7.11

MAPPING EROSIVE POTENTIAL ACROSS THE UNITED STATES

Greg Johnson * and James Marron
USDA-NRCS, National Water and Climate Center, Portland, Oregon
and
Christopher Daly and George Taylor
Oregon State University, Corvallis, Oregon
and
Steven Hollinger and Jim Angel
Illinois State Water Survey, Champaign, Illinois

1. INTRODUCTION

Water erosion is a significant issue in the United States, and globally. The Natural Resources Conservation Service (NRCS) of the U.S. Department of Agriculture (USDA) is the lead agency in the federal government charged with promoting practices that will encourage conservation and reduce soil erosion by both water and wind on private lands in the United States. For several years, the NRCS has utilized the Revised Universal Soil Loss Equation (RUSLE) for estimating annual soil loss from the erosive action of water at the farm scale (Renard et al., 1997). RUSLE utilizes averaged climate statistics in combination with soils, local topography and other information to estimate soil erosion and pollutant movement and loadings. Climate inputs include mean monthly precipitation and temperature, as well as a couple of variables that provide information about the probability and intensity of erosive rain storms.

In the past, these climate inputs were determined at specific points (climate stations), and reference climate stations were selected to represent homogeneous erosive regions across the country. Previous climate work for RUSLE relied on older data from a relatively limited number of climate stations (Wischmeier and Smith, 1978; Renard, 1997). Such an approach was sufficient for its time, but newer precipitation data have indicated changes may be occurring in the frequency of intense precipitation that have prompted concern about potential changes in soil erosion by water (Nearing, 2001; Karl and Knight, 1998). At the same time, spatial climate analytical tools have been developed to allow accurate estimation of climate surfaces with high spatial resolution over large areas, including the U.S. (Daly et al. 2002). Thus, the NRCS commissioned the Illinois State Water Survey (ISWS) to develop new precipitation statistics needed by RUSLE for thousands of stations, and collaborated with the Spatial Climate Analysis Service (SCAS) at Oregon State University (OSU) to then take these point data and develop new spatial climate surfaces of the needed climate inputs for RUSLE. This paper briefly describes the production of two key climate maps needed by RUSLE: The so-called R-Factor, and the 10 year return period value of the single storm Erosivity Index, or EI10.

* *Corresponding author address:* Greg Johnson, USDA-NRCS, National Water and Climate 101 SW Main St., Suite 1600, Portland OR 97204-3224; email: gjohnson@wcc.nrcs.usda.gov

2. DATA AND METHODOLOGY

2.1 *NOAA 15-minute Data*

The principal dataset used for these analyses were the time series of precipitation data recorded every 15 minutes at selected National Weather Service (NWS) Cooperative Observing Program stations. This dataset was perused for completeness and suspected errors by the ISWS, resulting in a total of 2,375 stations with more than seven years of data, covering the continental U.S.

A variety of relevant statistics were derived from these data. Precipitation analyses for RUSLE require an analysis of storms. In this case, a storm was delineated by a 6 hour or greater period of dry weather (no precipitation occurring). Using the 15 minute time series, storms could thus lap over days, and could incorporate many "bursts" of precipitation with dry gaps of up to 6 hours. The minimum depth resolution on the 15 minute gages is 0.1". Thus, in light precipitation situations, it was not unusual for there to be 1 to 2 hours between 0.1", and these 0.1" amounts were accumulated for a storm total until there were six or more hours with no precipitation recorded.

2.2 *RUSLE Precipitation Statistics*

Once a high quality 15-minute database was assembled, the data were subjected to various calculations. For each storm, the total storm kinetic energy, E, ($MJha^{-1}$) was computed by:

$$E = \sum_{r=1}^{m} e_r \Delta V_r \qquad (1)$$

where e_r is the rainfall energy in $MJha^{-1}mm^{-1}$, given by:

$$e_r = 0.29[1-0.72 \exp(-0.082\, i_r)], \quad (2)$$

where i_r is the rainfall intensity ($mmhr^{-1}$) for each storm increment (15 minute period). ΔV_r is the depth of rainfall in mm for the r^{th} increment of the storm, which is divided into m parts. Thus, if a storm lasts 3 hours, m=12 with these 15-minute data.

