and climatology. In the scope of this paper, only a few examples are summarized here as a background for our work. The University Corporation for Atmospheric Research (UCAR) presented a list of post-processing tools for weather visualization. Among them are: Integrated Data Viewer (IDV) [MMWE03], Visualization and Analysis Platform for Ocean, Atmosphere, and Solar Researchers (VAPOR) [CMNR07], and the Grid Analysis and Display System (GrADS) [TD98]. The latter was selected by the CIMA institute to perform their visualizations. GrADS is a visualization system that uses a mix of GUI and command-line scripts to derive post-processed data visualizations. Command-line scripts and programming features can be seen as an advantage in terms of flexibility, but also make the user experience and interaction difficult. Instead, visual interfaces are proven to be more effective in terms of cognitive productivity [War13].

The Ultrascale Visualization Climate Data Analysis Tools (UV-CDAT) [WDP*13] are a powerful system jointly developed by several institutions, universities, and private companies. The tool set integrates data analytics, ensemble analysis, uncertainty quantification, metrics computation, and visualization components for big data climate analysis. Also, the work of Song et al. [SYS*06] presented a visualization system that performs analysis of multi-dimensional atmo-

spheric data sets using physics-based atmospheric rendering, illustrative particles, and glyphs.

The aforementioned visualization systems are very powerful. They enable a full and flexible visual analysis, but they require many parameter settings and, in some cases, even programming tasks. On the contrary, our solution is oriented to solve operational weather forecasting, where forecasters need assistance for quick analysis. Most of the time they may not want to invest time in programming tasks, but instead work with a tool that allows them immediate access to the visual analysis of the data.

Potter et al. [PWB*09] presented Ensemble-Vis, a framework that combines multiple linked views to facilitate the visual data analysis of ensemble data, focused on short-term weather forecasting (small-time spans) and climate modeling (very long-time spans). They provided spatial overviews and temporal overviews combined with detailed statistical views. In our approach, we also provide multiple linked views that combine an overview with detailed views and spatio-temporal pattern analysis for a complete visual analysis of the data.

We are particularly interested in previous visualization systems available as web applications. Among them is WeatherSpark Beta [WS] which provides multiple views such as an integrated mapview, charts and glyphs depicting weather conditions (sunny, cloudy, rainy, etc.), and historical data for a given weather station or a given city on the globe. Other examples are Weather.com [TWC], Wetter.de [Wet], Weather Underground [WU], and also the 3D weather visualization system Terra3D [Ter]. These cases are mainly targeted at general users rather than domain experts. Related to the aforementioned tools, our domain experts stated: “the available web applications do not allow us to perform operations among forecasts, they do not provide us with a global overview, and do not allow us to compare multiple forecasts”.

3. Visual Interactive Dashboard (VIDa)

3.1. Overview

Our collaborators are meteorologists who work with the Weather Research and Forecasting (WRF) model [Roz06] adapted for their geographical region. The WRF model is an open source mesoscale numerical prediction model built on the basis of collaborative efforts of several institutions in the United States of America, with contributions from researchers around the world. Its optimum configuration and performance highly depend on the specific application. It includes different parameters such as geographical area, time of the year, and local forecast errors of the regional model [RSNP10].

The specific problem we are facing in this paper applies to operational weather forecasting. Forecasters need a tool

that provides them with straightforward visual mechanisms to explore a set of forecasts, with an agile interface that allows them to perform different operations in time and space. These needs are not covered by currently available systems. Applications such as GrADS, VAPOR, and UV-CDAT, require specific hardware, user training, and programming skills that make them unsuitable for forecasters' operational needs. Our solution allows them easy access to complete short-term weather forecast cycles. It provides them with a visual overview of multiple forecasts and runs at the same time. By using our application, forecasters can evaluate the complete panorama, and focus on specific forecast operations and analyses, without programming requirements or complex settings.

The CIMA institute's previous workflow consists of four main activities as shown in Figure 1. The first task (WT1) is the generation of a numerical weather forecast every 12 hours (each forecast has a total length of 48 hours). It generates 17 predictions (one every 3 hours) that are 3D representations of the atmospheric state corresponding to different times in the future. After the generation of forecasts, in the second task (WT2), simulation outputs are post-processed to derive new atmospheric information from the results. In the next task (WT3), the specialists create new visualizations that are generally two dimensional (2D) plots. Finally, in the last task (WT4), the visualizations are exported as images and presented on a website using 2D maps and plots.

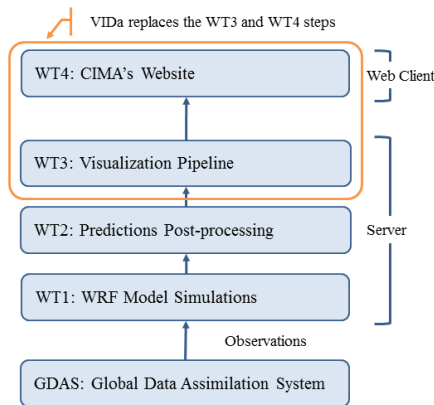


Figure 1: Task workflow: the new visualization pipeline is integrated in our collaborators' workflow at tasks WT3 and WT4. GDAS provides observational data for the workflow.

