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COUPLING OF MESOSCALE WEATHER MODELS TO BUSINESS OPERATIONS UTILIZING VISUAL DATA FUSION

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1. INTRODUCTION

In many industries weather conditions are a critical factor in planning business operations and making effective decisions. Typically, what optimization that is applied to these processes to enable proactive efforts utilize either historical weather data as a predictor of trends or weather forecasts of limited precision. Alternatively, numerical weather models operating at higher resolution in space and time with more detailed physics exist for short-term forecasting (i.e., a few days at the mesoscale) that offer greater precision and accuracy for a more limited region. Although such a model has occasionally been adapted for the specific three-dimensional geographic area and time-scale relevant to the aforementioned decision making (e.g., Carpenter and Bassett, 2001; Snook, 2001), usually it is not.

Mesoscale models can be utilized in variety of weather-sensitive decision-making efforts such as emergency planning, energy production, airline operations, risk assessment, agricultural activities, commodity trading, etc. For each of these applications, information is assessed and decisions are made based upon a variety of static and dynamic data sets, a subset of which are weather-related. The utilization of these data and the complexity of the decision-making process changes when high-resolution predictive data are incorporated. These applications imply the coupling of weather simulations with other models, analyses and data.

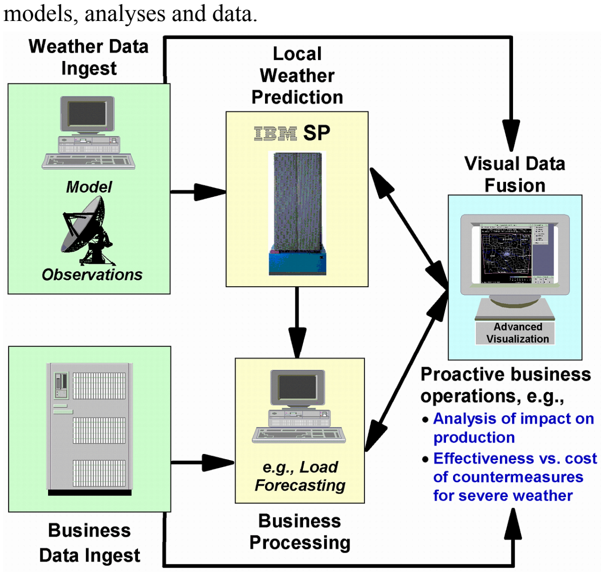

Figure 1. Visual data fusion for weather applications.

In order for mesoscale models to be utilized in such applications some adaptation is required, including customization of the computational grid and model parameterization focused on the specific weather sensitivity of the business operation process in question. To enable effective assessment and appropriate decisions, focused visualizations must also be designed to integrate business and weather model data, yet still be driven by user goals. These visualizations must employ appropriate mapping of user goals to the design of pictorial content by considering both the underlying data characteristics and the (human) perception of the visualization (Treinish, 1999a). Hence, the resultant visualizations may not show forecasts of weather phenomena directly but the derived properties, which are influenced by weather, and are of direct relevance to the decision maker or industry specialist. In these cases, the information is in terms of the impact of weather, not weather variables produced by a simulation. The problem is illustrated schematically in Figure 1. Two traditional data generators are shown on the top and the bottom (weather and non-weather, respectively). Although visualization is applicable to both, typically this is mutually independent. An approach of visual data fusion to address the visualization design problem in such applications is proposed as one method of coupling mesoscale models to business operations.

2. DATA FUSION

Data fusion is *simply* the integration of multiple data sets. This notion is derived from the fact that understanding of phenomena from a scientific basis, creating an engineering design, or assessment for sound decision making requires the utilization of data from many distinct sources. Traditionally such tasks have utilized a single data set, but as a result is often incomplete for larger-scale problems that are becoming more prevalent today. In parallel with the growth in problem complexity are additional factors that make the need for data fusion more practical and thus, more pervasive. The relative availability of relevant data enables a comparison study for a data generator as much as it does an independent analysis. Secondly, data generators have become more capable and accessible. Digital data acquisition is easier and cheaper. Computational simulations are gaining fidelity and detail while becoming more practical to compute. From verification of computational and experimental models to steering simulations with real-world observations, bringing data from multiple sources together is much more powerful than using each source separately. Visualization is critical to this integration, without which the beneficiaries of such data would be overwhelmed by volume or complexity (Uselton et al, 1998).

Data from multiple sources require care in their presentation so that artifacts due to the visualization process are not introduced by data fusion and erroneously interpreted as features in the data. For example, the data may not be uniformly available for the spatial domains being examined. Each of the data sets to be "fused" are generally not geographically co-registered and are defined on differing geometric structures. Further, the coordinate system for visualization and interaction may need to differ from those native to the data sets of interest.

These issues have been considered by others in a variety of applications including earth science, physics, astronomy and medical imaging (Uselton et al, 1998). In the majority of these cases, the user goals focused on analysis or verification as opposed to data assessment as illustrated in efforts to com-

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pare computational fluid dynamics results with experimental data from wind tunnels (Keely and Uselton, 1998). More recent work has considered decision support (Bisantz et al, 1999) but from a human factors perspective.

