

Exploring Relationships Between Geomorphic Factors and Wheat Yield Using Fuzzy Inference Systems

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Abstract. Discovery of relationships between geomorphic factors and crop yield is a promising step toward spatial decision support of farming technology problems. A study of relationships between geomorphic factors and yield requires simulation of a non-linear system with poorly quantified uncertainties. Contrasted against conventional mathematics, a fuzzy inference system (FIS) employs fuzzy if-then rules to model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. In this paper, the utility of the FIS method for determining relationships between geomorphic factors (elevation, slope, aspect, curvature, and upslope contributing area) and yield is investigated. Parameters of FISs are identified using a dataset comprising over 6300 spatial points within 63 ha of an undulating farm field in Colorado. The single-input FISs designed in this study were used to identify several geomorphic dependencies of the spatial yield, which are presented graphically. Several two-input FISs were also developed to compute geomorphic yield dependencies. For practical application, these two-dimensional dependences are presented as 3D images and contour maps.

1. Introduction

With implementation of techniques of precision agriculture, there is the opportunity to collect data associated with yield and geomorphic factors. In particular, elevation data can be gathered using a geographical positioning system (GPS) mounted on an all-terrain vehicle. The yield can be collected with a yield monitor linked to GPS (*e.g.*, Green and Erskine 2004).

A study of relationships between geomorphic factors and yield is associated with simulation of non-linear systems. It should be pointed out that modeling based on conventional mathematical tools often is not well suited for dealing with non-linear systems. By contrast, a fuzzy inference system employing fuzzy if-then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative

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analyses. In this paper, we analyze relationships between geomorphic factors and yield using a fuzzy inference system (FIS) method to identify features of the data obtained by Green and Erskine (2004).

2. Methods

Alternative FIS methods and the field dataset are described below.

2.1. FIS and its adaptive version - ANFIS

FIS is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The basic structure of a FIS consists of two components: a fuzzy *rule base*, which contains a selection of rules, and a *reasoning mechanism*, which performs the inference procedure upon the rules and given facts to derive a reasonable output. Given crisp or fuzzy inputs, the FIS computes the output of the system. Some advantages of fuzzy systems include the ability to model non-linear systems, and the fact that it is based on natural language.

There are two types of fuzzy inference systems: Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined.

Mamdani's fuzzy inference system is the most commonly seen fuzzy methodology. It was proposed by Mamdani and Assilian (1975). Mamdani's effort was based on fuzzy algorithms for complex systems and decision processes (Zadeh 1973). The advantages of the Mamdani system are its intuitive, widespread acceptance, and its suitability to human input.

Sugeno (1985), or Takagi-Sugeno-Kang, introduced another system of fuzzy inference that is similar to the Mamdani system in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno systems is that, in the Sugeno system, the output membership functions are either linear or constant. The Sugeno system works well with linear techniques and with optimization and adaptive techniques.

There are some modeling situations in which the user cannot just look at the data and discern what the membership functions should look like. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. This is where the so-called *neuro-adaptive* learning techniques can be useful.

This problem can be addressed with an *Adaptive Neuro-Fuzzy Inference System* (ANFIS). The ANFIS was created by Jang (1993) in order to combine the advantages of both *Fuzzy Inference Systems* of Sugeno-type (FIS) and *Artificial Neural Networks* (ANN). ANN models for non-linear systems are able to create internal structures from the input-output dataset (data driven approach). The ANFIS method is ideal for interpretation of nonlinear systems, like soil-plant-air systems.

ANFIS is a class of adaptive networks that are functionally equivalent to fuzzy inference systems. Given an input-output dataset, the parameters of membership functions in fuzzy variables of antecedents of fuzzy rules are modified (this process is termed *learning*) using a well-known back-propagation algorithm or hybrid algorithm based on a combination of back-propagation and least squares estimate (LSE). The back propagation is an iterative gradient descent algorithm designed to minimize the mean squared error between the actual outputs and the desired outputs.

The data set is divided into two separate data sets – the training data set and the testing data set. The training data set is used to train or calibrate the ANFIS, whereas the testing data set is used to verify the accuracy and the effectiveness of the trained ANFIS model. During the validation, it is possible to assess the degree of reliability of each obtained model in terms of a correct simulation of the phenomenon. After the learning process, one obtains an FIS that corresponds with reality and can be easily interpreted.