Although a vast amount of information is presented to the users in their previous workflow, we have recognized that their visualizations have certain drawbacks. For example, they visualize the information using a static interface that makes interaction difficult. Additionally, they display different views that cannot be linked or compared. We have modified their previous workflow by integrating our new visualization pipeline into tasks WT3 and WT4.

The result of this integration is a new visualization system named Visual Interactive Dashboard (VIDa). VIDa is a client-server system with a web interactive interface displaying a full screen webmap and several linked windows that can be visualized or hidden by using a menu, as shown in Figure 2. These windows include: date selector, variable selector, minimap timeline, webmap spatial filters, meteograms, curve-pattern selector, and operations.

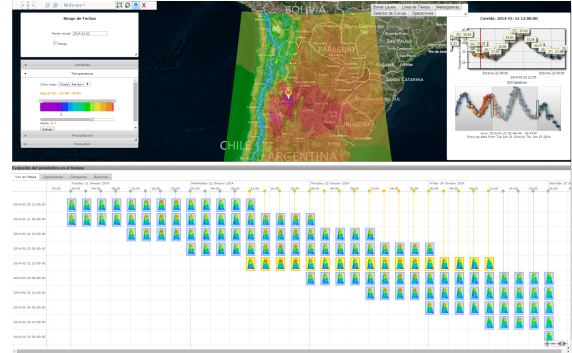


Figure 2: Screenshot of our Visual Interactive Dashboard (VIDa).

3.2. Visualization components

VIDa visualizes a complete series of short-term weather forecasts, for a given date and a given variable, in a timeline of 2D geo-referenced minimaps (see Figure 3). The timeline provides an overview, where the user can identify interesting forecasts and detect salient features. The user can select a minimap and then visualize the associated 2D scalar-field projection in an integrated mapview. Also, the user can select two or more minimaps and perform different operations with the forecasts. Then, the user can visualize the results on the map, select different zoom levels, and apply spatial and temporal filters. Additionally, we provide a meteogram view, where the user can visualize detailed information about the temporal evolution of multiple runs.

Furthermore, we introduce a novel curve-pattern selector that makes use of domain expert knowledge for the detection of particular local weather phenomena (see Figure 4). It consists of an intuitive visual tool for pattern sketching and classification, a set of configuration options, and an automated technique to perform the classification. Although the components of the control are similar to others used in previous work, the selection and combination of them as presented in our control provide a simple and flexible tool for meteorologists when utilized for weather forecasting. Using the curve-pattern selector the user can sketch meaningful patterns in a 2D coordinate graph. Once the curves corresponding to patterns are sketched, the user can map the curve-patterns to a color scheme. The curve-pattern selection and its associated parameters can be saved and reused in order to facili-

tate and accelerate the analysis process. This information, in conjunction with the operation mode and specific parameters, are then used by an automated algorithm. Our algorithm compares and classifies the behavior of multiple 2D scalar-fields in time. Results are presented in an integrated single view (see Figure 4g).

Minimap timeline The newly introduced minimap timeline is a key characteristic of our application given its capability to show a synthesized overview of complete 48-hours cycles of short-term weather-forecasts (see Figure 3). Forecasters need to easily navigate through future predictions, as well as past events. Each minimap represents a forecasted meteorological variable and is depicted as a geo-referenced 2D colormap. The colormap is a UTM (Universal Transverse Mercator) grid projection of a 2D scalar-field, that is adjusted to the pixel coordinates of the webmap. The timeline groups the minimaps by date and hour of each run. It shows the minimaps corresponding to all the calculated forecasts for a particular date (see Figure 3). Using the horizontal axis, domain experts can analyze the temporal evolution of a meteorological variable. Using the vertical axis, they can analyze multiple forecasts that correspond to a given date and time. Both axes provide the user with a complete overview of the short-term forecast cycle.