3. APPROACH

To enable visual data fusion, a perspective of data management must be adopted by introducing an uniform data model that is matched to the structure of the data as well how such data are used. This implies a generalized mechanism to classify and access data as well as efficiently map data to operations. The implementation of such a data model effectively decouples the management of and access to the data from the actual application. This encapsulates the variety of sampling and representations for diverse data and provides uniform access. It it then a prerequisite to building applications that utilize the data sets to be integrated (Treinish, 1999b). One consequence of such a data (model)-centric approach is that the same operation(s) can be applied to data sets that need to be visually fused or correlated (i.e., displayed and interacted together) without introducing superfluous interpolation or resampling to a common mesh. The latter process implies a modification to the data, whose impact could be hidden in subsequent visualization. Further, if a specific visualization task requires a cartographic projection, then these data sets can be independently warped by the prerequisite transformation. Any geometric distortion that is introduced is due only to the actual projection since the data and topology remain invariant through such a transformation. It is also independent of the choice of realization or rendering technique or cartographic projection, and hence, provides a framework for experimenting with different visualization strategies. As a result, the fidelity of the original data sets is preserved in a coordinate system suitable for dynamic interaction. It implies that correlative visualization for visual fusion can be approached from four perspectives. In all cases, the specific choices are dictated by the goal of the visualization task(s) as defined by the individuals or applications utilizing the data.

1. <u>Image Level</u>. The capability to look at multiple sets of data in exactly the same fashion (i.e., visual comparison within a common framework). This can be achieved with multiple visualizations in adjacent windows or mosaiced together for qualitative comparison. These visualizations are usually static, but might be accompanied by synchronized animation sequences or geometric transformations in which the representations are linked. Outside of the latter, interaction is typically indirect. This class of data fusion can be represented as a function, **F**, of different images or data sets, such that **F** = a, b, ...

2. <u>Common View</u>. The capability to utilize a variety of visualization strategies within a chosen coordinate system dictated by one of the data sets or independently by user task. This represents a visual fusion which can support both direct and indirect interaction, including numerical querying. All of the relevant data are registered within this common viewing framework. Qualitative comparisons are clearly supported, but direct quantitative comparisons are defined by interaction. This class of data fusion can be represented as **F**, such that **F** = f(a, b, ...).

3. <u>Data Level</u>. The capability to numerically compare distinct data sets using either of the two previous approaches for visualization. This does require the transformation (e.g., interpolation) of one or more data sets to a common basis (mesh, coordinate system, etc.) from which derived quantities can be calculated (e.g., point-wise operations). The visualizations may involve the original data and/or the derived data. From the discussion earlier this can violate the principle of preserving fidelity at the cost of supporting numerical comparisons. This class of data fusion can be represented as **F**, such that **F** = a(b), **F** = f(a), etc.

4. <u>Multiple Views</u>. The capability to numerically and visually compare multiple data sets, particularly when some of the data sets do not have a common basis for visual fusion. In this case, the utilization of a variety of different strategies is required, some of which must be in separate instead of a common framework. Interaction may be complex because separate metaphors for direct interaction are required for each framework, although common methods for indirect interaction are feasible. Unlike case 1, quantitative access is supported such that linked displays would indicate related numerical values or "regions" of commonality that are queried.

4. APPLICATIONS

To evaluate the aforementioned approach to data fusion, it is applied to problems that relate to economic and societal impacts of weather. In particular, three applications are considered in increasing complexity from the data fusion perspective: emergency planning, aviation and electricity demand forecasting. In each case, the goal is to provide products or techniques that can be utilized in a timely fashion to address specific business problems under the assumption that the model results are generated sufficiently fast at an appropriate level of precision. In all of these examples, a customized version of the Regional Atmospheric Modeling System (RAMS) is employed to generate the example forecast data (Pielke et al, 1992)

4.1 Emergency Planning

Weather-related catastrophes have led to over $48B in property insurance claims from 1989 to 1993 in the US. In North Carolina alone, ten major hurricanes from 1983 to 1996 resulted in about $50B worth of damage, almost $30B of which led to losses by insurance companies (Kunkel et al, 1999). Hence, disaster planning or hedging for underwriting risk-related insurance can benefit from improved weather predictions. In both cases, the impact of weather is relevant in visualization but not the weather data directly. Although georeferenced visualizations are required, the illustration of time-dependent factors related to property loss due to severe weather are needed, not merely a visualization of predicted wind velocity, for example. Usually, an *Image Level* approach is applied as shown in Figure 2. Each image contains a simple two-dimensional map of a set of glyphs colored by a different parameter. The glyphs are located at the centroid of the area associated with zip codes.

However, the glyph locations are <u>only</u> marked on the map when a set of conditions on house value, population and estimated damage due to wind are met. Therefore, a *Common View* approach is more efficient by leveraging user interaction as illustrated in Figure 3. The user is free to interactively set the conditions and animate in time corresponding to the weather simulation in hourly steps. The weather prediction data are from a RAMS run at 8 km resolution centered over Dallas. This enables the determination of areas of greatest impact due to severe weather. Essentially, it represents a sim-