After E values were calculated for each storm they were summed over periods of interest. In this case, monthly total storm kinetic energies were desired, which were then examined, as well as summed to obtain annual R values. Monthly and annual R-Factors are used in RUSLE, and are calculated using:

$$R = \frac{1}{n}\sum_{j=1}^{n}\left[\sum_{k=1}^{q} E_k (I_{30})_k\right]_j \quad (3)$$

where I_{30} is the maximum 30-minute precipitation during each storm event, j is an index of the number of years (or months, if calculating R for each month) used to produce the mean, k is an index of the number of storms each year (or month), q is the number of storms per year (or month), and n is the number of years (months). If mean monthly R values are computed, then they are summed to obtain the mean annual R value, which is a value that is typically used for mapping, and comparing values spatially across a region, or nationally.

Because of the large amount of missing data in the 15-minute data, the final EI values used to compute the R-factor were computed using a relationship between the daily erosivity values based on the 15-minute rainfall (dependent variable) and the total daily rainfall at the 15-minute stations (independent variable). The relationship was of the form:

$$EI_d = a * P_d^b \quad (4)$$

where EI_d is the erosive index on a given day (d), using the formulation for E and I above, P is the total precipitation on day d, and a and b are coefficients (Richardson et al., 1983). Separate regression coefficients were developed for each 15-minute station. While seasonal coefficients could be developed, only the annual coefficients were used because some regions of the country did not have enough observation in multiple seasons to consistently compute seasonal regressions. Each 15-minute station was paired to an independent daily precipitation recording station. The daily stations were either collocated with the 15-minute station or were the nearest daily station to the 15-minute station. Using daily precipitation data to estimate EI, and thus R resulted in better temporal coverage, but reduced the final set of usable stations to approximately 1400 across the continental U.S.

One other precipitation statistic is used in RUSLE, and was computed and spatially distributed. That statistic is called the 10-year return period value of the Erosion Index, or EI10, and it gives information about the frequency and intensity of large precipitation events. It is computed by determining the maximum erosion index (EI) for each year, which is simply the $E*I_{30}$ value shown above in the equation for R. Then, this time series of annual maximum EI values were then fitted using the Generalized Extreme Value (GEV) distribution, and from this the 10-year return period EI value (EI10) was determined for each station. L-moments procedures were utilized to ensure spatially consistent and regionally accurate and reliable values.

2.3 *Spatial Distribution of R-Factor and EI10*

A mean annual R value is computed using (3) above, and then EI10 is calculated using the procedures described above, for each station. In the implementation of RUSLE in the NRCS and other agencies and user groups spatially homogeneous values of R and EI10 are necessary. In general, in most regions east of the Rocky Mountains spatially-averages values by county were desired. In the past, a few representative climate stations were used to represent whole counties, or even groups of counties. However, with newer technologies, it was desired to develop these spatial averages using other methods.

The NRCS has collaborated with the SCAS to produce new climate maps and digital, high resolution climate coverages of the U.S. in recent years. This same technology was employed to generate new R-Factor and EI10 maps of the continental U.S. The SCAS uses the Parameter-elevation Regressions on Independent Slopes Model (PRISM) system to generate gridded climate surfaces. PRISM is a knowledge-based approach to mapping climate that seeks to combine the strengths of human-expert and statistical methods (Daly et al., 2002; Daly et al., 2001). PRISM uses point data, a digital elevation model (DEM), other spatial data sets, a knowledge base, and expert interaction to generate estimates of annual, monthly and event-based climatic elements that are gridded and compatible with Geographic Information Systems (GIS).

Two methods of spatially distributing R and EI10 values were evaluated. These were called "direct" and "derived" methods. The direct method utilizes PRISM directly on the more than 2000 point values of R Factor and 1400 or so values of EI10 across the U.S. The PRISM mean annual precipitation grid of the U.S., developed for the USDA-NRCS utilizing 1961-1990 mean monthly precipitation at more than 8,000 NWS Cooperative Observing and NRCS SNOTEL stations, was used for each grid cell prediction. In PRISM, each cell (in this case, approximately 4 km square, based on a 2.5 arc-minute resolution DEM) receives an individual regression prediction of R-Factor or EI10 versus mean annual precipitation, for all relevant and close stations in the vicinity of the grid cell. Please refer to the PRISM papers for a complete discussion of the PRISM methodology. Mean annual precipitation was chosen as the base layer for the regressions rather than elevation or other background variables, as it was determined through experimentation that it produced the best regression predictions of R-Factor and EI10.

