# Modelling ecological success of common pool resource systems using large datasets


## A Abstract

Social-ecological systems (SESs) are undoubtedly complex. Their complexity presents a major obstacle in research, in particular for the question which system attributes have to be in place to make ecological success probable. To overcome the many problems due to complexity, we suggest several solutions, which – in their combination – enable us to develop a quantitative model of the ecological success of SESs. First, the limitations of single case studies may be overcome by analysing larger data sets from one source. Among the advantages are the comparability of case studies and a broad quantitative basis for statistical analyses. Second, due to the complex and non-linear relationships *between* system attributes, a method is required that is able to cope with these problems. We use artificial neural networks (NN), a non-parametric statistical method. Third, a review of existing frameworks and the literature ensure that almost all relevant system attributes are actually taken into account, not only a fraction.

The resulting model, although still limited by a small case number (n = 122), explains the ecological success of irrigation and fisheries dealing with CPR-problems satisfactorily ($R^2 = 0.68$), mean standard error (MSE) = 0.02). Such a model could be used for policy-advice e.g. by NGOs or national governments trying to support community-based resource management.



*Keywords*: social-ecological systems, common pool resources, complexity, non-linearity, artificial neural networks, database


## B INTRODUCTON – Complexity as obstacle in SES-research

### *1 Number and interactions of variables*

Analyzing social ecological systems (SESs) and their ecological success in particular is a complex task. Biophysical as well as social influences have to be taken into account, and thus the number of relevant variables is enormous. Large databases like IFRI (international forestry resources and institutions, http://www.sitemaker.umich.edu/ifri/home) collect up to 1000 variables. In combination with the many interactions between these variables, this is perhaps the main reason why there is no ‘solution’ for designing a successful rule system that fits all or at least a majority of systems (Ostrom, Janssen, and Anderies 2007). Therefore, many studies are pessimistic whether constructing a general model of SESs with regard to their success is feasible at all (e.g. Agrawal 2001). Another obstacle is the unfortunate restriction of many research activities to one or few case studies (Poteete and Ostrom 2008). All too often, researchers have been trapped by one of these two extremes: either it is claimed “this case is unique”, therefore conclusions are posited to not be generalisable or “one-solution-fits-all”-schemes are proposed. In our opinion, both traps can and should be avoided. While it is true that there will not be a single solution for all or many systems, there are indeed general patterns to be discovered without losing the pecularities of each respective case (see section D, Results).

Still, there have been attempts to tackle the complexity of SESs. Most notable are meta-analyses (e.g. Pagdee, Kim, and Daugherty 2006), extensive reviews (e.g. Baland and Platteau 1996) and research linked on a global scale building up large-N databases (e.g. IFRI, http://www.sitemaker.umich.edu/ifri/home). This article focuses on the analysis of such large-N databases with data mining methods.

This approach has several advantages. First, a larger number of cases makes it possible to actually *compare* systems, a precondition of finding general patterns across SESs.

Second, meta-analyses face problems when comparing cases, since data has not been collected using the same methodology. Problems include missing or only small intersections of sets of variables collected in different research projects or – if they do exist – reduced comparability, because definitions and measurement methods are not the same across studies. This applies especially to social concepts like *social capital* or *heterogeneity of an actors' group* that are notoriously hard to define (Putnam 1995; Pretty 2003).

Third, in general, more variables are collected, simply due to the often bigger size of such research programs. This is important, because it is known that some system attributes may reverse direction of influence in the presence of other attributes (Agrawal and Chhatre 2006). For example, a SES with a high dependence of the user group on the resource may be judged to be in constant danger of overharvesting. However, e.g. in combination with high social capital or good leadership a high dependence may lead to sustainable behaviour. If this relation were true, a researcher without data on social capital would not see a pattern in regard to dependence. Since most studies work with a handful of factors only this is a major problem, because the full set of relevant factors for success might be as large as 40.,

## 2 Non-linearity of relations

It is often assumed that relationships between variables are linear. *However*, many authors agree that the interactions between system attributes like size of resource system, number of actors or heterogeneity of the group are often *non-linear* (Agrawal and Yadama 1997; Nagendra 2007). Heterogeneity of the focal group is a case in point. Both very homogenous or very heterogeneous groups are assumed to perform worse than a moderately mixed group, resulting in a curvilinear relationship of heterogeneity with ecological success or an even more differentiated impact (Baland and Platteau 1996; Frey and Ostrom, forthcoming).