ANFIS is much more complex than ordinary FIS, and is not available for all of the fuzzy inference system options. Specifically, ANFIS only supports Sugeno-type systems, and these must be first or zero-th order Sugeno-type systems. Also, all output membership functions must be the same type, either linear or constant. Moreover, ANFIS cannot accept all the customization options that basic fuzzy inference allows. That is, users cannot make their own membership functions and defuzzification functions.

2.2. Dataset and geomorphic indicators

The dataset from a farm field in eastern Colorado (Green and Erskine 2004) includes 1997 winter wheat yield (Yield) and several geomorphic indicators derived from a 10-m digital elevation model with cm-level vertical accuracy: Slope, Aspect, Curvature, LnSCAsink, LnSCAfill, and Wifill .

Yield (Mg/ha) is defined by harvester-mounted yield monitor interpolated onto a 10 m grid. Slope (percent) is the first spatial derivative of elevation (rise over run). Aspect (degrees) is defined as slope azimuth expressed in degrees from North (i.e., East facing slope has Aspect = 90 degrees). Curvature (m^{-1}) is defined as the 2nd derivative of elevation. LnSCAsink is the log-transformed specific contributing area (SCA) without sink filling. SCA (m) is defined as the upslope contributing area per unit contour length. LnSCAfill is the log-transformed specific contributing area (SCA) with sink filling. Wifill is the topographic wetness index, computed from SCA and Slope (for more details, see Green and Erskine 2004).

3. Results and discussion

Several fuzzy inference systems (FISs) were designed for simulation of the spatial relationships between geomorphic factors and grain yield. To accomplish this task, we used the Fuzzy Logic Toolbox belonging to MATLAB's environment (MathWorks, 2001). Parameters of FISs are defined using the dataset considered above. The main characteristics of these FISs are given in Table 2. The RMSE in Table 2 is the minimized value of the root mean squared error between measured and simulated values of yield with each FIS.

Table 2. Characteristics of different FIS models. All models tested used triangular membership functions with 5 terms.

Fuzzy Inferenece System (FIS)	Number of terms in membership functions	RMSE (Mg/ha)
Single-input (Slope)	5	0.900
Single-input (LnSCAsink)	5	1.106
Single-input (LnSCAfill)	5	1.088
Single-input (Wifill) F	5	0.952
Two-inputs (Slope and LnSCAsink)	5	0.844
Two-inputs (Slope and LnSCAfill)	5	0.833
Two-inputs (LnSCAsink and LnSCAfill)	5	1.081
Two-inputs (Wifill and Slope)	5	0.829
Two-inputs (Wifill and Aspect)	5	0.920

By using the single-input FISs designed in this study several yield-dependences were obtained, which are presented graphically (Figure 1).