The second method, called the derived method, was examined due to its potential for accurate mapping without the full expenditure of resources associated with full PRISM operation. This method first establishes a regression of R or EI10 against mean annual precipitation using all of the stations in the ISWS analysis. Through various tests it was determined that the best regression was in log-space. Residuals of the log R or log (EI10) vs. log (mean annual precipitation) nationwide regression were standardized. These standardized residuals were then spatially distributed to a grid of the same resolution as the mean annual precipitation map using simple inverse distance weighting. The resulting smoothed gridded layer of standardized residuals then was added to the predicted grid to obtain the derived gridded layer of either R-Factor or EI10 for the U.S.

3. RESULTS

Four maps are shown to illustrate the comparison between the direct and derived methods, described above. Figure 1 is a graph of the log of the R-Factor versus the PRISM-derived mean annual precipitation value for all stations across the U.S. used in the analyses. A strong linear regression is evident.

Next, the inverse-distance-weighted gridded map of the standardized residuals from the Figure 1 regression are mapped and shown in Figure 2. Note the strongly positive residuals in the lower desert areas of California and Arizona, and across the southern and western portions of Texas. In general, the Great Plains had positive residuals, indicating that, relative to the whole U.S., the R-Factor in that region is higher than their mean annual precipitation would indicate. Similarly, the interior Northwest had negative residuals, indicating R-Factor, and thus erosive rains, were relatively smaller than would be expected based upon their mean annual precipitation (MAP). These strong regional patterns were instructive about the precipitation climate of the nation, and showed that the derived method potentially could be used for creating R-Factor and EI10 maps.

The R-Factor gridded map using the derived methodology outlined above is shown in Figure 3. The map closely resembles older versions of the R-Factor map (Wischmeier, 1962; Renard, 1997), produced using older data sets. However, the older maps lack the spatial complexity that is possible using newer GIS technologies, such as was demonstrated here.

The R-Factor map developed using PRISM directly on the R-Factor point values is shown in Figure 4. The differences between this and the derived map in Figure 3 are quite subtle, but are significant in some areas. This is mostly true along the Gulf Coast, in south Florida and along the Carolina coast where the direct map values are as much as 80 units less than the derived map. The direct map has higher values than the derived map in the higher mountains of the West, which is characteristic of PRISM. PRISM vertical extrapolations based on elevation have been proven to be quite accurate, whereas the simpler derived methodology is based on regressions using mostly lower-elevation location data (where most 15-minute precipitation stations are located).

In general, the PRISM-direct R-Factor map is smoother than the derived map due to two factors: 1) the direct approach used 20 stations for each pixel's calculations and the derived approach used only 11; and 2) the direct values are predictions for a locally-calculated linear regression between log MAP and log R-Factor, rather than an exact interpolation of residuals from the U.S.-wide regression function in the derived method, which is more sensitive to individual station values and outliers.

Lastly, the new EI10 gridded map of the U.S. based on the PRISM direct method is shown in Figure 5. This map differs more strongly from the derived EI10 map than the direct vs. derived R-Factor maps, although the general features of the map remain the same: highest values along the Gulf Coast, a plume of higher values northward into the Central Plains and Iowa, as well as along the Southeast Coast, and very low values over the western U.S, as well as relatively low in New England.

In general, the PRISM direct method appears superior to the derived method, particularly in areas of complex climate (mountainous West, coastlines, etc.). Thus, these direct-method maps will be utilized by the USDA-NRCS for the next generation of RUSLE utilization.

4. CONCLUSIONS

A methodology to develop new R-Factor and EI10 maps of the United States using 15-minute precipitation data analyses at 2000 or so stations, in combination with the climate mapping capabilities of the PRISM system, has been demonstrated. It is envisioned that these gridded products will become the standard for use in the RUSLE water erosion predication system utilized by the USDA and many other groups. The improved spatial accuracy of this method, in combination with newer data and GIS capabilities will make this a superior system for estimating soil erosion across the nation.

5. REFERENCES

Daly, C., W.P. Gibson, G.H. Taylor, G.L. Johnson and P.A. Pasteris, 2002: A knowledge-based approach to statistical mapping of climate. *Climate Research* **(In Press)**

Daly, C., G.H Taylor, W.P. Gibson, T.W. Parzybok, G.L. Johnson and P.A. Pasteris, 2001: High quality spatial climate data sets for the United States and beyond. *Trans. ASAE*, **43**, 1957-1962.

