COMBINING PHYSICAL LAND DEGRADATION INDICATORS

Attempting to combine and interpret land degradation indicators is important for our understanding of land degradation processes and for our forecasting of what might be the general effects of environmental change. Combining different indicators is challenging. How can it be done in a way which is both meaningful and unbiased? Here are two different approaches of combining land degradation risk indicators. One is based on using the Z-scores of each indicator, and the other is based on fuzzy logic.

Z-SCORE APPROACH

A difficulty in combining land degradation indicators is that their value ranges and distributions are often very different. One way to overcome this is to firstly transform each indicator into a Z-score. The Z-scores are more comparable and more easily combined using a simple formula (e.g. adding). Converting to Z-scores has the effect of transforming the original distribution of a variable to one with a mean of zero and standard deviation of one. A Z-score quantifies the original value in terms of the number of standard deviations that the value is from the mean of the distribution. Equation 2 is the formula for converting an original value into a Z-score.

Figure 6 Land degradation risk map generated by combining erosion surface and salinisation risk surface using Z-scores

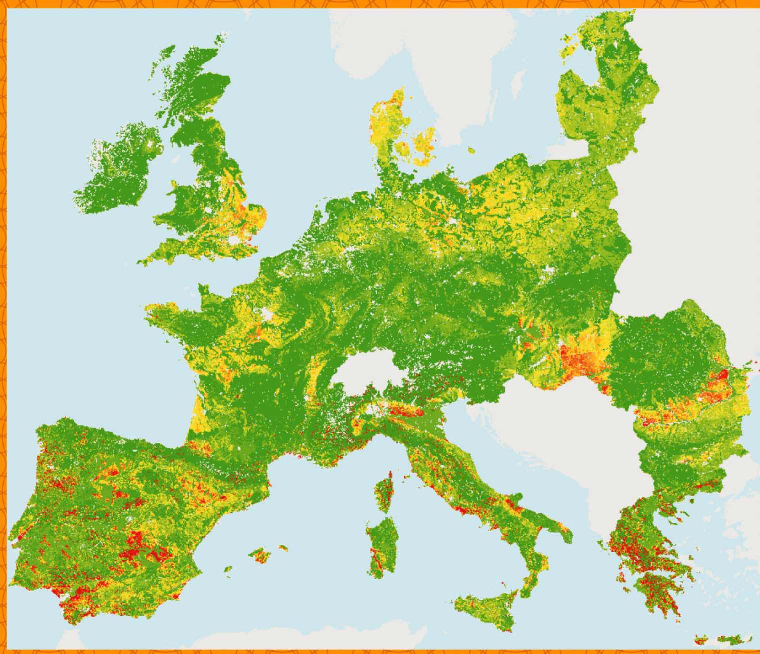
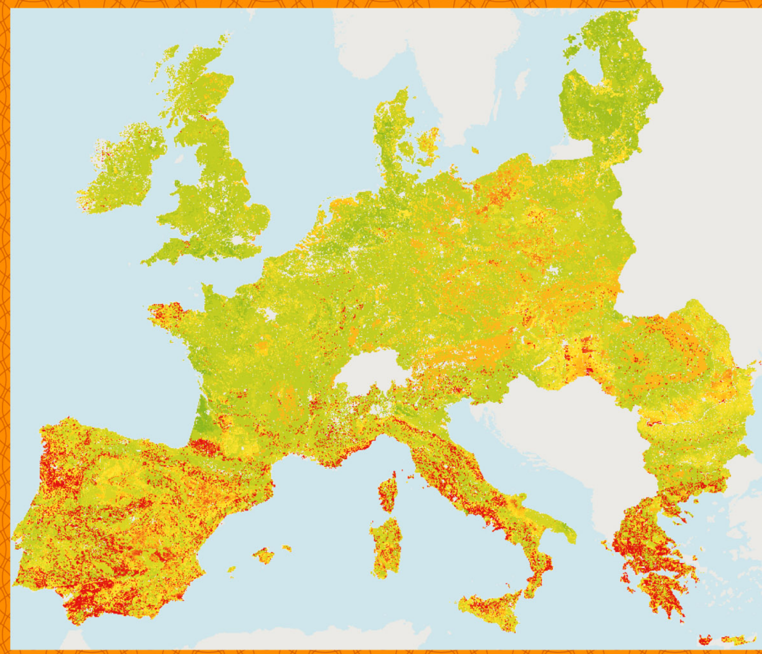