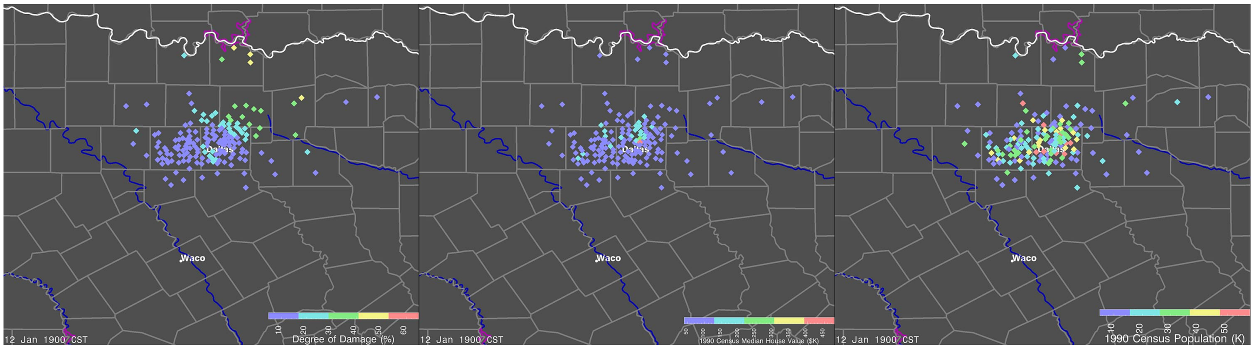

Figure 2. ***Image Level*** **data fusion of mesoscale weather model results with demographic data over an 800 x 800 km domain at 8 km resolution centered over Dallas. Colored glyphs at zip code locations illustrate a subset of demographic and derived data.**

ple method to specify a query against various data sets, which are then used to constrain a visual integration for display and interaction. This approach becomes *Data Level* because the forecast data are interpolated to zip code locations in order to support the query constraints. These thresholds can also be augmented to include other relevant demographic, customer or property data. The demographic data shown are derived from available census information (`http://tiger.census.gov`).

In this example, the conditions for display are enhanced to include a simple computational model. The level of wind-induced damage is based upon analysis of effects on typical residential buildings from severe weather (Unanwa et al, 2000). This approach to data fusion may be useful for planning purposes by an insurance company or deployment of repair crews by a utility or local highway department.

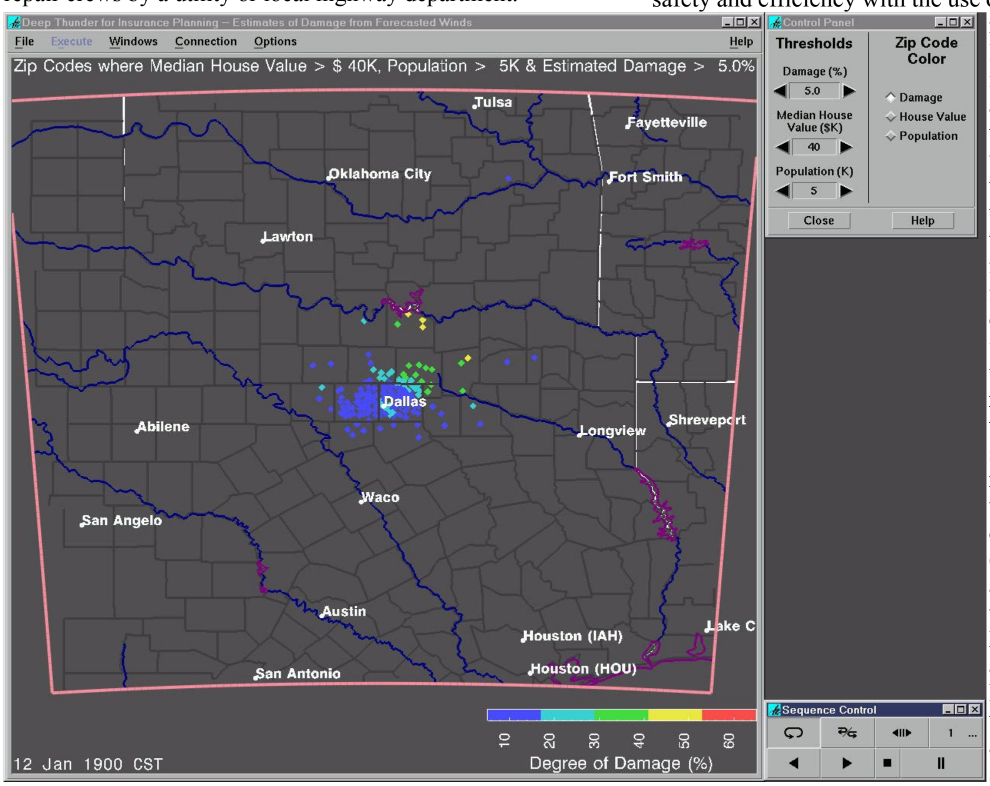

Figure 3. ***Common View*** **data fusion showing the relationship between demographic data and a mesoscale model in a screen capture of an interactive session. This also is a** ***Data View*** **data fusion because the locations of estimated damage are calculated from the weather model data.**

4.2 Aviation

There is an obvious and direct correlation between weather-related factors and business productivity in the operation of an airline. For example, the 16 largest airlines based in the US estimate that the average direct cost due to weather-related delays and cancellations is $269M. On average that implies $40K per cancellation and $150K per diverted flight. However, that does not include the fact that canceled or diverted flights lead to additional flight delays, which can easily imply much greater financial impact. There are also additional costs for insurance payouts or lost time for employees related to encounters with turbulence (Qualley, 1997).