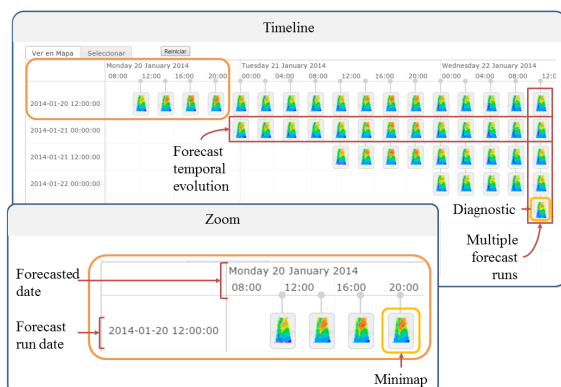


Figure 3: *Minimap timeline overview. It shows a crossed view of multiple forecast runs and predictions, depicting the temporal behavior of a given variable. It also shows the “diagnostic” which is a reference forecast created with observational data.*

Mapview The mapview allows users to visualize a given forecast or the result of a given comparison at different levels of detail. Forecasters can focus on specific regions, apply spatial filters, and analyze linked information. The process starts when the user selects a minimap from the timeline. The user can visualize one or more 2D scalar-fields corresponding to a meteorological variable as overlays on the map. The

mapview zoom level ranges from zero to twenty-three, depending on the geographical location. For zoom level zero, the entire world map fits into an image of 512x512 pixels, but for each increasing zoom level the pixel space expands by a factor of two in both axes.

Curve-pattern selector Forecasters need to quickly identify and analyze specific trends or phenomena, and afterwards estimate the effects of those phenomena in their model. Our curve-pattern selector is especially helpful for this analysis. Forecasters can specify patterns related to particular characteristics of the data. A curve-pattern represents the qualitative temporal evolution of a variable at a particular spatial location.

Employing the minimap timeline, the user selects the time steps to be included in the analysis (see Figure 4a). These selected time steps do not need to be consecutive or uniformly distributed. Then, an arbitrary curve that spans part or the full length of the selected time steps can be drawn by the user (Figure 4b). The curve-pattern can also be composed of several disconnected segments. Once a curve is drawn, the curve-pattern selector displays all possible curves that closely match the drawn curve as described in Section 3.3 (see Figure 4c). The same section also describes how the delta and mode parameters are utilized in the similarity metric of the curve-pattern classification. The application establishes the maximum number of possible curves to visualize depending on performance and usability factors. From all possible combinations the user selects the curves that are meaningful for her/him (Figure 4e). The tool allows the user to associate a given color with each curve-pattern or a group of curve-patterns. The curve-pattern itself can be selected by the user and associated with a color. The color is chosen from a particular color scheme (Figure 4d). The selected curves become the curve-patterns that will be used to perform the classification (Figure 4f). The results (Figure 4g) are visualized as a new layer in the mapview.

Forecast operation tool The operation component combined with the timeline allows for a complete analysis of the short-term weather forecast. It enables users to perform forecast comparisons among an arbitrary number of forecasts. By using the timeline, multiple forecasts can be selected in the horizontal axis as well as the vertical axis, and the operation is applied to them. Operations such as subtraction, mean, and standard deviation give useful information to assess forecast uncertainty. The subtraction between forecasts allows the user to detect significant changes in forecasts initialized at different times. By analyzing the subtraction results, the user can detect where the spatial differences are and how significant they are. An extensively used method for the estimation of forecast uncertainty is to compute the standard deviation among a group of forecasts predicted for the same date and time. Other operations such as the computation of the mean among a group of forecasts provide a

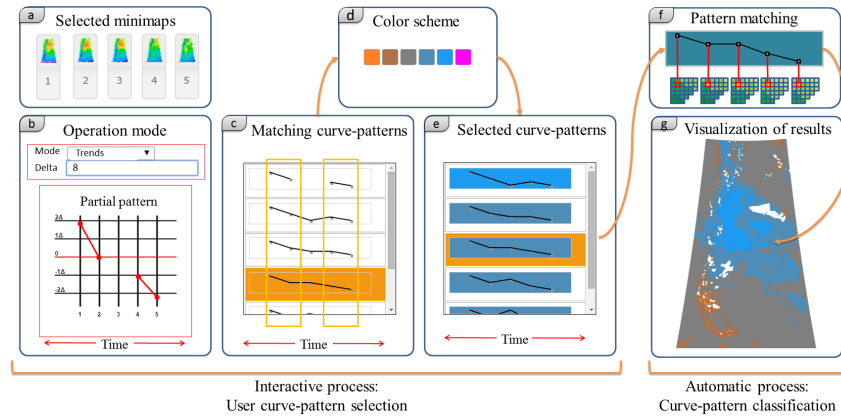


Figure 4: Curve-pattern analysis process: (a) The selected forecasts that predict 2D scalar-fields for a given date and time. (b) The curve drawing allows the user to sketch the desired patterns. (c) The selectable list of possible patterns shows the curve matches. (d) The selected color scheme. (e) The selected curves show the curve-patterns chosen by the user and its associated colors. (f) Pattern matching process for each pixel of the selected minimaps. (g) Visualization of the curve-pattern classification.

more accurate estimation of the future evolution of the atmospheric variables compared to the individual forecasts. Finally, the addition of multiple forecasts can be useful for the analysis of variables such as accumulated precipitation. In this case, the users can interactively select a consecutive set of time steps that best suits their application.