Moreover, most interactions between influencing factors are simply not known, adding to a general high level of uncertainty. For example, the influence of social capital on success is assumed to be linear – the higher the trust and the closer the network structure, the better the ability of the group to coordinate and decide on locally adapted and fair rules. In addition, costs for monitoring and sanctioning should be low. However, it might be that social capital is dependent on the presence of strong leadership (Gutiérrez, Hilborn, and Defeo 2011). Therefore, although there might be a linear relation between social capital and ecological success, this relation is mediated by other influences like leadership in this case. Hence, without knowledge of the many relationships among system attributes, it is virtually impossible to construct a precise general model, because all the relevant relationships and their respective regressions would have to be entered.

In consequence, an appropriate statistical method to analyze SESs must

- be able to deal with large data sets,
- be able to determine the various interactions between variables *by itself* (i.e.without the researcher specifying it in advance) and
- be able to cope with non-linearity.

Fortunately, there are such methods, one of them being *artificial neural networks (NN)*. They are a rather complex non-parametric statistical tool (e.g. Reed and Marks 1999). Given a training set of data (consisting of input, i.e. independent variables, and output, i.e. the dependent variables) neural networks fit a (non-linear) function between the given values from input (here: SES attributes) to the output (here: ecological success of SES).

A wide range of disciplines (see Widrow, Rumelhart, and Lehr 1994) attest to the successful use of neural networks ranging from climate modelling (Knutti et al. 2003) and face recognition in computer science (Rowley, Baluja, and Kanade 1998) to automated stock trading in economics (Fernández-Rodríguez, González-Martel, and Sosvilla-Rivero 2000). In particular, good results

have been achieved in medicine (Khan et al. 2001) or genetics (O'Neill and Song 2003), because data quantity and quality are especially good in these disciplines.

Among the disadvantages of using NN is that the data set to be analyzed must not be too small in order for the nets to find general patterns. Furthermore, it is widely assumed that NN remain black boxes, that is, they produce implicit, but not explicit models. If this were true, their *predictive* capabilities would still remain intact, but scientifically this is of less value, because even a working model, i.e. a trained neural network yielding good predictions, could not be decomposed further to understand why it is such a good predictor. However, advanced methods recently developed (Thrush, Coco, and Hewitt 2008; Yeh and Cheng 2010; Gevrey, Dimopoulos, and Lek 2003) allow to open the black box and to determine estimates of relative impact for each input factor.

## 3 Organizing variables via a framework

If many variables are available, it is necessary to organize them, a task that is facilitated by *frameworks*. There are several frameworks for SESs (see Binder et al., forthcoming for a comparison). For our purposes, the SES framework (Ostrom 2009) is most suited for two reasons. The CPR-database, which we analyse here (see section C2 & C3) has been a starting point for the development of the framework. The SES framework is, in addition, perhaps the most widely used. Based on this framework and an extensive literature review, 24 system attributes have been derived and are used to organize the variables. A definition of each attribute, including the reasons why it is important for ecological success in SESs, can be found in Frey et al. (Frey and Rusch, forthcoming). Each system attribute is only included if at least four empirical peer-reviewed studies qualify it as relevant for success.

| ***Resource*** | ***Resource Units*** | ***Actors*** | ***Rule System*** | ***External Effects*** |
|---|---|---|---|---|
| Size | Manageability | Number | Group boundaries | Exclusion |
| Boundaries | Regeneration capacity | Composition | Participation | Relations |
| Accessibility | | Social capital | Legal certainty | Capabilities to adapt to change |
| Initial condition | | Dependency on resource | Administration | |
| | | Dependency on group | Information | |
| | | | Characteristics of rules | |
| | | | Fairness | |
| | | | Control | |
| | | | Compliance | |
| | | | Conflict management | |

Table 1: Twenty-four system attributes relevant for the ecological success in SESs

As can be seen in table 1, these system attributes are on a higher abstraction level than variables and are used to subsume and bundle similar variables (see section C, Methods, for details).

There has been much debate on how to define the output – success. However, it often consists of three dimensions: *social success* (often measured as some form of equity or contentedness of the actors), *economic success* (often measured via some indicator of wealth or efficiency in costs to

benefits) and *ecological success* (often measured by the productivity or condition of the resource (e.g. biodiversity) (Pagdee, Kim, and Daugherty 2006). Due to data limitations, we restrict this analysis to ecological success.

