Web-Based Map-Algebra Challenges: A Polygon Solution

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Abstract

ArcIMS is optimized for rendering vector and static spatial data, but is less suited for manipulating raster and dynamic data through grid calculations. This issue was a central challenge in the strategic model of human and climate interactions with wildfire developed in the EPA Star Grant-funded "Wildfire Alternatives" (WALTER – http://walter.arizona.edu) project. To overcome this constraint, a polygon ArcSDE layer that imitates grid cells was employed as the foundation for all model inputs and outputs. This "grid-polygon" layer matches the minimum mapping unit of the original raster input layers. The grid-polygon cell attribute tables stored in the model database are joined through ArcIMS with the ArcSDE layer's business table. This setup permits the use of map algebra to calculate cell values on-the-fly so that user-specified parameters can be passed on and used by the Web application for the model. Model results are then rendered in ArcIMS by using database driven color maps.

1. Introduction

Natural resources and environmental quality are considered at risk across 190 million acres of U.S. forests and rangeland due to wildfire. Complex associations of human and natural factors are involved in this risk. Altered wildfire regimes jeopardize the sustainability of many ecosystems. Climate factors (Swetnam and Betancourt 1998) and human activity (Cardille et al. 2001) can be precursors to increased fire activity at a variety of temporal and spatial scales, and fuel buildup from years of fire suppression increases the severity of fires. Population expansion into previously open spaces has exacerbated the problem by placing people and their property at risk, particularly in the southwestern U.S. where population is increasing rapidly and the wildland urban interface continuous to expand rapidly.

Strategic wildfire planning and fuel management strategies could be greatly improved by a decision support system (DSS) that incorporates the long-term influences of climate in fire probability analysis and the assessment of values at risk of damage or loss. The importance of different values varies with the perspective of the individual and thus integration with fire probability in an overall risk assessment is difficult (Hardy et al. 2001). Addressing these challenges is the focus of Wildfire Alternatives (WALTER - http://walter.arizona.edu), an EPA STAR Grant project being conducted by a multidisciplinary research team at the University of Arizona. The objective of WALTER is to enhance the ability of wildfire managers to improve the health and sustainable productivity of fire-prone ecosystems through a web-based, spatially dynamic decision support system that is capable of integrating assessments of fire probability with values at risk (Morehouse et al. 2000). This is being accomplished with a strategic planning model called Fire-Climate-Society (FCS-1) that will allow decision makers to construct risk assessment maps under multiple climate scenarios and varying perspectives of values at risk in four venues: three sky islands in southeastern Arizona (Catalina/Rincons, Huachucas, Chiricahuas) and the Jemez Mountains, New Mexico.

2. Fire-Climate-Society Model (FCS-1)

The FCS-1 model is composed of two submodels, one to model the probability of fire due to natural and human factors, and the other to model the values at risk due to fire. The use of satellite data and online mapping software is clearly required to create a model that is useful over landscape scales and that can be used online. The map of each factor outlined below is constructed with a 1 km minimum mapping unit, the finest resolution at which spatially distributed climate information can be reasonably integrated due to data limitations.