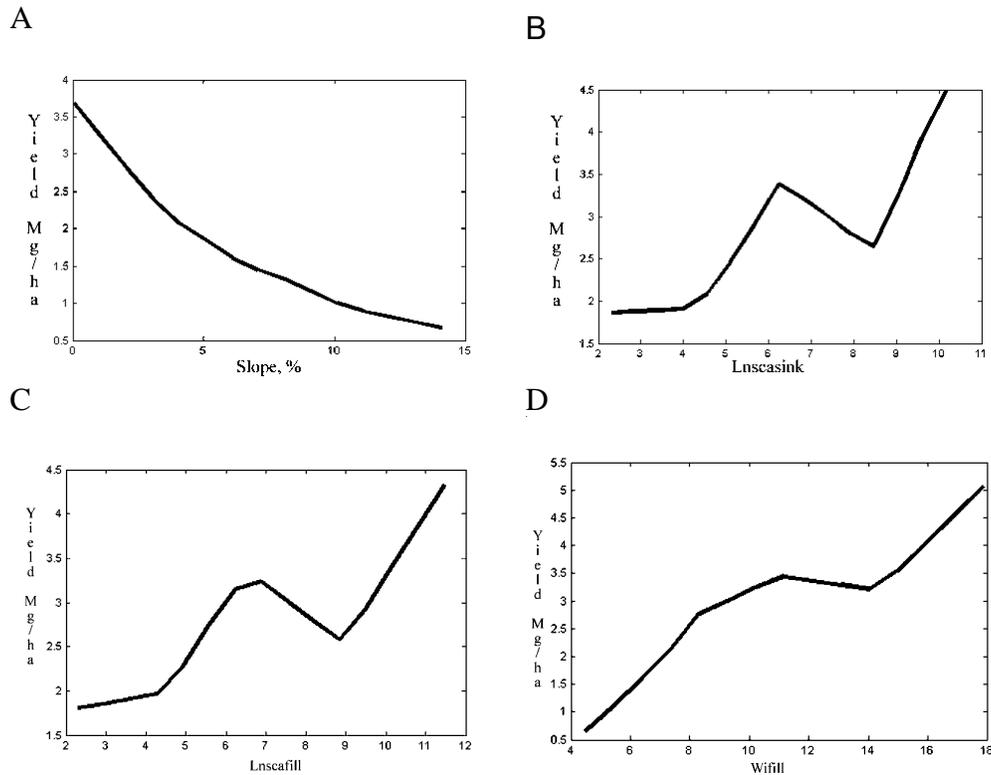


Figure 1. Yield-dependence of Slope (A), LnSCAsink (B), LnSCAfill (C), and Wifill (D) computed using the single-input FIS.

The two-dimensional yield-dependences of the geomorphic factors were computed using the two-input FISs in Table 2, resulting in the following response surfaces (Figures 2-6). Comparing Figures 2 and 3, for example, the yield response to slope is nearly identical for low values of SCA computed either with sinks (LnSCAsink) or without (LnSCAfill). However, differences between the two response surfaces are large for higher values of SCA, where the effects sink filling are manifested. These differences were not apparent from Figure 1B and 1C using the single-input FIS method.

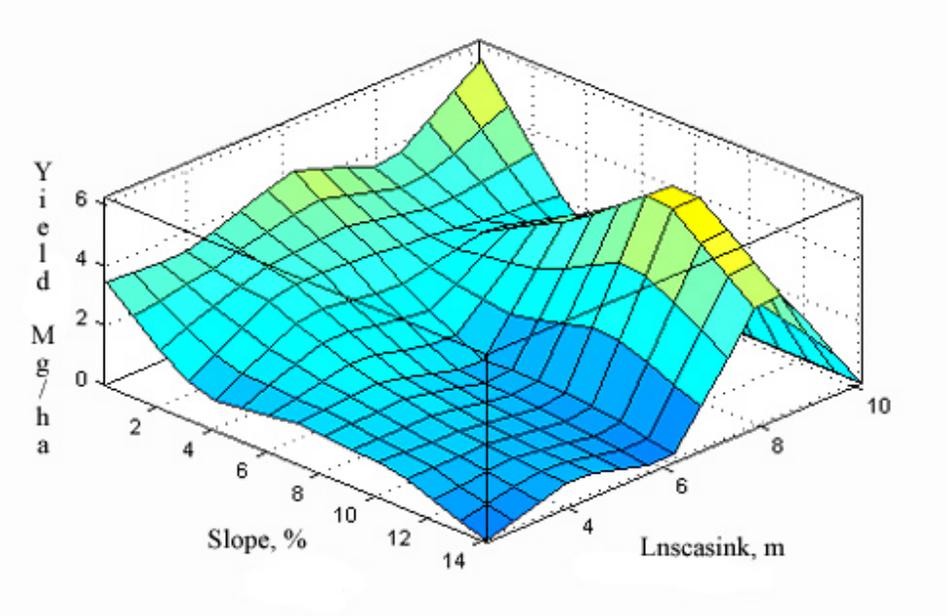


Figure 2. Yield-dependence on Slope and LnSCAsink computed using the two-input FIS.