Ecological success is split into four indicators (stability, quality of resource system, quality of resource units, externalities). For example, the indicator *stability* can be approximated by the variable 'duration of the current rule system', whereas the *quality of the resource system* is captured by variables like 'condition of the system: the physical condition of the system is as well maintained as is economically feasible given the terrain and technology available to the farmers or agency managing this system' where answers range Likert-style from 'System is in excellent condition' to 'System is in very bad condition'. In sum, 19 variables in the available data capture and measure different aspects of ecological success. This gives a very detailed and differentiated picture of systems ranging from very successful to failures (for recoding details, see section C, Methods).

# C METHODS

## 1 Hypotheses

Previous studies on system attributes contributing to the success of SESs support each other only partially. Considering the arguments above, this comes as no surprise. The following paragraph provides a short overview of some larger-N studies: in co-managed fisheries, a study of Cinner et al. (Cinner et al. 2012) cites market access and users' dependence on resources as strongest influence on overexploitation in 42 systems, while Gutierrez (Gutiérrez, Hilborn, and Defeo 2011) sees strong leadership, individual or community quotas, social cohesion and protected areas as most relevant to success in 130 co-managed fisheries worldwide. In a meta-analysis of 69 community-based forestry case studies, 'congruence between the biophysical and socioeconomic boundaries of the resources has the strongest association with the success of CFM' while strong leadership, monitoring and sanctioning are also important (Pagdee, Kim, and Daugherty 2006). These results support the "no panacea" verdict of other authors (e.g. Meinzen-Dick 2007) although there seems to be agreement on at least some success factors. It is, however, unsatisfactory to not know whether the differences are due to different sectors, different methods or just different variables collected.

We suggest that the discussed partial agreements and disagreements are at least partly due to the non-linear and complex nature of SESs. Therefore, we try to test the following hypotheses using artificial neural networks on a small set of SES data (n = 122):

*Hypothesis 1 – Non-linearity:* Assuming non-linear relations between system attributes, NN should perform better (predict ecological success more accurately) than multivariate linear regressions. If this hypothesis is supported, this is an indication for non-linear relationships between system attributes.

*Hypothesis 2 – SES can be analysed above case level:* Doubts have been raised about the generalisability of results regarding SES performance. This is further fueled by inconsistent results concerning which system attributes are relevant for the success and which are not. We hypothesise that on a level of description abstract enough to make different kinds of SES comparable, there are patterns allowing to reliably explain SES performance. If NN are able to predict SES performance equally well or even better *across sectors*, this could count as evidence in favour of this hypothesis.

## 2 Description of data

In order to capture the complexity of SESs, it is necessary to collect a set of variables as broad as possible. The database used here is a compilation of case studies put together by the Workshop in Political Theory and Policy Analysis at Indiana University lead by Elinor Ostrom. The case studies were coded by different reviewers and entered into the database during the years 1986 to 1991.

*Governing the Commons* (Ostrom 1990) draws on some of these cases in this database.

Data for each case was entered by one person, checked by another and corrected by a third person to ensure inter-rater reliability and correctness of data entries. The case studies are a selection of CPR-research world-wide, comprising 66 irrigation, 56 fishery, 2 forestry case studies and 1 other (myok). Only cases that had sufficient information about both biophysical and social aspects as well as outcomes – often screened from more than one publication – were entered into the database. The unit of analysis is one user group appropriating one type of resource unit from one resource system using one rule set. If other groups appropriate from the same resource or the rule set changed, this results in another data set.

Excluding the three cases of forestry and myok, 122 irrigation and fishery cases remain. Each case potentially has values for 592 variables. Variables are of different data types, ranging from free texts (e.g. 'Please write an abstract of the document being screened.'), yes/no-questions, matrices and numbers (e.g. 'Surface area of resource in square meters') to Likert-scales (e.g. '[...], the balance between the quantity of units withdrawn and the number of units available is: (1) Extreme shortage, (2) Moderate shortage, (3) Apparently balanced, (4) Moderately abundant, (5) Quite abundant'.

## 3 Coding process

In order to be able to feed the information available in the CPR database into the NN for analysis, the available data is recoded and combined. First, we excluded IDs, names, screener information and empty variables as irrelevant from the variable set. We then recoded and combined the remaining variables using a two-stage procedure.