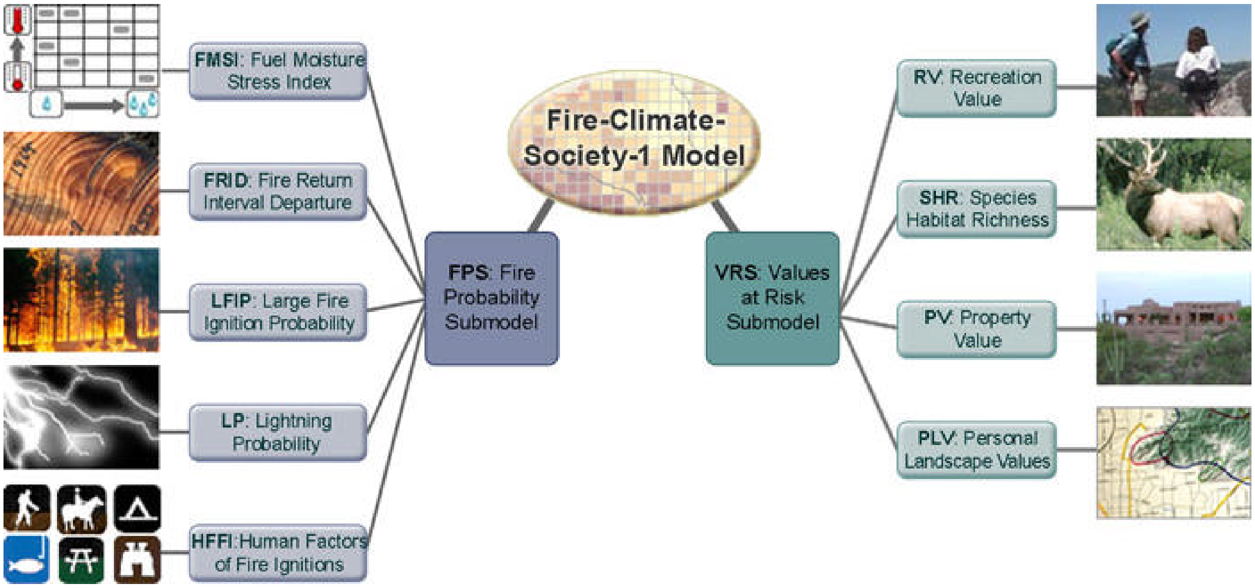


Figure 1: Fire-Climate-Society Model diagram.

2.1. Fire Probability

The components of the Fire Probability Submodel (FPS) bring to the Model the biophysical and human factors that influence the likelihood of fire (Table 1). For example, fuel moisture is modeled as a fuel moisture stress index derived from bi-weekly fire season Normalized Difference Vegetation Index (NDVI) (e.g. Nemani and Running 1989). The human factors of fire ignition are modeled using proximity to features like roads, campgrounds, and urban areas.

Fire Probability Submodel Components	
Fuel Moisture Stress Index (FMSI)	Fire-season, time-dependent fuel moisture conditions relative to those assessed from 1989 to 2004. For a relative measure at each pixel, we calculate departure from average via the negative z score.
Fire Return Interval Departure (FRID)	An index of the historical interval between fires for each vegetation type, and the years that have elapsed since the last fire.
Large Fire Ignition Probability (LFIP)	Probability of fires that will grow to greater than 250 acres within a vegetation type, standardized into a density map based on the total area in each vegetation class.
Lightning Probability (LP)	Probability of a lightning strike, based on the spatially explicit density of lightning strikes per 100 ha per year in each research venue.
Human Factors of Fire Ignition (HFFI)	Based on the spatial relationship between human activities (travel, recreation, etc.) and the location of human caused ignition.

Table 1: Fire Probability Submodel components

2.2. Values at Risk

The FCS-1's Values at Risk Submodel (VRS) has four components that bring to the Model the perceived values that are at risk from a wildfire: recreation value, property value, wildlife value, and the value attributed to the landscape by humans (Table 2) (Johnson et al. 2003). For example, maps of recreation value were created for the top ten recreation activities in each of the four venues. Viewsheds were created by calculating Euclidean distance grids and visibility surface grids from features of interest that were then weighted by the proportion of visitors who participated in each activity. Species habitat richness was used as a proxy for the diversity of fauna because landscape-scale species diversity maps were not available for the WALTER study venues.

Values at Risk Submodel Components	
Recreation Value (RV)	Based on a proximity/viewshed analysis of the top ten recreation activities in each venue (where they potentially were and the view from those locations).
Species Habitat Richness (SHR)	A proxy for the diversity of fauna, made up of a spatially explicit sum of the GAP-model habitats for mammals, amphibians, reptiles and birds.
Property Value (PV)	Tabular housing data joined to census block-level data. Total housing value assigned proportionally based on area of intersection with the 1-km project grid.
Perceived Landscape Values (PLV)	Personal perceptions of risk assigned to areas at risk of wildfire, based on participatory, map-based interviews at each of the WALTER venues.

Table 2: Fire Probability Submodel components

2.3. Weighting and Integration

Each of the components of FCS-1 provides information on either fire probability or values at risk, so none can stand alone as an integrated risk assessment. Stakeholder feedback from the outset of FCS-1 development emphasized the need for an operational model that could integrate risk assessment elements through expert knowledge of local conditions. Of concern was the fact that stakeholders with different value systems would place differing levels of importance on the building blocks that make up the components of FCS-1. This is particularly evident when trying to integrate the human and biophysical characteristics of the model.

To address this issue, a methodology for assigning weights based on personal opinion was developed. Where there are multiple criteria and interrelated choices, weighting decisions become complex. Saaty (1980) developed a mathematical method to decompose and synthesize this complexity through the Analytical Hierarchy Process (AHP) by reducing these decisions into a series of one-on-one comparisons. The AHP process was chosen to address strategic fire planning, where each sub-model component is compared to each of the other components in a pairwise fashion on an integer scale of 9-1-9 by each individual participant (Figure 2). This same scale is also used to compare the relative importance of the two sub-models.