3.3. Curve-pattern analysis

Identification of trends and anomalies Forecasters need tools to detect and analyze trends and anomalies, especially model errors, to assess forecast uncertainty and to produce more accurate predictions. Here, a trend is considered to be a general behavior that is expected for a forecasted meteorological variable. For example, a continuous increase in temperature in a given region over a period of time is a possible expected behavior.

The goal of our curve-pattern analysis is the comparison and classification of multiple 2D scalar-fields in time and space simultaneously in order to identify trends and anomalies. Our technique applies to meteorological variables such as temperature, humidity, and pressure. By means of the curve-pattern selector, users can make an interactive selection of prospective curve-patterns that could be meaningful to them. For example, the forecaster can specify a curve-pattern that corresponds to a sudden drop. In the case of temperature, it could indicate the presence of a cold front. We assume that this is possible, under the hypothesis that only a few of all possible combinations are practically meaningful to the users. Those curve-patterns are subsequently used to classify the 2D scalar-fields. Identification of specific features in the data depends highly on the nature of the meteorological variable and on the kind of analysis the user wants to apply. For instance, a case can be applied to

the temperature variable, where the user chooses an increasing curve-pattern, a decreasing curve-pattern, and a constant curve-pattern (within a certain threshold), among others.

Curve-pattern classification The analysis based on curve-patterns can be helpful for the detection of specific characteristics in the temporal evolution of meteorological variables represented as 2D scalar-fields. The curve-pattern classification works in two different modes: temporal evolution mode and forecast verification mode. The temporal evolution mode can be beneficial to detect significant trends or changes in the behavior of a variable (e.g., sudden drops in temperature associated to weather fronts). In the forecast verification mode, forecasts are compared with a 2D scalar-field created on the basis of available observations. This 2D scalar-field is referred to as “diagnostic” in meteorological terminology. In this mode, the curve-pattern analysis can be helpful for the identification of regions with different error growth rates. It helps forecasters to gain experience on the behavior of forecast errors associated with the numerical model under different weather conditions. The metric used for this mode is the absolute value of the “bias”. The bias is defined as the difference between the diagnostic and the forecast. This is a measure of the forecast error commonly used in forecast verification analysis [JS11].

In addition, the user selects a set of minimaps from the timeline (see Figure 3). Each selected minimap represents a 2D scalar-field meteorological variable stored as a matrix with a resolution of $N * M$, longitude and latitude respectively. We define a curve for each position (*longitude, latitude*) across the k matrices, where k is the number of selected minimaps. The curve represents how the meteorological variable changes in the temporal domain. The curve will be composed of $k - 1$ line segments. The set

of all these curves describes the temporal evolution of a variable in an entire region. By employing the curve-pattern selector, the user defines a set of curve-patterns. The curve-patterns are curves also composed of $k - 1$ line segments.

The algorithm classifies the curves against the curve-patterns. The distance between a curve-pattern segment and a curve segment is measured using a global parameter named *delta*. A curve-pattern and a curve will match if each of the segments differs not more than $\text{delta}/2$. Parameter *delta* acts as a threshold on the Y-axis and it also establishes the Y-axis scale. We perform an analysis on each point (*longitude*, *latitude*) of the 2D geo-referenced matrices and represent the results in a new matrix with the same dimension. The (*longitude*, *latitude*) coordinates are transformed to pixel coordinates. In case that a curve matches one of the curve-patterns, the color of this pattern is mapped to the pixel coordinate corresponding to the (*longitude*, *latitude*) of the point. Otherwise, the pixel is rendered with a transparent color. The results of this operation are visualized as a new layer on the mapview.

4. Implementation

Our solution is built as a system with a visual frontend and a server backend. The frontend presents a visual interface implemented as a web application with multiple linked views. It was developed using HTML5, JavaScript, and jQuery technologies. Additionally, TeeChart charting components were used to implement the meteogram, and vis.js was utilized for the timeline. The backend uses the GPU computing engine and core libraries for processing weather forecast information. It was developed using C++ and OpenCL technologies for the GPGPU. Bing Maps services were used for the mapview component. The backend storage is based on a PostgreSQL geo-spatial database management system and database processes to import and to store the inputs provided by the WRF model.

Our data comes from a customized regional WRF model implemented over a region centered at latitude $38^\circ S$ and longitude $63^\circ W$. The covered area is discretized into a regular grid, with a resolution of 149 by 299 points, in Lambert Conic Conformal projection, and a distance between points of 15 km.

5. Evaluation

We show the potential of our technique through a series of case studies. For all of them, the meteorologists chose the temperature variable at an altitude of two meters above the land surface. Temperature is one of the most influential variables in activity planning, decision making, and productivity. The case studies cover an analysis of the temporal trends and an analysis of model errors to perform forecast verification.