Karl, T.R. and R.W. Knight, 1998: Secular trends of precipitation amount, frequency, and intensity in the United States. *Bull. Amer. Meteor. Soc*, **79**, 231-241.

Nearing, M.A., 2001: Potential changes in rainfall erosivity in the U.S. with climate change during the 21st century. *J. Soil and Water Conservation*, **56**, 229-232.

Renard, K.G., G.R. Foster, G.A.Weesies, D.K. McCool, and D.C. Yoder, coordinators, 1997: Predicting soil erosion by water: A guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). USDA, Ag. Handbook no. 703, 404pp.

Richardson, C. W., G. R. Foster, and D. A. Wright, 1983: Estimation of erosion index from daily rainfall amount. *Trans. ASAE*, **26,** 153-160.

Wischmeier, W.H. and D.D. Smith, 1978: Predicting rainfall erosion losses--a guide to conservation planning. USDA, Ag. Handbook no. 537.

Wischmeier, W.H., 1962: Rainfall erosion potential. *Ag. Engineering*, **43**, 212-215.

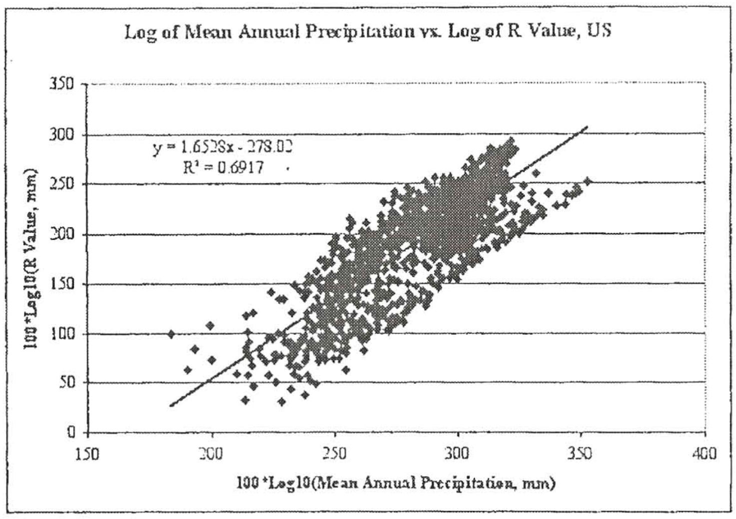


Figure 1. Log of mean annual precipitation versus log of R-Factor for all stations used in these final analyses.