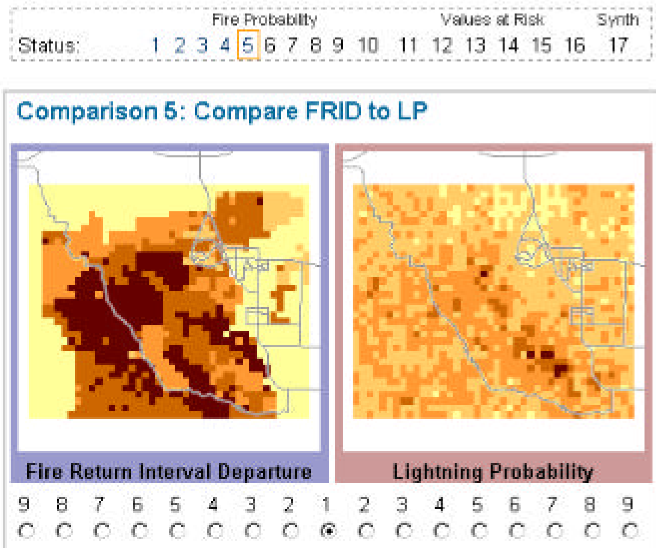


Figure 2: Fifth of seventeen AHP pair-wise comparisons.

These preference scores are then synthesized through a matrix averaging (eigenvector) method (Saaty 1980) in order to assign weights to the criteria. These weights are multiplied against the "alternatives" which in the case of FCS-1 are the 1-km map cell values for each of the model components. A linear combination of the weighted sub-model components creates the fire probability map and a values at risk map. A linear combination of the weighted sub-models creates the final FCS-1 risk assessment. Figure 3 provides an example of the final model output.

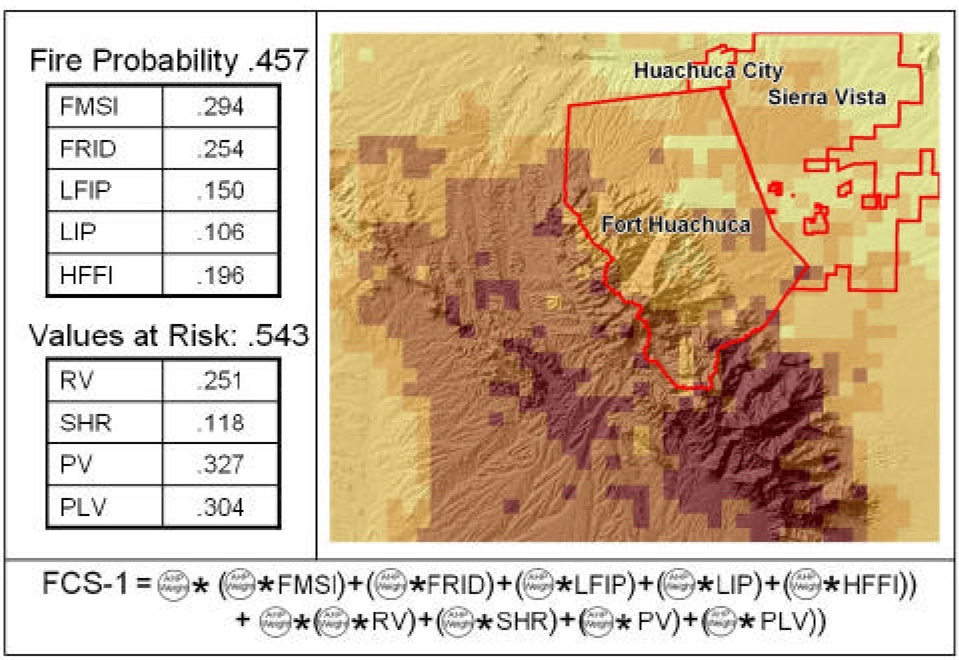


Figure 3: Sample AHP output and final map for Huachuca Mountains, where darker areas have higher risk.

This modeling approach also makes it possible to integrate the preferences of a group of people in order to visualize their combined preferences. Feedback from the stakeholders who conducted beta tests of FCS-1 emphasized how the combination of AHP and interactive maps facilitated the graphic display of complex relationships inherent to wildfire risk assessment.