We worked with two domain experts that are specialists in weather forecast research. Both of them are senior

researchers with more than 30 years of combined experience. One of them is in charge of an important governmental weather agency. To perform the case studies we conducted unguided sessions where the application was presented to the users. While the users explored the application, we took notes and learned about their feedback. These sessions were done several times, each one followed by a period where feedback was incorporated into the application. These iterations concluded when their feedback was entirely positive.

Analysis of temporal trends

In this case study the users were looking for salient features or trends. A key point in this analysis was to differentiate cases that contained unexpected information from those that contained expected information. The meteorological variable temperature expressed two well-known behaviors corresponding to a diurnal curve (increasing values) and a nocturnal curve (decreasing values) of temperature development. The meteorologists focused on interesting patterns that might occur at the same time but on different days, i.e., one, two, and three consecutive days. In this case, the users selected a set of forecasts from the same run, predicted at the following time steps: 0-hours, 24-hours, and 48-hours. Then, they selected the operation mode as temporal evolution, indicating a *delta* of 8° Celsius as differences between forecasts. Finally, they selected a qualitative list of different curve-patterns represented in terms of a large positive variation, a small positive variation, a large negative variation, a small negative variation, or no variation, and its corresponding colors, using a color scale in the YIQ color space.

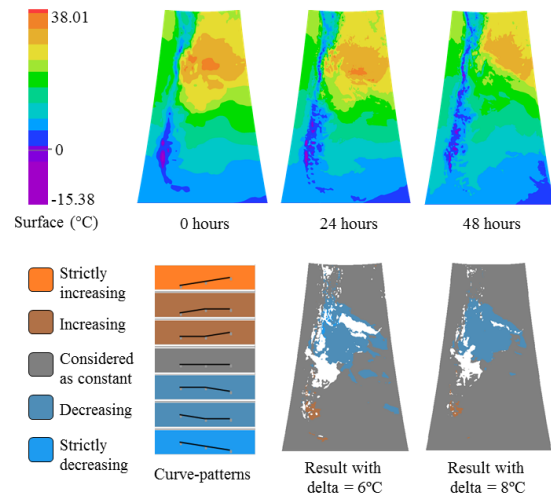


Figure 5: Trend analysis: the largest temperature drops, just after the passage of the cold front, are indicated in cyan tones. Orange tones in the south of the map indicate increasing temperature. Results are presented using two different delta values: 6° and 8° Celsius.

Figure 5 shows a visualization of the results of our curve-pattern classification using two different *delta* values. The classification is applied to the three aforementioned time steps. In the resulting images, the spatial areas with decreasing temperature are visualized in cyan tones, and increasing temperature areas are visualized in orange tones. A large spatial region is covered with cyan tones in the center region of the map, as it is shown in the Figure 5. This region corresponds to a cold-front event that was moving from south to north near the center of the domain and produces a significant temperature drop. The figure shows two results associated with *delta* values of 6° and 8° Celsius. Larger delta values create more relaxed conditions of similarity against the patterns and therefore larger spatial areas can be associated with each pattern. This can be noticed by comparing the cyan spatial areas in the results. White areas correspond to regions of the map that do not match any pattern.

Forecast verification

The main goal of forecast verification is to improve the quality of weather forecast models. Improvement of a weather forecast model requires an efficient error analysis. In this case study we present an analysis of model errors among multiple runs. Due to the chaotic nature of the atmospheric flow, a forecast error usually increases with the forecast lead time. However, the rate of growth strongly depends on the weather phenomena present at the particular time and region. In this analysis, the users want to identify spatial areas where the error increased.

Every day, two short-term 48-hour forecast cycles were run at time 0000 UTC and at time 1200 UTC. Therefore, we had 4 forecast runs and a diagnostic in a complete short-term 48-hour forecast cycle. In this work we use the diagnostic generated by the Global Data Assimilation System (GDAS) [GDAS]. From the timeline, the user selected a targeted date and time for the forecast runs. The vertical axis aligned all the runs from the selected date and time (see Figure 3). In this case, the users selected the operation mode for forecast verification and a suitable *delta* of 8° Celsius. The users also selected a subset of curve-patterns, representing increasing errors and associated colors. They also applied the YIQ color space as before, but only with orange tones to represent positive changes.

The spatial areas, where the error presented a major increase and a major rate of change, are depicted with orange tones (see Figure 6). These areas correspond to the position of the cold front discussed in the previous case. As cold fronts are characterized as areas where the temperature gradient is strong, small errors in the location of these atmospheric boundaries produce large errors in the forecasted temperature as can be seen in the figure. This case shows how the tool can facilitate the analysis of the numerical-model performance under different atmospheric conditions.

In this case, the performance is affected by the cold front introducing large errors in the forecasts.