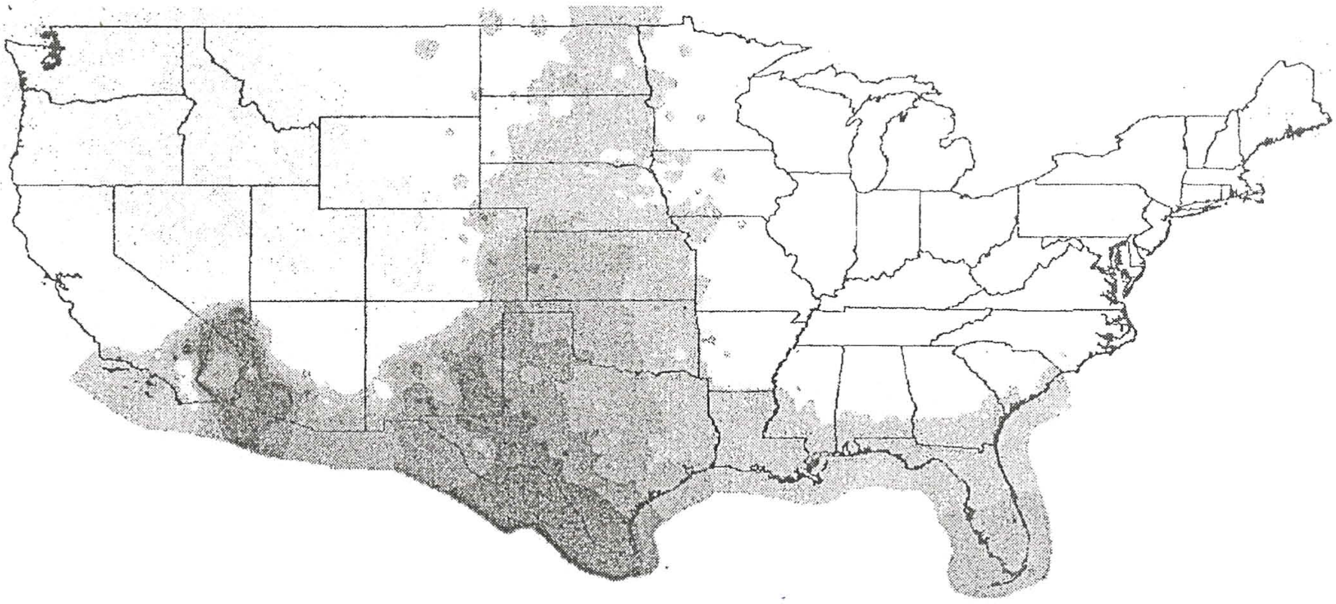
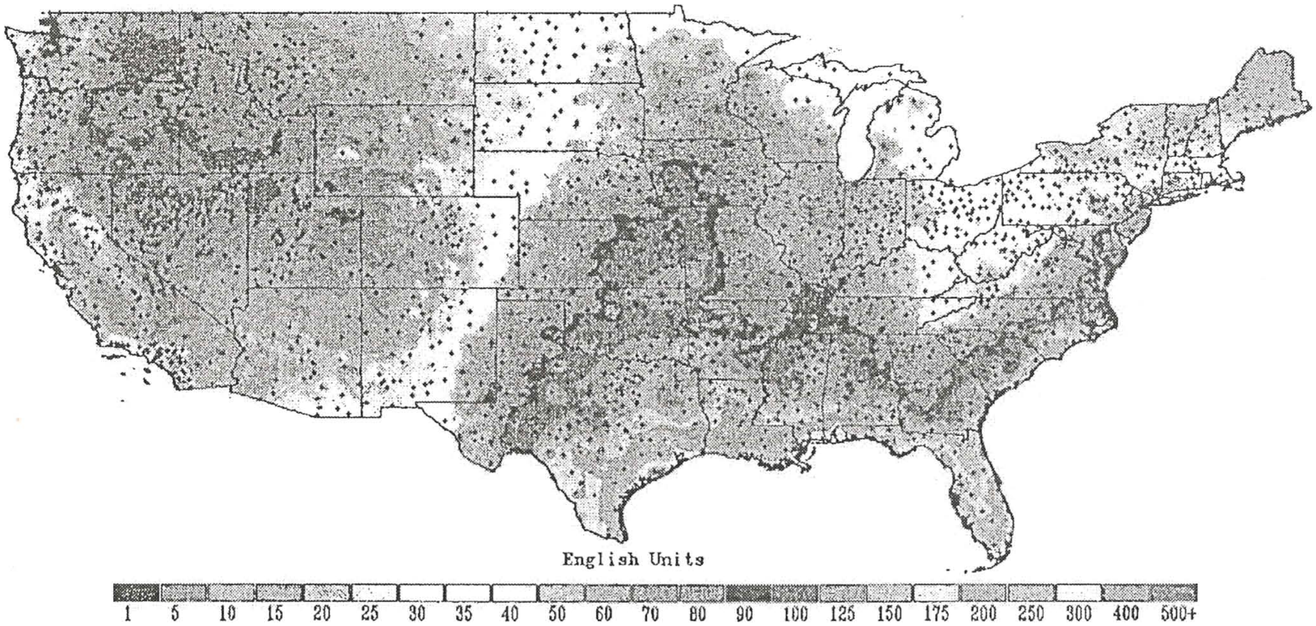


Figure 2. Interpolated R-Factor standardized residuals from the regression shown in figure 1. The blue and pink areas indicate positive residuals, and the green and yellow indicate negative.

PRISM EI10 - United States
Direct Method



Spatial Climate Analysis Service
Oregon State University
August 2001 Draft
Funded by U.S. EPA

Figure 5. EI10 gridded map obtained using PRISM directly. Units are in hundreds of foot-ton force-inch/acre-hour-year.