3. ArcIMS Implementation

The implementation of the FCS-1 web application requires the last step of the model calculations to be performed in real-time (Figure 4). It requires user inputs in the form of a Fuel Moisture Stress Index (FMSI) layer and weights developed by the AHP process for the nine input layers and two sub-models. All input raster layers have been pre-generated and the web application requires simple cell-on-cell map algebra operations in order to display the fire risk assessment map.

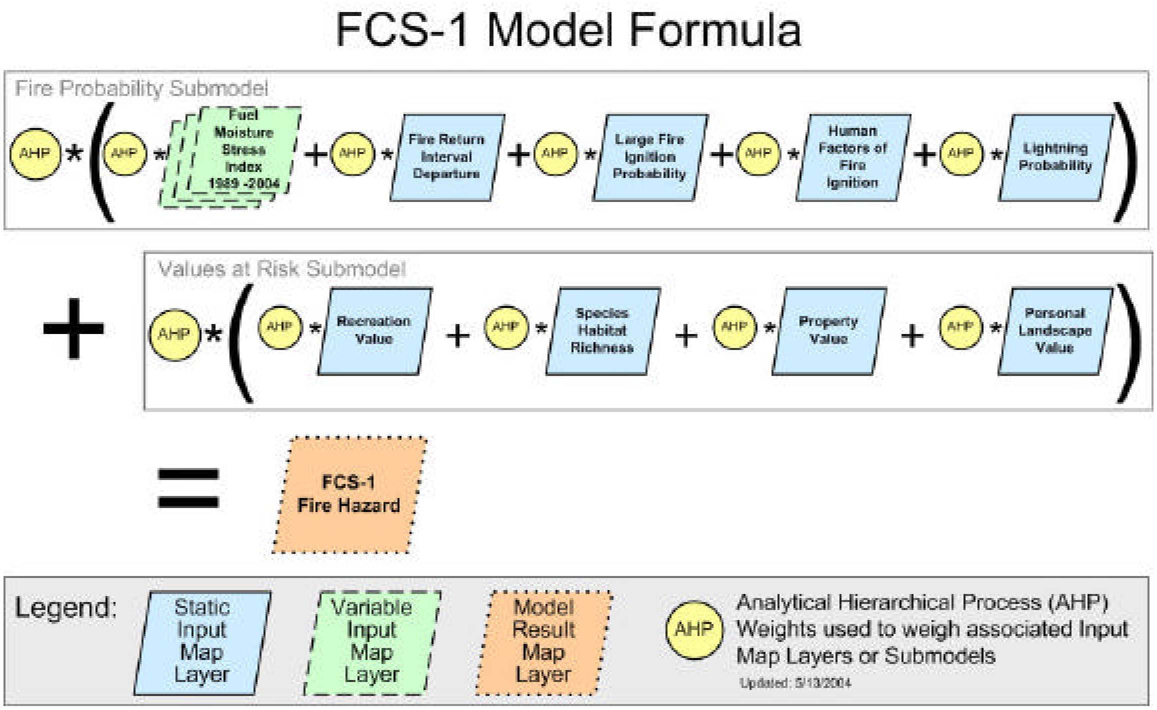


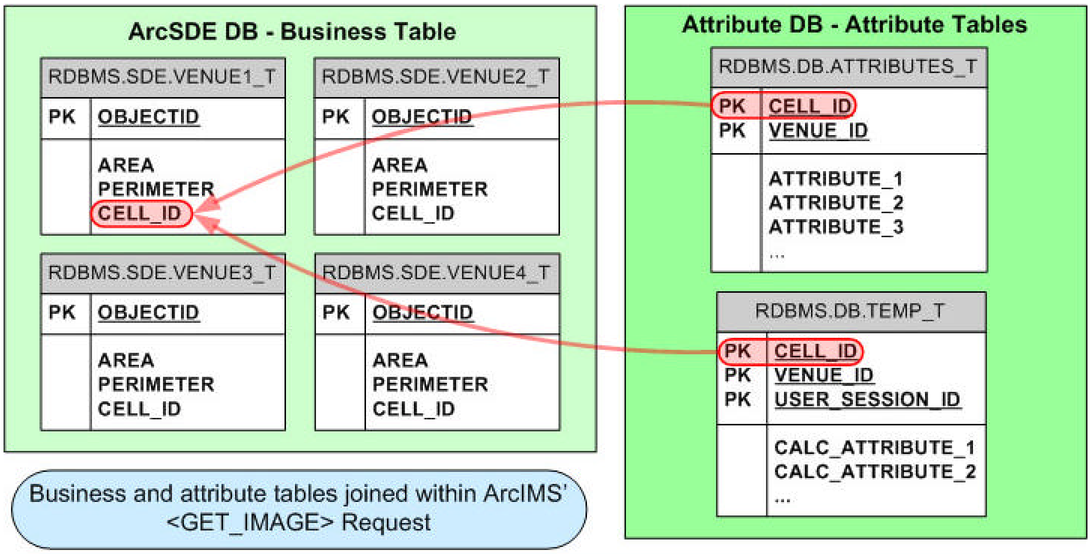
Figure 4: Final model calculation executed within FCS-1 web application.