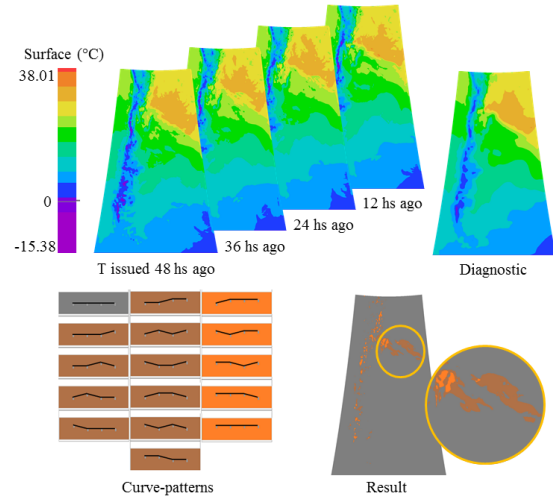


Figure 6: Forecast verification using multiple runs. It shows the passage of a cold front. This is observed as errors in the forecasted temperature shown in oranges tones.

Forecast uncertainty analysis

In this case study we present an analysis of forecast uncertainty among multiple runs. The standard deviation operation is applied on them to visualize their dispersion, which is a measure of forecast uncertainty. The users selected the same four multiple forecasts as in the previous case study. The users found more dispersion in the results over north central Argentina (see Figure 7). This area of large forecast uncertainty is associated with a displacement of a cold front. Fronts are associated with strong gradients in the temperature field, and even small changes in the forecasted positions of these systems can produce large changes in the values of the forecasted temperature. This results in an increased uncertainty in the area.

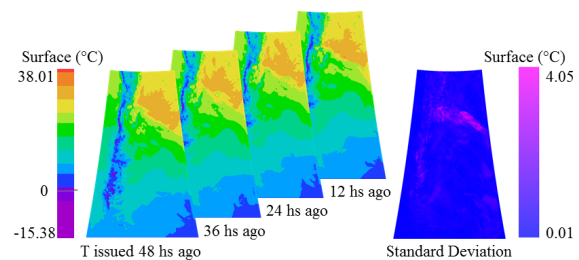


Figure 7: Forecast uncertainty analysis. The standard deviation shows the dispersion of the forecasts in different regions of the map.

Lessons learned

An important outcome of the iterative participatory design approach was that we quickly realized the importance of having a visual overview of the entire set of short-term weather forecasts. The minimap timeline turned out to be a key component of the whole system. This is due to its capacity to show multiple forecasts in a single view, with the additional benefit that it could be extended to visualize information about multiple ensemble forecasts. Furthermore, the constant feedback from experts also showed the importance of keeping a simple visualization interface.

The meteorologists' feedback was highly positive because current applications do not allow them an easy comparison between forecasts initialized at different times. Instead our solution exactly provides them with easy-to-use functionality specifically designed for this task. One of the prominent aspects of VIDa is the flexibility with which the user can select a group of forecasts and compute operations. Another very valuable characteristic is the simplicity of the user interface. In particular, the domain experts emphasized the straightforward use of the timeline and the curve-pattern selector. One of our domain experts stated: "Now, with these mechanisms, forecasters who are interested in different areas of the country, can focus on what is happening, what the tendencies would be, and the significance of the model errors". The experts said that one of the major impacts of our system was the capability to display all the cycles of short-term weather forecasts in a single view. They mentioned that with our solution, it is now possible for them to synthesize the temporal evolution of weather forecasts along the timeline. Moreover, they can identify salient features and significant variances at one glance.

Further feedback was related to the use of our tool to perform forecast operations. A meteorologist stated: "One of the most important and challenging issues related to weather forecasting is the assessment of forecast uncertainty and VIDa provides us with different ways to analyze it. Uncertainty changes from one forecast to another, and with VIDa we can estimate it using the operations that it provides". For a forecaster, it is very useful to compare differences among the last available information and the information provided from previous forecasts. Our solution could also be used to analyze forecasts coming from different models. The meteorologist added: "These capabilities are extremely useful to detect changes in the atmospheric variables and the level of forecast uncertainty for a particular situation".

The domain experts also stated that the curve-pattern selector and the curve-pattern classification are key components of the system. The flexibility of the curve-pattern selector opens new scenarios of analysis. This is particularly useful in operational weather forecasting where they need a rapid analysis of forecast trends. Additionally, the same tool can be used for forecast verification. The curve-pattern selector allows the users to define, save, and reuse a given set

of curve-patterns. They found these functionalities very useful. This is because some scenarios cover a large number of possible curve-pattern behaviors making the selection of an appropriate set a challenge. By saving and reusing the curve-pattern sets, they can work on and refine them repeatedly in order to tackle this challenge.

While our software is still a prototype in the CIMA institute, our collaborators plan to deploy it as a standard tool available for operational weather forecasting.

6. Conclusions

In this paper we presented a solution to address weather forecast analysis. Our approach provides a quick overview of short-term weather forecasts by means of a minimap timeline. By employing the timeline, the user can then narrow down the visual analysis of the meteorological variables. He/she can apply different operations over two or more forecasts, in order to analyze forecast uncertainty. Moreover, we introduced a curve-pattern selector tool and a classification technique for the analysis of multiple forecasts. By means of the curve-pattern classification, temporal trends and forecast model errors can be identified and analyzed. Finally, our solution implements a web front-end that runs on the Internet, which facilitates the broadcasting of the information.