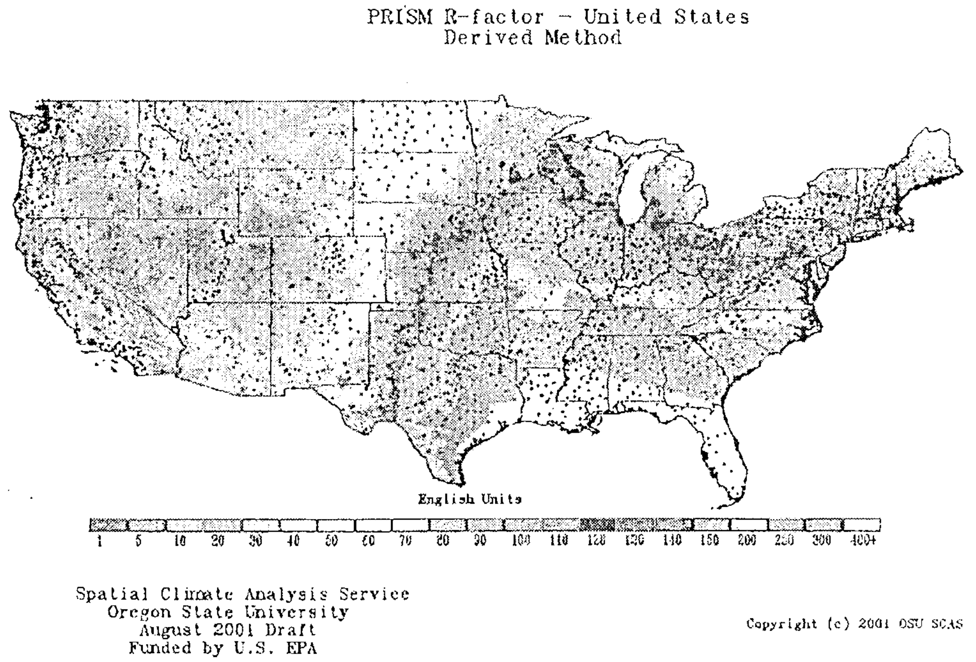


Figure 3. R-Factor gridded map using the Derived Method. Station locations are shown as black dots. Units are in hundreds of foot-ton force-inch/acre-hour-year.

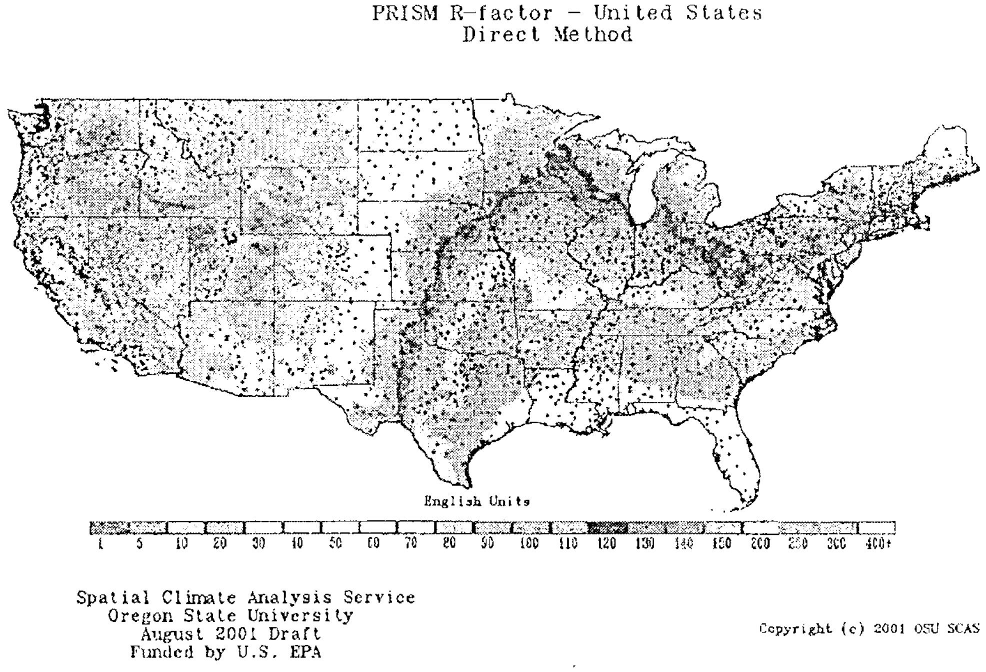


Figure 4. R-Factor gridded map obtained using PRISM directly. Units are in hundreds of foot-ton force-inch/acre-hour-year.