Route planning, dispatch, snow removal planning, de-icing deployment, etc. can all be better supported for both safety and efficiency with the use of improved weather information. This is why airlines typically invest in infrastructure and staff to acquire and analyze weather data. As is conventional in the industry, this investment consists of two key parts. The first is the interpretation of the results of synoptic-scale models, which provide coarse forecasts a few days into the future. The second type of information is near-real-time analysis of weather observations from sensors at and nearby major airports as well as the instrumentation deployed by the NWS (e.g., NexRAD). Such data are very useful for short-term (i.e., minutes to hours) detailed planning and airline operations. However, there is a gap in what is conventionally available -- namely, cloud-scale over the next 24 to 48 hours for areas of key interest to an airline such as around major airports. Information of this class can be derived from appropriately configured, mesoscale weather models operating sufficiently quickly to produce localized, high-resolution forecasting information. This could include predictions of severe storms (damaging winds and hail for parked aircraft, high winds and precipitation to prevent aircraft landings and takeoffs, sufficient snow and ice to require de-icing of aircraft, plowing of runways), cloud ceilings and visibility (poor enough to impact aircraft landings and takeoffs), turbulence and icing surfaces, upper air winds (for flight planning), etc.

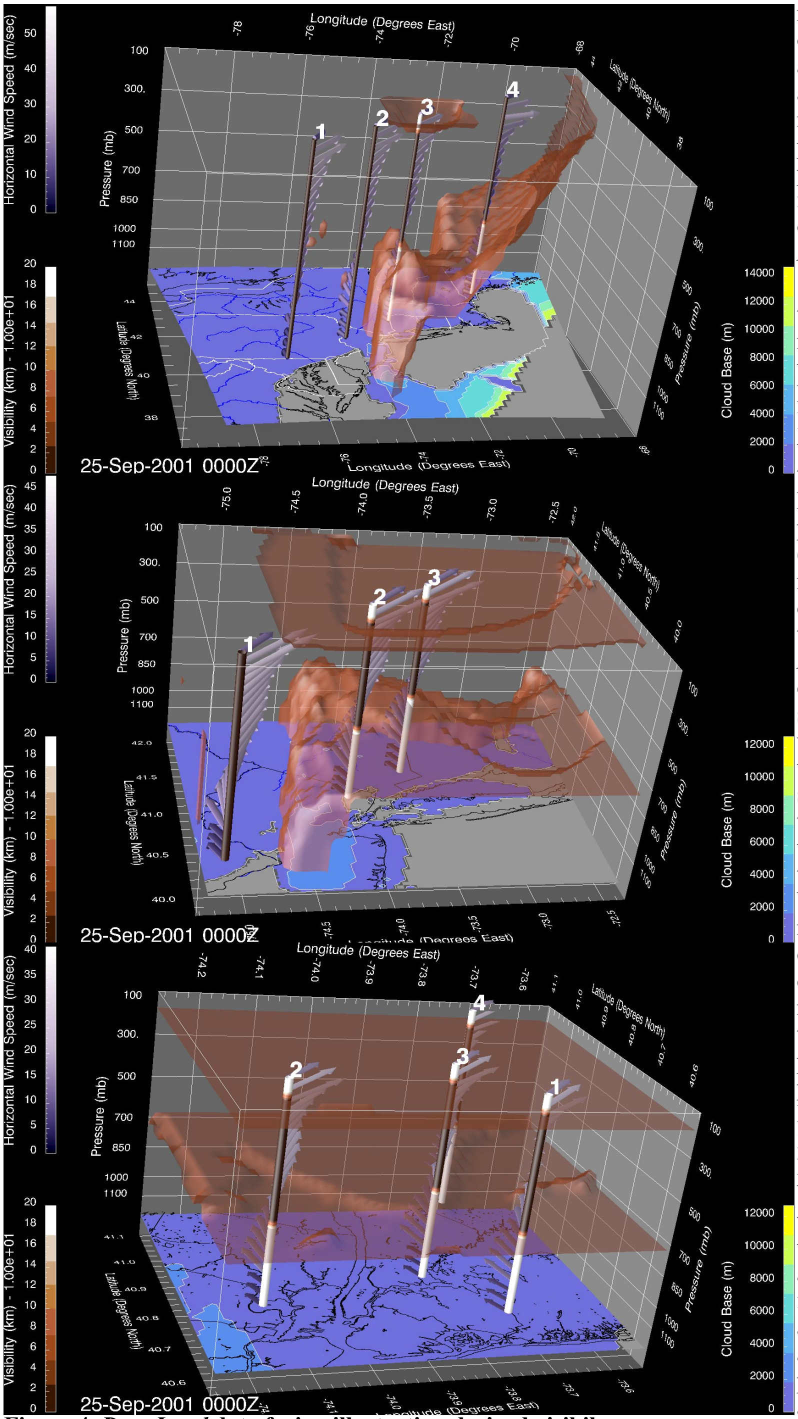

Figure 4. ***Data Level*** **data fusion illustrating derived visibility properties from nested mesoscale model cloud predictions along with wind and other cloud data at three resolutions (16, 4 and 1 km) focused on New York City.**

To illustrate these ideas, an adaptation of an operational use of RAMS has been made (unpublished -- see `http://www.research.ibm.com/weather/NY/NY.html` for more information). This capability is derived from earlier work supporting the 1996 Centennial Olympic Games in Atlanta (Snook et al, 1998). Currently, one or two 24-hour forecasts are produced each day on a 3-way nested configuration of 62x62x31 at 16, 4 and 1 km resolution focused on New York City. Each model run requires about two hours of compute time on twenty-four 375 MHz Power3 processors of an IBM RS/6000 SP (i.e., fast enough for operational applications). Among the enhancements to RAMS is a suite of interactive and production visualization tools, which also supports dissemination via web browsers (Treinish, 2002). One operational product is focused on aviation and is a simple example of *Data Level* data fusion, which is shown in Figure 4.