Figure 8 Land degredation risk map generated by combining erosion surface and salinisation risk surface using fuzzy inference



Equation 2 For calculating Z-scores

Z-SCORE = (VALUE – MEAN) / (STDDEV)

mean is the mean of all values
stddev is the standard deviation of all values

Figure 6 below is a map of a surface generated by adding the Z-scores of the Erosion surface depicted in Figure 2 with those of the Salinisation Risk surface depicted in Figure 5.

FUZZY MODELLING APPROACH

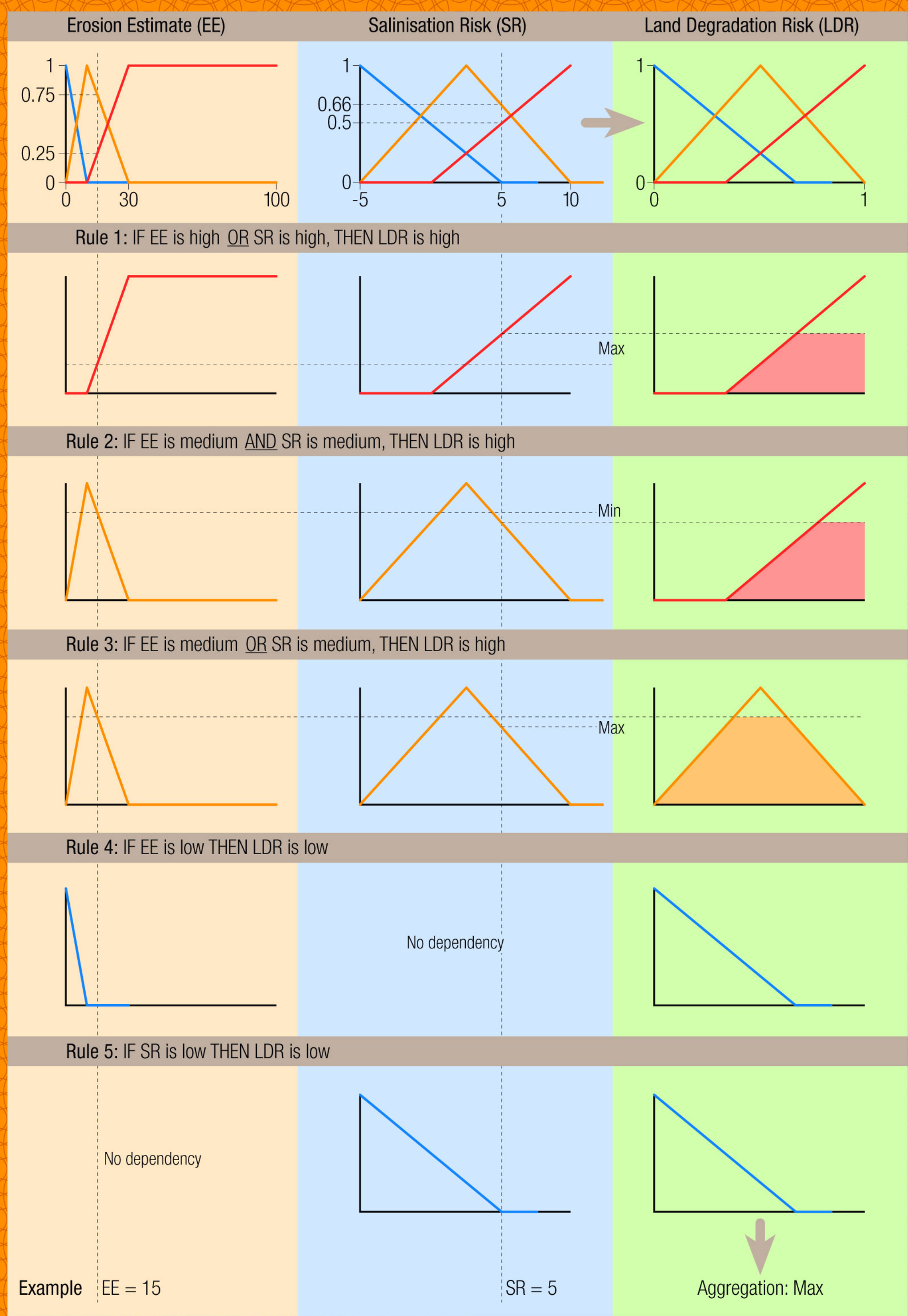
Fuzzy modelling provides another way of combining variables into land degradation risk surfaces. There are three components to a fuzzy model:

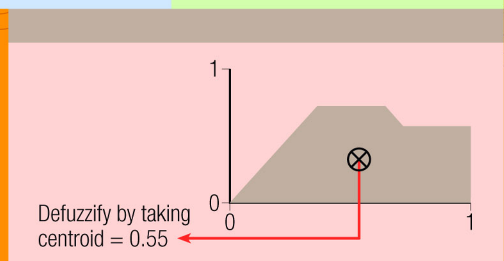
1. *A set of membership functions, which define the degrees of membership of values to fuzzy sets;*
2. *A rule base, which is a collection of fuzzy IF-THEN rules; and*
3. *A fuzzy inference engine that drives the model by execution of the rules base in response to a set of fuzzy inputs.*

From the ranges of the erosion estimates and the salinity risk surfaces shown in Figures 2 and 5 respectively, the membership functions depicted at the top of Figure 7 were defined. Along the X-axes of these membership functions are the values for each variable and the Y-axis scales the degree of membership from zero at the intersection of the X-axis to one above. It can be seen that every erosion estimate has a non-zero degree of membership for all values in the range [0, 30], for salinity risk values in the range [0, 5] belong to all three fuzzy classes (low, medium and high) to some degree. The five rules in Figure 7 constitute the rule base and the entire diagram illustrates how a pair of input values are parsed by each rule and how the result of this are combined and defuzzified into a land degradation risk value. It should be noted that this is but one way of performing fuzzy inference and that there are a number of alternatives. Also, fuzzy inference is usually used in far more complex circumstances with many more rules and more complex membership functions.

Figure 8 is a map of the resulting land degradation risk surface. It has a similar pattern to the surface depicted in Figure 6, though the maps look different at a glance.

Figure 7 Fuzzy inference diagram





FURTHER POINTS

The erosion surface shown in Figure 3 uses land use as an input and is really an estimate of how much eroded material there is likely to be for a given 1km cell. Arguably, Figure 3 does not show the likely effects of erosion in terms of land degradation risk and that to do this some further translation is needed.

The salinity risk maps (Figures 3 and 4) were based expert opinion coded as a mathematical equation. A fuzzy model could have been employed instead. I this way a salinity based land degradation risk indicator could have been generated in a single step.

It has been reasoned that the simplifying assumptions made in the generation of the surface depicted in Figure 5 are appropriate, but the assumption may be flawed. Nonetheless some further analysis of the salinity surfaces should be done. Are the combined land degradation risk indicators depicted in Figures 6 and 8 broadly correct? Perhaps the next step is to collate feedback and do some more detailed work in case study areas.

There is a need to produce estimates of land degradation risks under different environmental change scenarios and incorporate socio-economics in a more integrated way. Arguably, the difference between land degradation risk estimates under different environmental change scenarios is what is most interesting.

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