First, three raters independently decided for every variable which indicator(s) of which factor(s) it pertained to best. The mean number of variables per indicator was 4.3 and the mean number of indicators per factor 2.4. Inter-rater reliability was $\alpha = 0.72$ (Krippendorff's alpha) on 1,764 decisions, while remaining disagreements were solved in group discussion. In a further step, the corresponding author combined redundant variables into single more informative ones, and created suitable measures, e.g. by calculating durations from raw year data, etc. Finally, all data was normalised to the range of -1.0 to 1.0, which is a technical requirement of the NN.

In stage 2, three raters again independently decided how important in their estimate each variable was for its respective indicator in relation to the others. In addition, it was estimated how important each indicator was within the respective factor, given its now known concrete composition. Inter-rater reliability at this stage was good (variable to indicator level: $\alpha = 0.843$ (Krippendorff's alpha), 786 decisions; indicator to factor level: $\alpha = 0.884$, 258 decisions).

Using the average importance ratings of the three independent raters, the final data was calculated in two additional steps. First, variables were combined into indicators using weighted summing, weights representing the average importance estimates of the three independent raters, and skipping over unavailable data, i.e. if one data point was missing, its relative weight was set to zero for this case. Only the remaining available data points were used to build the indicator level value. Still, in some cases there was not enough data available to construct indicator information. Thus, in a second step, we imputed the missing data points on the indicator level using automated step-wise linear regression model selection. Missing values were predicted by the best regression models found. Overall, 1,558 of 10,750 (about 14,5%) data points on the indicator level were imputed this way. Finally, the now completed indicator data was again aggregated using weighted summing, weights representing the average importance estimate of the three independent raters, to give the final factor level data to analyse.

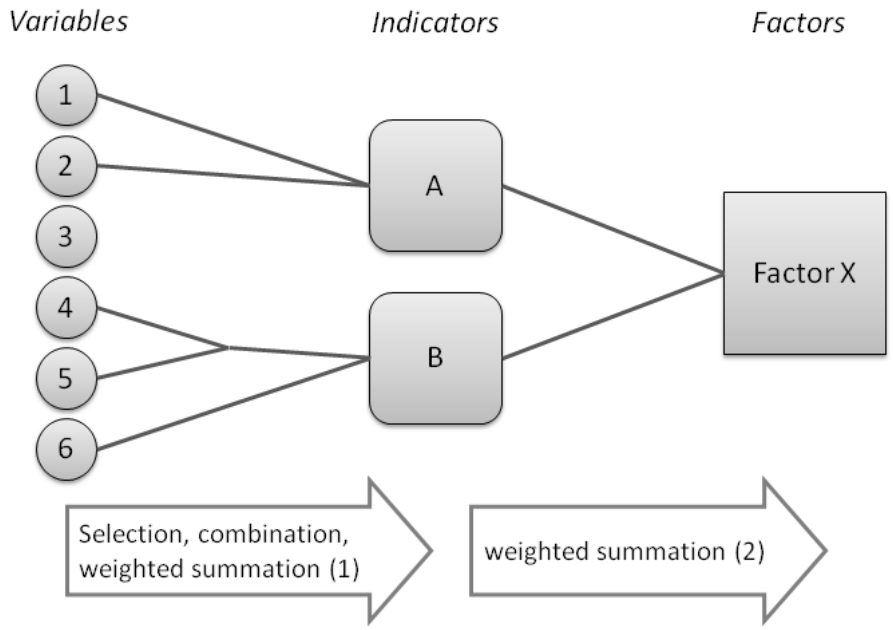


Figure 1: Data preparation scheme. Variables (left) are selected, combined and summed to yield indicator level values (middle) which are then summed to yield factor level data.

The coding procedures just described resulted in data available for 24+1 factors, i.e. 24 SES system attributes and one measure of the ecological performance of the system for 122 cases.