The three images in Figure 4 correspond to the three modelling nests at 16, 4 and 1 km resolution, from top to bottom, respectively, which are snapshots of an animation with one-hour time steps. Each contains a brown, translucent, three-dimensional surface shown in vertical pressure coordinates, which corresponds to a boundary where the derived visibility is 10 km. This visibility is based upon extinction properties of cloud water, ice and precipitation (i.e., Stoelinga-Warner, 1999), which is determined from the modelled upper air. Its on-demand calculation and visualization within a three-dimensional geographic scene represents *Data Level* data fusion. This isosurface is not a cloud boundary. Thus, the volume inside the surface represents relatively clear air, that is, visibility over 10 km. If no surface is visible then there are no clouds predicted at that time step, and thus, the visibility is high. At the bottom of the scene is a set of colored contours, typically in increments of 2 km, corresponding to the height in meters of the forecasted cloud base as shown in the color legend to the lower right. Areas in gray imply no cloud data. The cloud base contours are overlaid with maps of coastlines and state boundaries in black and rivers in blue. The volume is marked at either three or four locations with set of colored poles. These locations correspond to major airports (16 km nest: 1 = DCA, 2 = PHL, 3 = LGA, 4 = BOS; 4 km nest: 1 = PHL, 2 = EWR, 3 = HPN; 1 km nest: 1 = JFK, 2 = EWR, 3 = LGA, 4 = HPN). The poles are color contoured by the derived visibility using the color legend to the lower left. At each of 21 pressure levels, the horizontal wind is shown via arrows. The arrows are colored by horizontal wind speed following the legend to the upper left. The arrow length also corresponds to speed. This approach presents information relevant to flight planning as opposed to direct meteorological analysis.

4.3 Electric Utilities

Another application of a predictive weather model is to forecast load on a power-generation facility or transmission lines for efficient running of the facility or for power trading. In both cases, meteorological information is an important input as weather is a primary driver for electricity demand. It has been estimated that the annual cost of under or over predicting electricity demand due to poor temperature forecasts is several hundred million dollars in the US alone. Erroneous weather data associated with startup-shutdown of generation units can be worth $500K per day during peak load periods or conservatively $8M annually to a regional power authority. In addition, improved severe storm predictions to reduce outage time can save a few hundred thousand dollars a year for a typical utility (Keener, 1997). Decisions in this industry are driven by diverse non-weather data and processes including load forecasting and econometric models, customer demographics, geography of power facilities, etc. that are not usually well integrated. The weather information currently used is relatively coarse leading to poor and costly decisions. Typically, hourly forecast surface temperature and dew point values averaged over a large geographic region are employed. Alternatively, more accurate data at greater frequency which are distinct for different loads by geographic location and altitude can be applied coupled with other factors that influence load (e.g., storm and cloud predictions). Since there is a relationship between accuracy in load prediction vs. economic efficiency (i.e., an under prediction implies having to buy power at a premium and over prediction means resources are wasted), coupling of weather forecasts with econometric models is also feasible.

To provide a simple illustration of these ideas, first consider Figure 5. It contains two frames (18Z and 6Z) of a 24-hour animation with 10-minute time steps (24-hour run initiated at 12Z). They were generated by the same operational environment outlined in the previous section. Each image shows a topographic map overlaid with coastlines, and state and county boundaries. An additional overlay is present, which is a map of the southeastern portion of the major components of the electricity transmission system in New York State (i.e., lines of capacity greater than or equal to 115 kV). The forecasted surface temperature from the three RAMS nests are combined into a multi-resolution structure (Treinish, 2000) and then interpolated to the geographic location of the transmission lines. The results are color contoured and (*Data Level*) fused with the other maps. The model prediction shows considerable variation in temperature along this system over a 12-hour period, thus illustrating the potential for mesoscale modelling in support of electricity transmission operations.

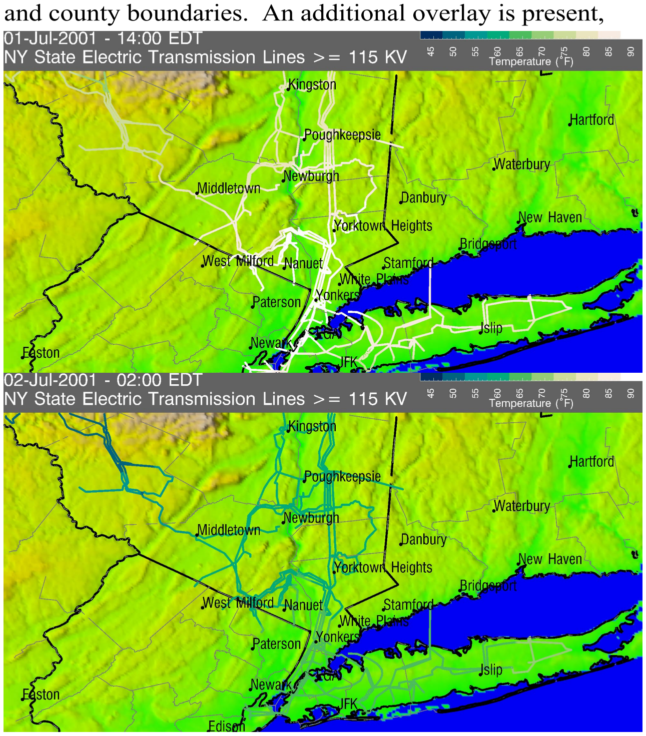

Figure 5. ***Data Level*** **data fusion of temperature data from an operational nested mesoscale model with electricity transmission lines in New York State at two different forecast times from a single model run.**