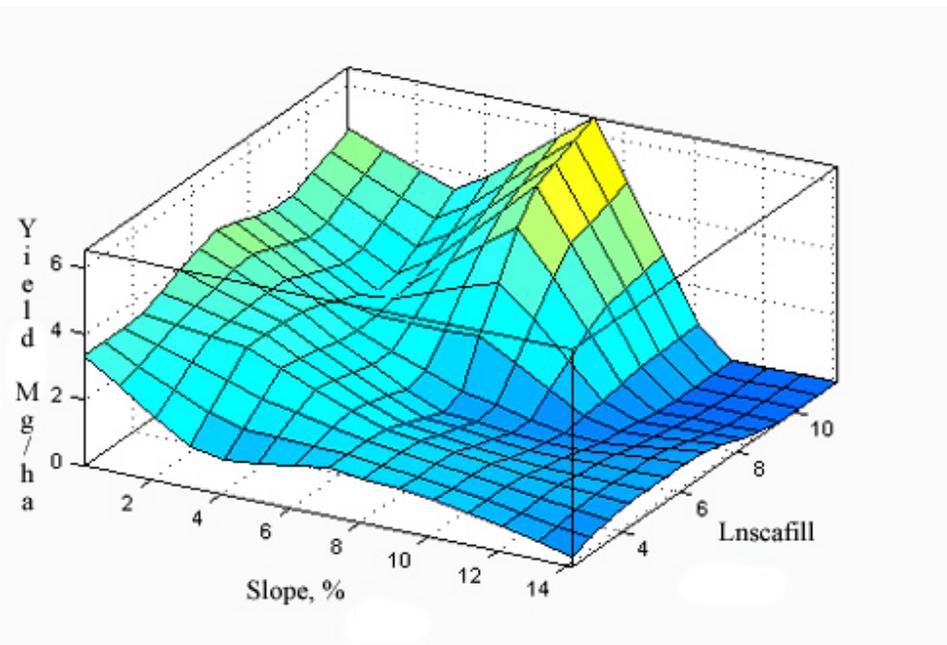


Figure 3. Yield-dependence on Slope and LnSCAfill computed using the two-input FIS.

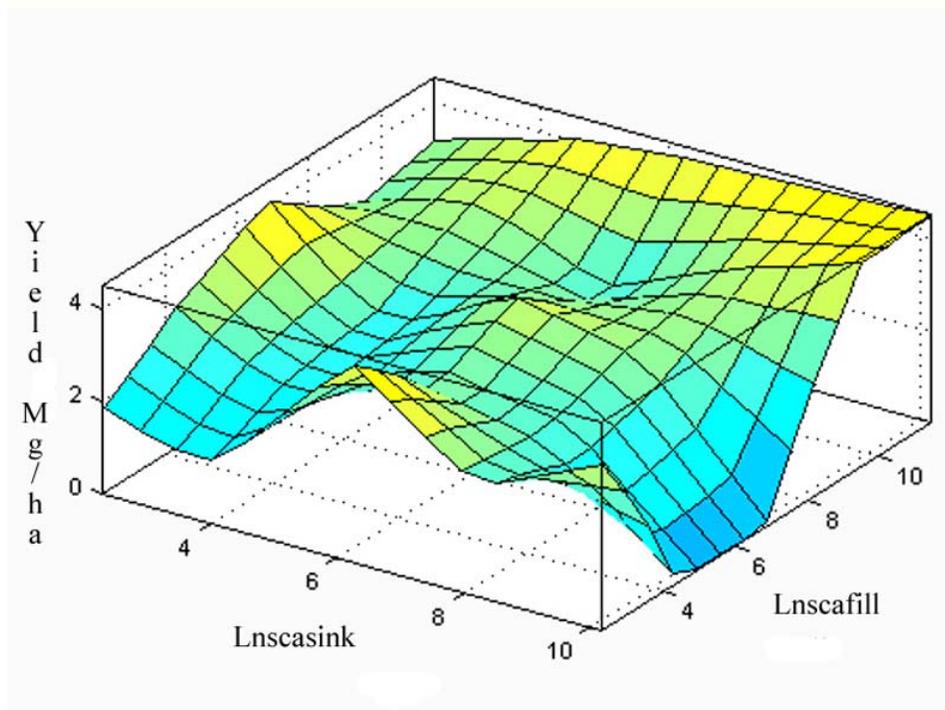


Figure 4. Yield-dependence on LnSCAsink and LnSCAfill computed using the two-input FIS.