We plan to extend our application by adding more functionality to the minimap timeline in order to display information about ensemble forecasts and vertical levels of altitude. Future work will include also the analysis of data from different models. Analyzing ensemble uncertainties and keeping a historical record of the output may serve as a basis for the further investigation of model errors, error growth, and regional behavior of errors among many other applications.

7. Acknowledgments

The work presented in this paper has been partially supported by the LACCIR Institute, the UBACyT-20020130100820BA project, and the ViMaL project (FWF - Austrian Research Fund, no. P21695). The authors thank Rodrigo Pelorosso for his technical help.

References

- [AA06] ANDRIENKO N. V., ANDRIENKO G. L.: *Exploratory Analysis of Spatial and Temporal Data: A Systematic Approach*, 2006 ed. Springer, 2006. 2
- [AMST11] AIGNER W., MIKSCH S., SCHUMANN H., TOMINSKI C.: *Visualization of Time-Oriented Data*. Springer, London, UK, 2011. doi:10.1007/978-0-85729-079-3. 2
- [BAP*05] BUONO P., ARIS A., PLAISANT C., KHELLA A., SHNEIDERMAN B.: Interactive pattern search in time series. *Proceedings of SPIE 5669*, 2 (2005), 175–186. doi:10.1117/12.587537. 2
- [BM10] BRUCKNER S., MÖLLER T.: Result-driven exploration of simulation parameter spaces for visual effects design. *IEEE*