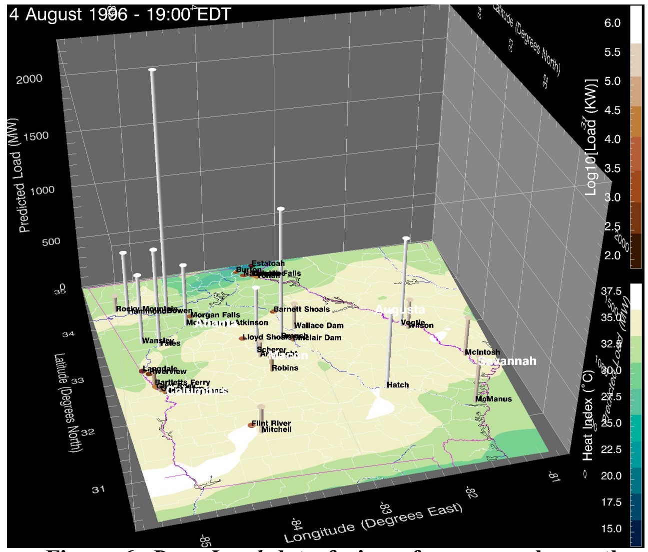

Figure 6. ***Data Level*** **data fusion of a mesoscale weather model at 8 km resolution centered over Atlanta with a prediction of electricity demand at power plants operated by Georgia Power. The demand is calculated from a model whose input is derived from the numerical weather prediction.**

This capability can be further enhanced by using upper air model results to better correspond to the elevation of overhead lines and apply them to map a derived transmission efficiency as a function of location and time. (The data for the electricity transmission system are available courtesy of the GIS Unit, New York State Department of Public Service.)

A more complex example is shown in Figure 6 via *Data Level* fusion. It contains a map of Georgia with forecasted heat indices at 8 km resolution. Major cities and locations of the generators owned and operated by Georgia Power, the local electric utility, are shown by name. (These and other data from Georgia Power are available in the public domain via `http://www.georgiapower.com`.) Each power plant location is also marked with a pin. whose height and color indicate a predicted electricity demand. A dual encoding is used because the capacities of the power plants range over five orders of magnitude. Hence, height is a linear mapping while color bands are scaled logarithmically. The load is computed interactively as a function of temperature, humidity and time of day from a simple model. The temperature dependence is based upon a polynomial approximation of the relationship between historical data of power demand and weather observations, shown in Figure 7 (Robinson, 1997). Regression on the data from summer weekdays in the southeastern United States after outliers are removed yields,

$$W = 1.146 - 0.0225T - 0.000240T^2 + 0.0000397T^3 \quad (1)$$

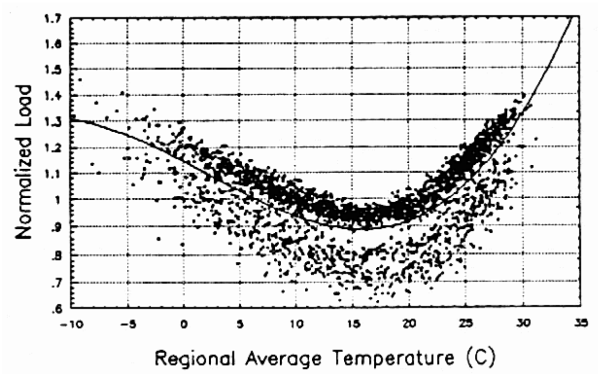

Figure 7. Weather-dependent energy load, *W(T)*.

The temporal variation is based upon a spline fit of hourly electricity requirements for mid-week days in urban and suburban tropical environments, which is consistent with other results in the literature (Chang and Li, 1998). That component is shown in Figure 8, which is then normalized.

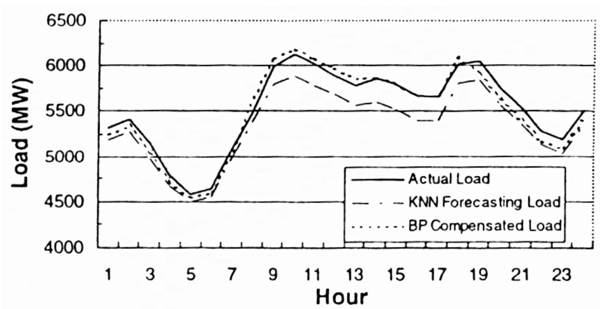

Figure 8. Diurnal, mid-week energy load, *N(t)*.

The temperature and temporal components are combined for a total estimated load, L, such that

$$L = C[(0.2768809N(t) + 0.7231191)(W(T_{HI})/2.9175)] \quad (2)$$

The function is scaled by the rated power plant capacity, C, using published data (`http://www.georgiapower.com/newsroom/plants.asp`). Heat index, T_{HI}, is employed as a more accurate measure of demand than simply temperature. It is an apparent temperature derived from both temperature and humidity as an indicator of personal comfort during the summer (Rothfusz, 1990). Therefore, it is directly related to air conditioning usage and thus, electricity demand. The weather model results are interpolated at each time step to the location of each of the power plants. An example for the specific 24-hour period of the forecast is shown in Figure 9 for the largest power plant operated by Georgia Power (Bowen).