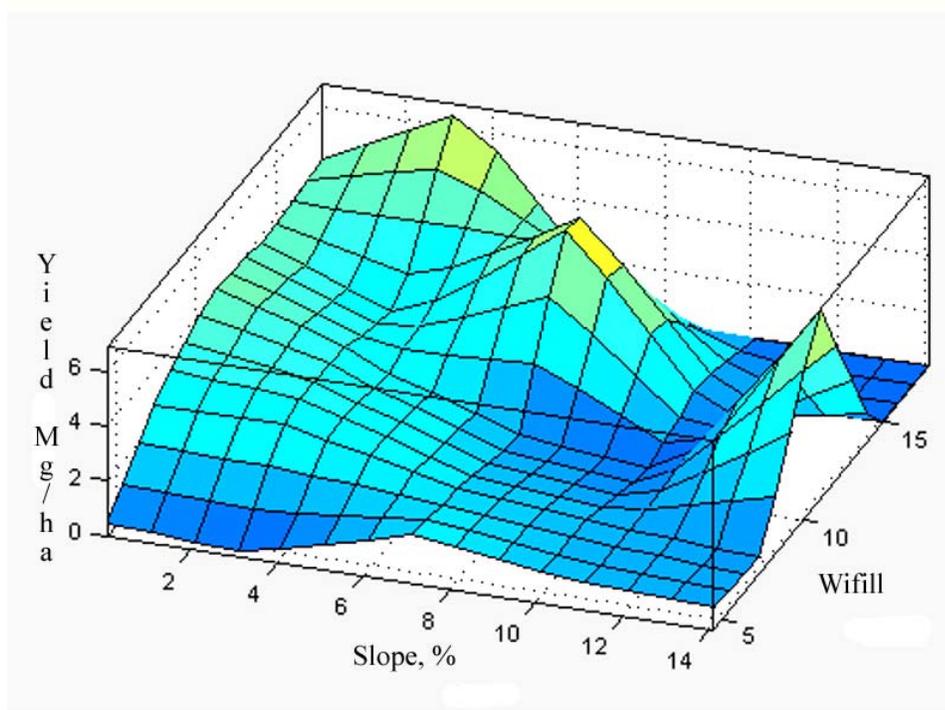


Figure 5. Yield-dependence on Wifill and Slope computed using the two-input FIS.

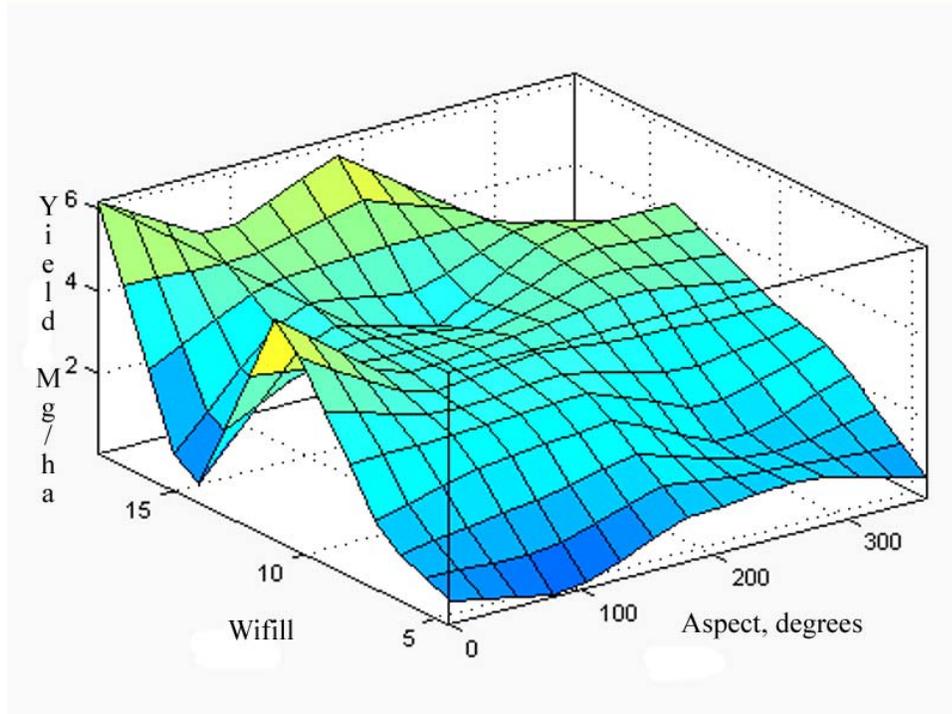


Figure 6. Yield-dependence on Wifill and Aspect computed using the two-input FIS.