- Transactions on Visualization and Computer Graphics* 16, 6 (October 2010), 1467–1475. 2
- [CGB*05] COTO E., GRIMM S., BRUCKNER S., GRÖLLER M. E., KANITSAR A., RODRIGUEZ O.: MammoeXplorer: An advanced CAD application for breast DCE-MRI. In *Proceedings of Vision, Modelling, and Visualization 2005* (November 2005), pp. 91–98. 3
- [CMNR07] CLYNE J., MININNI P., NORTON A., RAST M.: Interactive desktop analysis of high resolution simulations: application to turbulent plume dynamics and current sheet formation. *New Journal of Physics* 9, 8 (2007), 301. 3
- [FKSS06] FAILS J. A., KARLSON A., SHAHAMAT L., SHNEIDERMAN B.: A visual interface for multivariate temporal data: Finding patterns of events across multiple histories. In *IEEE Symposium on Visual Analytics Science And Technology* (October 2006), IEEE Computer Society Press, pp. 167–174. doi: [10.1109/VAST.2006.261421.2](https://doi.org/10.1109/VAST.2006.261421.2)
- [GDAS] GLOBAL DATA ASSIMILATION SYSTEM: Global Data Assimilation System, accessed in November, 2014. URL: <http://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-data-assimilation-system-gdas.8>
- [GHA*08] GLATTER M., HUANG J., AHERN S., DANIEL J., LU A.: Visualizing temporal patterns in large multivariate data using modified globbing. *IEEE Transactions on Visualization and Computer Graphics* 14, 6 (2008), 1467–1474. doi: <http://doi.ieeecomputersociety.org/10.1109/TVCG.2008.184.3>
- [HS04] HOCHHEISER H., SHNEIDERMAN B.: Dynamic query tools for time series data sets: timebox widgets for interactive exploration. *Information Visualization* 3, 1 (March 2004), 1–18. doi: [10.1145/993176.993177.2](https://doi.org/10.1145/993176.993177.2)
- [JS11] JOLLIFFE I. T., STEPHENSON D. B.: *Forecast Verification: A Practitioner's Guide in Atmospheric Science, 2nd Edition*. John Wiley and Sons Ltd, 2011. 6
- [KBK11] KRSTAJIC M., BERTINI E., KEIM D. A.: CloudLines: Compact Display of Event Episodes in Multiple Time-Series. *IEEE Transactions on Visualization and Computer Graphics* 17 (2011), 2432–2439. 2
- [KLM*08] KEHRER J., LADSTÄDTER F., MUIGG P., DOLEISCH H., STEINER A., HAUSER H.: Hypothesis generation in climate research with interactive visual data exploration. *IEEE Transactions on Visualization and Computer Graphics* 14, 6 (October 2008), 1579–1586. 2
- [KLM*12] KONYHA Z., LEŽ A., MATKOVIĆ K., JELOVIĆ M., HAUSER H.: Interactive visual analysis of families of curves using data aggregation and derivation. In *Proceedings of the 12th International Conference on Knowledge Management and Knowledge Technologies* (New York, NY, USA, September 2012), i-KNOW '12, ACM, pp. 24:1–24:8. doi: [10.1145/2362456.2362487.2](https://doi.org/10.1145/2362456.2362487.2)
- [KSU*13] KÖTHUR P., SIPS M., UNGER A., KUHLMANN J., DRANSCH D.: Interactive visual summaries for detection and assessment of spatiotemporal patterns in geospatial time series. *Information Visualization* (2013). doi: [10.1177/1473871613481692.2](https://doi.org/10.1177/1473871613481692.2)
- [MHG10] MALIK M. M., HEINZL C., GRÖLLER M. E.: Comparative visualization for parameter studies of dataset series. *IEEE Transaction on Visualization and Computer Graphics* 16, 5 (September 2010), 829–840. 2
- [MMWE03] MURRAY D., MCWHIRTER J., WIER S., EMMERSON S.: The integrated data viewer: a web-enabled application for scientific analysis and visualization. In *19th Conference on International Interactive Information and Processing Systems for Meteorology, Oceanography, and Hydrology* (2003), American Meteorological Society. 3
- [PWB*09] POTTER K., WILSON A., BREMER P.-T., WILLIAMS D., DOUTRIAUX C., PASCUCCI V., JOHNSON C. R.: Ensemblevis: A framework for the statistical visualization of ensemble data. In *IEEE Workshop on Knowledge Discovery from Climate Data: Prediction, Extremes*. (October 2009), pp. 233–240. 3
- [Roz06] ROZUMALSKI R.: *WRF Environmental Modeling System - User's Guide*, release 2.1.2.2 ed. National Weather Service SOO Science and Training Resource Center, May 2006. 3
- [RSNP10] RUIZ J. J., SAULO C., NOGUÉS-PAEGLE J.: WRF model sensitivity to choice of parameterization over south america: Validation against surface variables. *Monthly Weather Review* 138, 8 (August 2010), 3342–3355. 3
- [SGB13] SCHMIDT J., GRÖLLER M. E., BRUCKNER S.: VAICo: Visual analysis for image comparison. *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (December 2013), 2090–2099. 2
- [SYS*06] SONG Y., YE J., SVAKHINE N., LASHER-TRAPP S., BALDWIN M., EBERT D.: An atmospheric visual analysis and exploration system. *IEEE Transactions on Visualization and Computer Graphics* 12, 5 (September 2006), 1157–1164. doi: [10.1109/TVCG.2006.117.3](https://doi.org/10.1109/TVCG.2006.117.3)
- [TD98] TSAI P., DOTY B.: A prototype java interface for the Grid Analysis and Display System (GrADS). In *Proceedings of 14th International Conference on Interactive Information and Processing Systems for Meteorology, Oceanography, and Hydrology* (1998), pp. 11–16. 3
- [Ter] TERRA3D: Terra3D, accessed in April 2014. URL: <http://www.terra3d.de/>. 3
- [TWC] THE WEATHER CHANNEL: The Weather Channel, accessed in April, 2014. URL: <http://www.weather.com/weather/map/interactive.3>
- [War13] WARE C.: *Information Visualization: Perception for Design*. Information Visualization: Perception for Design. Morgan Kaufmann, 2013. 3
- [WDP*13] WILLIAMS D., DOUTRIAUX C., PATCHETT J., WILLIAMS S., SHIPMAN G., MILLER R., STEED C., KRISHNAN H., SILVA C., CHAUDHARY A., BREMER P.-T., PUGMIRE D., BETHEL W., CHILDS H., PRABHAT M., GEVECI B., BAUER A., PLETZER A., POCO J., ELLQVIST T., SANTOS E., POTTER G., SMITH B., MAXWELL T., KINDIG D., KOOP D.: The Ultra-scale Visualization Climate Data Analysis Tools (UV-CDAT): Data Analysis and Visualization for Geoscience Data. *IEEE Computer* 99, PrePrints (2013), 1. LBNL-6278E. doi: [http://doi.ieeecomputersociety.org/10.1109/MC.2013.119.3](https://doi.org/10.1109/MC.2013.119.3)
- [Wet] WETTER.DE: Wetter.de, accessed in April 2014. URL: <http://www.wetter.de/>. 3
- [WP13] WARE C., PLUMLEE M. D.: Designing a better weather display. *Information Visualization* 12, 3-4 (2013), 221–239. 2
- [WS] WEATHER SPARK: Weather Spark, accessed in April, 2014. URL: <http://weatherspark.com/>. 3
- [WS09] WOODRING J., SHEN H.: Multiscale time activity data exploration via temporal clustering visualization spreadsheet. *IEEE Transactions on Visualization and Computer Graphics* 15, 1 (2009), 123–137. doi: [10.1109/TVCG.2008.69.3](https://doi.org/10.1109/TVCG.2008.69.3)
- [WU] WEATHER UNDERGROUND: Weather Underground, accessed in April, 2014. URL: <http://www.wunderground.com/>. 3