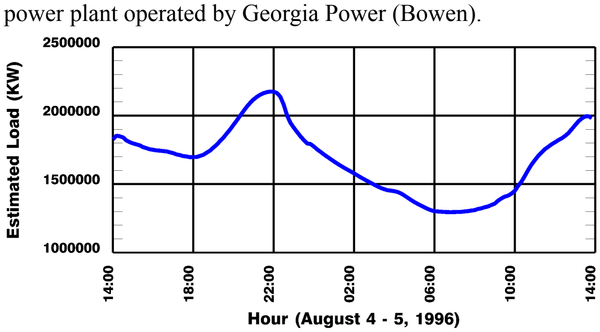

Figure 9. Predicted power demand at a specific generator site derived from a weather-model-driven load forecast.

All of these capabilities are illustrated in Figure 10, which is a screen capture of a prototype of an interactive application for detailed load forecasting. The user has the ability to select the type of power plant (fossil, hydroelectric and/or nuclear), what data to show on the map (e.g., weather, geographic or other customer/demographic) and to query individual power plants (i.e., by visual selection). The results of the query include the predicted load at each time step (as fine as every 10 minutes) as well as a plot of predicted load over 24 hours with weather data at that location. The interactive application is then a *Multiple View* fusion.

The visual fusion techniques of Figures 6 and 10 are combined in Figure 11, which shows the load forecast at the power plants that use fossil fuels with a population map. The population data are shown as colored contours on a logarithmic scale to segment urbanized areas (red) and their location with respect to the power generators under the heaviest demand. Although these data are derived from static census sources, the same techniques would apply to similar but proprietary customer data owned by a regional electric utility.

5. IMPLEMENTATION

The applications shown in Figures 3 and 10 present a user interface based upon XWindow/Motif for indirect interaction and OpenGL for direct three-dimensional interaction in cartographic coordinates native to the weather simulation. They have been implemented with Data Explorer (DX) (Abram and Treinish, 1995). DX is a portable, open source, general-purpose software package for visualization and analysis (`http://www.research.ibm.com/dx` and `http://www.opendx.org`). A generic toolkit was used to avoid having to implement a graphics and computational infrastructure. Unlike traditional meteorological graphics or geographic information systems, DX is parallelized for multiprocessor systems and can utilize three-dimensional graphics accelerators. DX is built upon an unified data model that enables these applications to operate directly on the native gridded weather data without transformation or compression.

6. CONCLUSIONS AND FUTURE WORK

The visualization of applications of mesoscale weather modelling have benefited from a focus on specialized interfaces and tools matched to user goals and underlying visualization tasks. These are based on utilizing more complete design principles as well as accommodating the fact that the users' expertise will not be in weather modelling, but in the application domain.

Since the underlying toolkit is extensible tools can be reused between applications with similar user interface components. Although these applications and associated user goals are different, underlying data fusion requirements and visualization tasks are the same. Further, the need to employ a relatively simple user interface is desirable to reduce the effort for training of users in time-critical activities such as decision support. It also reduces the cost of development and maintenance, and enables more rapid iterative refinement with or adaptation to new users. Therefore, within any given application, incorporation of additional and more complex data sets can also be addressed. But the goal remains the same -- to develop simple interfaces and useful visual fusion.

The specific work discussed herein is on-going. One aspect of continued efforts will be to incorporate more sophisticated models or processing as the consumer of weather forecast data. For example, the simple load forecasting model can be enhanced to include wind speed and sunshine duration