ESRI's ArcIMS 4.01 is severely limited regarding raster data manipulation (this not being the product's objective), but its vector data capabilities enable a polygon-based solution. The polygon solution takes advantage of ArcIMS and ArcSDE's capability to join any database table with an ArcSDE vector layer's business table (the ArcSDE layer's original attribute table) in the same RDBMS. All of the model's original raster layers (GRIDs) for a study area have the same extent and cell resolution. Therefore, four ArcSDE polygon layers that emulate the raster cells for each study area can be used.

Every polygon in the "grid-polygon" layer has a unique cell ID to correspond with its attributes in an independent table: the model attribute table (ATTRIBUTES_T). The attribute table is stored in a separate database within the same RDBMS for administrative and maintenance reasons. For increased efficiency, all of a venue's attributes are stored in one table and identified by a study area or venue ID (VENUE_ID).

By creating a single dynamic map service (<MAP dynamic="true">) for all the venues, the number of ArcIMS map services was reduced. This grid-polygon map service includes reference layers such as roads, cities, and a shaded relief in its configuration file. The venues' grid-polygon layers, however, are added dynamically as needed within an ArcXML image request to ArcIMS (<GET_IMAGE>). Note that dynamically added layers cannot be queried within ArcIMS

To render a model input map for a venue, an image request that includes a <SPATIALQUERY> within a grid-polygon's <LAYER> tag is sent to the grid-polygon's ArcIMS map service. The XML tag specifies: the database table to be joined to the ArcSDE layer's business table, the field on which field to join the tables (CELL_ID), additional conditions such as a specific venue ID number, and the spatial extent of the join or <ENVELOPE> (Figure 5). A <VALUEMAPRENDERER> tag can be applied to any of the joined table's fields (ATTRIBUTE_1 etc.), effectively enabling one to render any model input maps.



ArcXML - On-the-fly joining of ArcSDE Business Table with static Attribute Table

```
<SPATIALQUERY where="SDE.VENUE1_T.CELL_ID = DB.ATTRIBUTES_T.CELL_ID and
DB.ATTRIBUTES_T.VENUE_ID = 1" jointables="DB.ATTRIBUTES_T">
        <SPATIALFILTER relation="area_intersection">
                <ENVELOPE minx="-1000" miny="1000" maxx="-1000" maxy="1000" />
        </SPATIALFILTER>
</SPATIALQUERY>
```

ArcXML - On-the-fly joining of Business Table with user generated attributes in Temp Table

```
<SPATIALQUERY where="SDE.VENUE1_T.CELL_ID = DB.TEMP_T.CELL_ID and DB.TEMP_T.VENUE_ID = 1
and DB.TEMP_T.USER_SESSION_ID = 333" jointables="DB.TEMP_T">
        <SPATIALFILTER relation="area_intersection">
                <ENVELOPE minx="-1000" miny="1000" maxx="-1000" maxy="1000" />
        </SPATIALFILTER>
</SPATIALQUERY>
```

Figure 5: ArcIMS on-the-fly join of ArcSDE business tables and custom attribute tables.

The same table-joining method can be applied to a table that has dynamic attributes - such as a user's model results - which are calculated just before rendering a map (TEMP_T; Figure 5). A user's FCS-1 model is calculated through a SQL request to the attribute database (Figure 6). The SQL statement multiplies the user-generated weights by the attribute table's fields corresponding to model inputs (ATTRIBUTE_1, etc.). The resulting records are stored in the temporary attributes table (TEMP_T) and identified by the user's session ID and a venue ID.