For practical application and interpretation these two-dimensional dependencies can be presented as contour maps. For example, Figure 7 maps the joint dependence of yield on normalized values of ‘Slope’ and ‘Aspect’:

$$'Slope' \equiv S/S_{\max}$$

where S denotes Slope in percent, and the subscript max denotes the maximum slope value in the dataset.

$$'Aspect' \equiv (\cos Aspect + 1)/2$$

where, $\cos(Aspect)$ equals 1 at either 0 or 360 degrees, so the normalized ‘Aspect’ in Figure 7 equals 0 for south, 1 for north, and 0.5 for either east or west. Thus, Figures 6 and 7 differ in the definition of Aspect.

Figure 7 shows that Aspect has little effect on yield for a given value of normalized Slope up to approximately $0.5 S_{\max}$. For $S_{\max} > 0.5$, Aspect plays a significant role (in this two-input space), with Yield peaking at $S = 0.75$ (or Slopes of about 10%) facing south. Gradients in yield response are also high in this area of the input space.

4. Summary and Conclusions

The use of FIS methods was demonstrated using high-resolution data from an agricultural field. In this case, the input data is “crisper” than in most applications of fuzzy theory, but fuzzy logic was useful for generating reasonably smooth response surfaces and revealed features of the yield

response to geomorphic attributes. Uncertainty or risk of yield failure below a threshold value could also be investigated with these FIS methods.

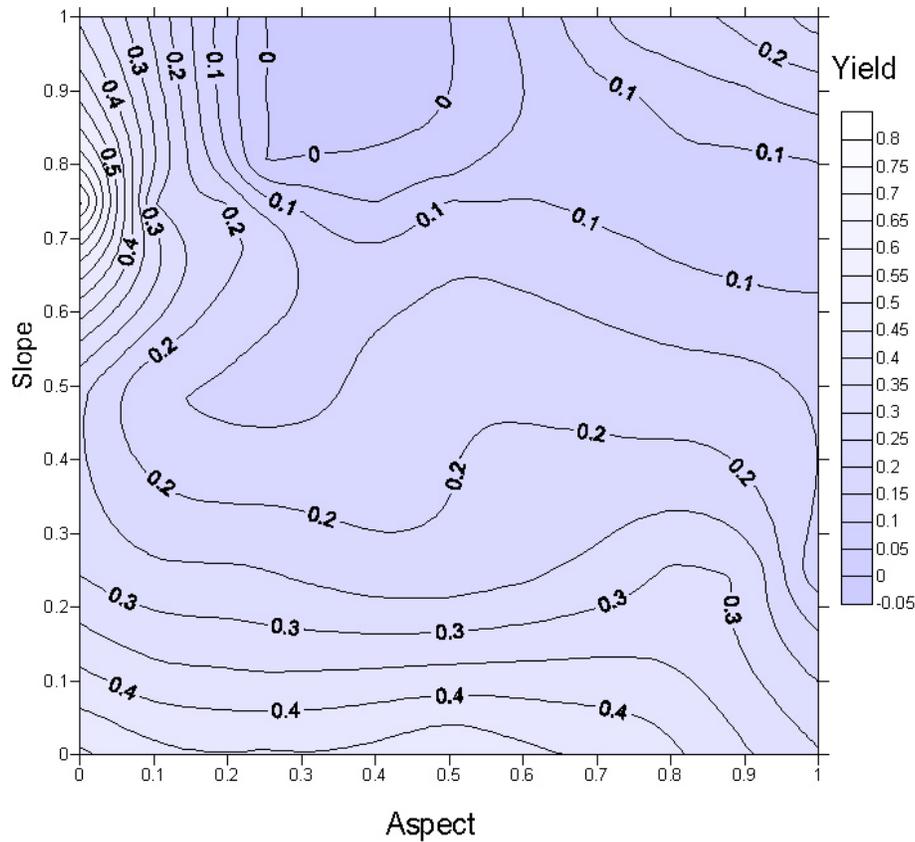


Figure 7. The yield-dependence on the slope and aspect computed using the two-input FIS. Here, Slope and Aspect were normalized to range from 0 to 1.

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