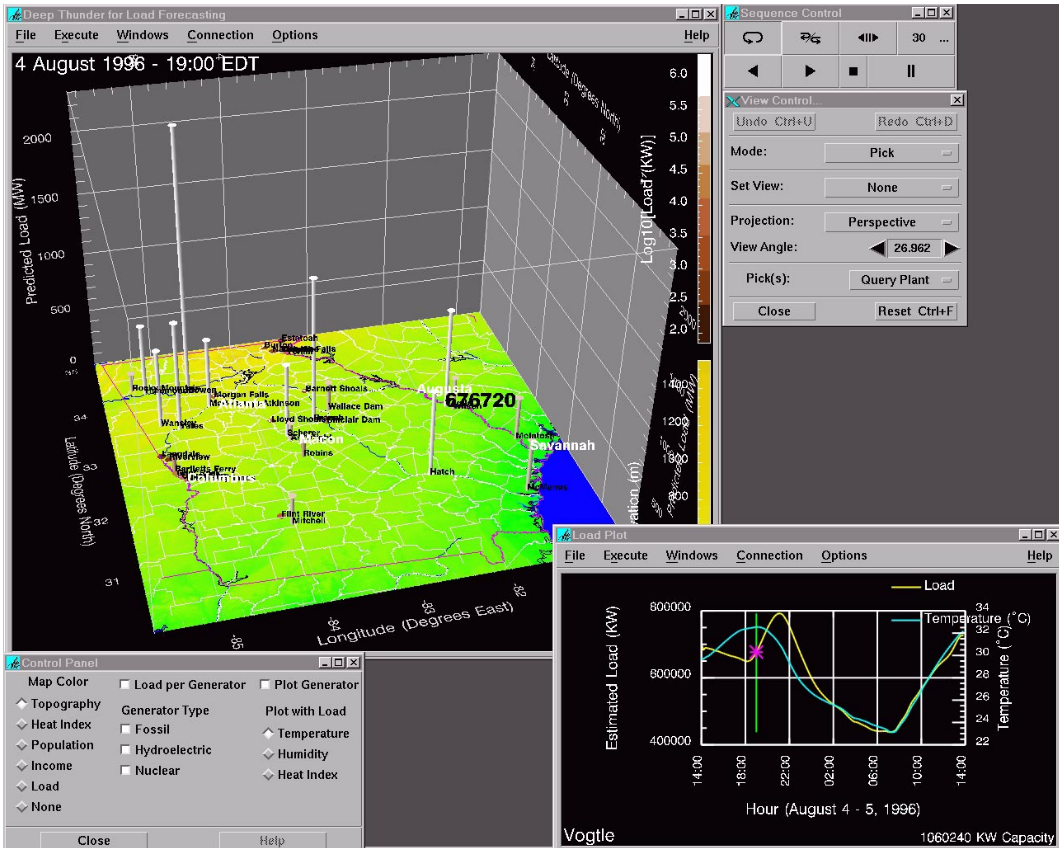

Figure 10. ***Data Level*** **(3d window) and** ***Multiple View*** **(with 2d plot) data fusion for energy load forecasting driven by a mesoscale weather model on a domain focused on Atlanta at 8 km resolution. This image is a screen capture of an interactive session. The multiple views are linked in time sequence and by interactive selection in the 3d window.**

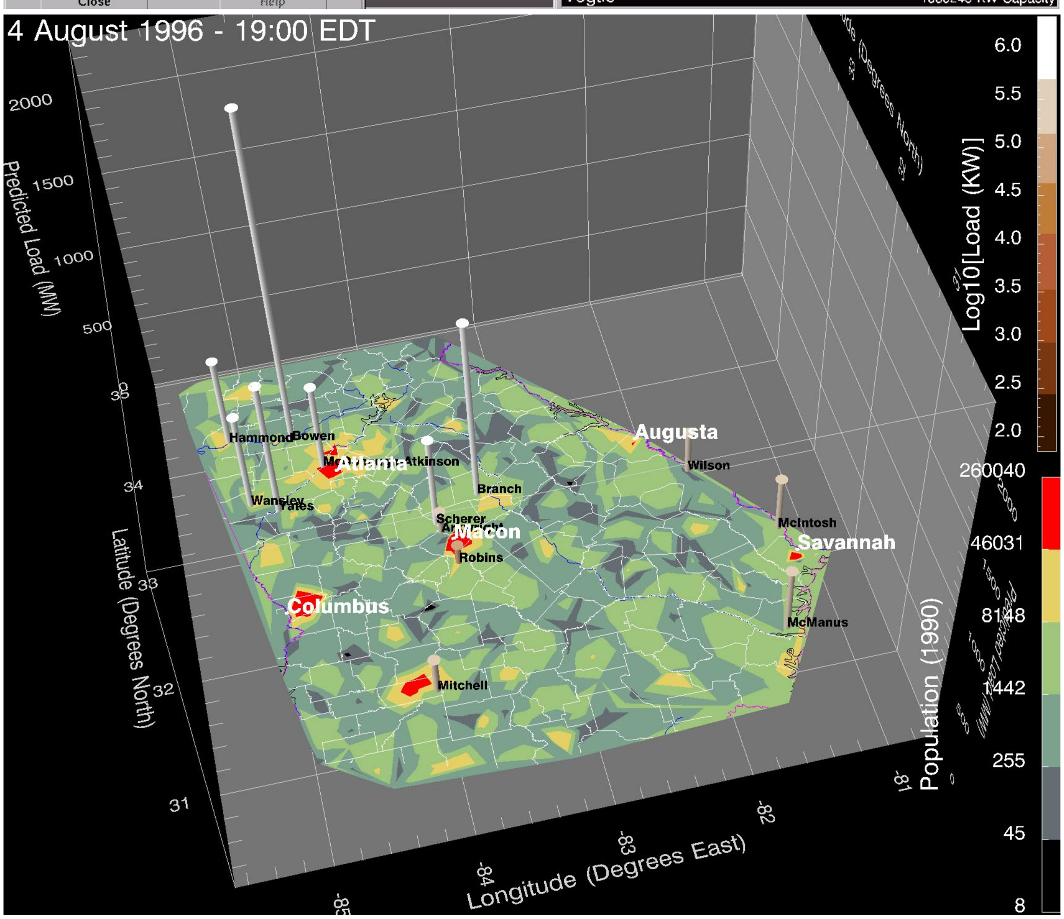

Figure 11. ***Data Level*** **and** ***Common View*** **data fusion to illustrate the correlation of a load forecast with demographic data. The proximity of fossil fuel power plants with high predicted load to major population centers (red) is easily seen.**

effects and also, adjusted for more realistic temporal variation based upon day of week and season. To aid in the decision making applications, migration to a probabilistic representation will also be advantageous. In addition, it is believed that these ideas can be extended to other application areas such as agriculture, finance, etc.

Mesoscale modelling can be used by businesses for competitive advantage or to improve operational efficiency and safety. Enormous potential exists for changing the typically reactive approach to such weather-sensitive operations to being proactive. Critical to success of such endeavors will be the timely production of visual products that are directly relevant to the decision-making process.

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