Map Algebra SQL Statement

```
INSERT TEMP_T (CELL_ID, VENUE_ID, SESSION_ID, CALC_ATTRIBUTE_1, CALC_ATTRIBUTE_2)
SELECT TEMP_T.CELL_ID, TEMP_T.VENUE_ID, 3333 AS TEMP_T.SESSION_ID,
        ((ATTRIBUTE_T.ATTRIBUTE_1 * 0.5) +
                (ATTRIBUTE_T.ATTRIBUTE_2 * 0.3) +
                (ATTRIBUTE_T.ATTRIBUTE_3 * 0.2)) AS CALC_ATTRIBUTE_1,
        ((ATTRIBUTE_T.ATTRIBUTE_4 * 0.5) +
                (ATTRIBUTE_T.ATTRIBUTE_5 * 0.3) +
                (ATTRIBUTE_T.ATTRIBUTE_6 * 0.2)) AS CALC_ATTRIBUTE_2
FROM TEMP_T
        INNER JOIN ATTRIBUTE_T
        ON (TEMP_T.CELL_ID = ATTRIBUTE_T.CELL_ID AND TEMP_T.VENUE_ID = ATTRIBUTE_T.VENUE_ID)
ORDER BY CELL_ID ASC
```

Figure 6: SQL statement to populate the temporary attribute table with a user's map algebra calculation (SQL Server 2000).

Once the temporary attribute table is populated, ArcIMS joins the table based on venue ID and the user's session ID. Each user on the system renders a different set of color coded maps. For efficiency, programmers elected to use one temporary table to store all the information specific to the users, rather than creating one table per user. The session ID is automatically generated by the application operating environment services in Tomcat 4.1.30.

4. Discussion

The web application was written using Java J2EE, Tomcat 4.1.30, and Struts 1.1. These technologies were selected to make the best possible use of development resources. Rather than investing time writing new security, database connection pooling, workflow, and property management solutions, programmers elected to use an open industry standard operating environment that provides these services. As a result, the development team was able to remain focused on the more complex, higher risk areas of the system:

- *Exposing a rich set of Encapsulated ArcIMS services via the ArcIMS 4.0.1 Java Connector Object Library.* These services were tailored to greatly simplify the interaction between the web-based solution and ArcIMS via the ESRI-provided Java Connector.
- *The workflow involved in gathering user input.* There are a total of 19 steps through which the user is guided in the process of gathering input that is ultimately used in the map algebra.
- *Matrix algebra and Eigen Vector/Value calculations for the Analytic Hierarchy Process (AHP).* As the core of the system, the complex mathematical operations that provide input to the map algebra were of particular interest to developers. They focused a great deal of energy on ensuring that these calculations are correct.

To overcome some of the limitations of the ArcIMS 4.0.1 Java Connector Object Library, the application captures the ArcXML request generated by the ArcIMS Java API and modifies the XML string to include the desired spatial query (Figure 5). Once this work-around was discovered, everything else fell into place.

The “grid-polygon” solution to our on-line map algebra requirements works very well, in part because the ArcIMS needs to render less than 10,000 polygons at a time, and there are relatively few simultaneous users. This method’s true limitations are the limited number of GRID cells that it can emulate. The SQL Server 2000 RDBMS used is not taxed much by running calculations on 100,000 records, but ArcIMS would require a very long time to render 100,000 polygons. It might be possible to overcome this limitation with the use of the polygon equivalent of pyramid layers, with the RDBMS resampling cell values on the fly. Instead of one grid-polygon per venue, one could use several layers with varying “polygon resolutions,” such as 1x1 km, 4x4 km, 8x8 km, 16x16 km, etc. To avoid duplication in storing attributes, one could use database views (akin to “virtual tables”) with resampled values instead of tables. However, we hope to be able to accomplish more sophisticated GRID analysis over much larger areas with the newly released ArcGIS Server.

Acknowledgments

We thank Anne Thwaits for reviewing this paper and Marek Caltik whose initial help through the ESRI ArcIMS User Forum lead as to an early breakthrough.

We thank the WALTER team at the University of Arizona for their efforts with the WALTER project: Chris Baisan, Gary L. Christopherson, Andrew Comrie, Mike Crimmins, John C. Dale, Calvin Farris, Wolfgang Grunberg, Michael Haseltine, Pamela Holt, Sara Jensen, Peter Johnson, Noah Lerman, Shoshana Mayden, Rachel Miller, Barbara J. Morehouse, Aaryn Olsson, Barron J. Orr, Jonathan T. Overpeck, Jodi R. Perin, Merrick Richmond, Heather Severson, Thomas W. Swetnam, Susan Taunton, Anne Thwaits, and Stephen R. Yool.

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