## 4 Analyses using artificial neural networks

The procedure of analysis using artificial neural networks is briefly described in the following. Artificial neural networks (ANN) are designed to reproduce the basic features of real neural networks. They consist of neurons and links between them. The links between neurons each carry a weight, representing the strength of that particular link between neurons. Neurons themselves have one main function. They read all incoming inputs and add them, yielding their own activation level which they propagate to all connected neurons. A simple, but analytically effective variant of ANN are ‘feed forward networks’ in which information is processed in one direction only (input to output). Thus, there are no loops or delayed feedback mechanisms in the network. Here, simple feed forward networks with a three layer architecture are utilised. These three layers of neurons are:

(1) 24 ‘input neurons’ whose activation level is determined directly by the data analysed;

(2) a systematically varied number of ‘hidden neurons’ which receive activation information from all 24 input neurons;

(3) one ‘output neuron’ which represents the final result of the calculation carried out by the network, i.e. the prediction of ecological success of a SES.

Figure 2 gives a schematic overview of a feed forward network with five hidden neurons.

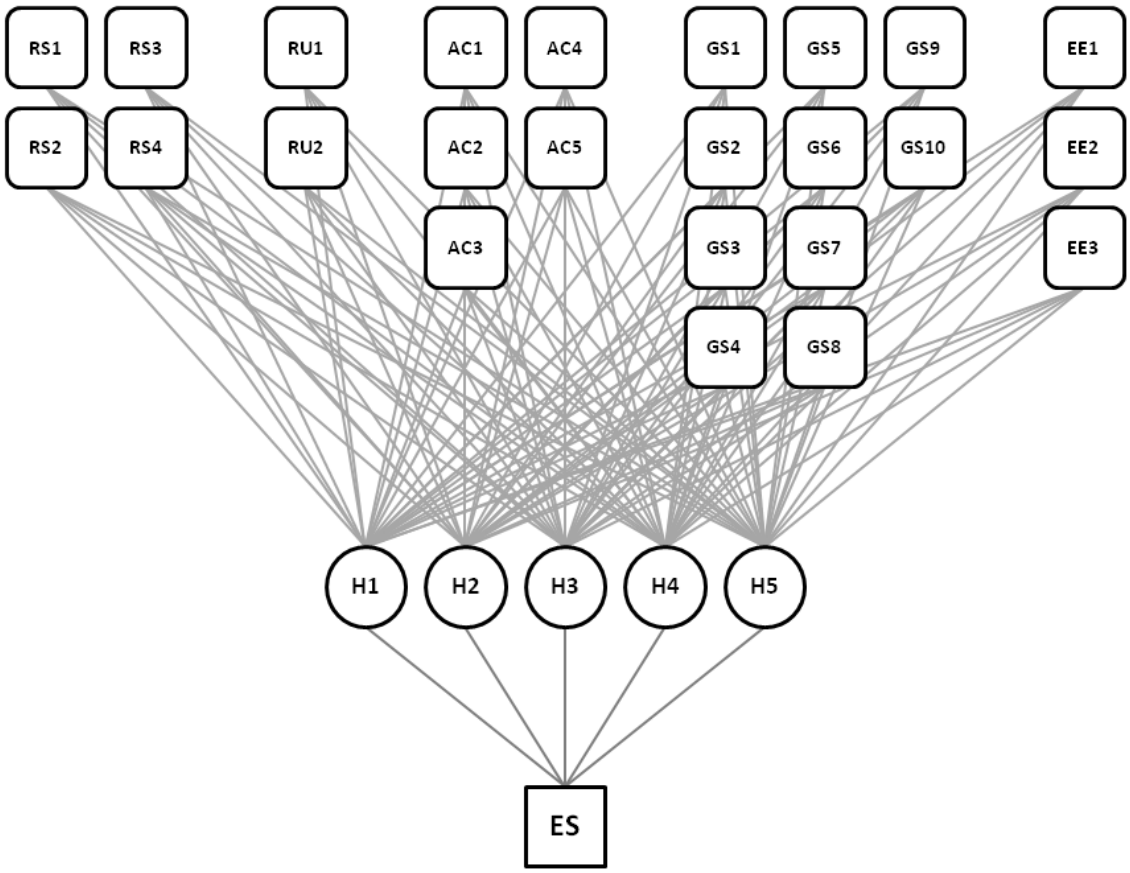


**Figure 2:** *Schematic overview of a feed forward network with five hidden neurons (H1-5), one output neuron (ES, i.e. 'Ecological Success') and 24 input neurons representing the 24 system attributes coded from the CPR data base (see* table *1). All calculations in the network are 'top-down', i.e. from input layer through hidden layer to output value, there are no feedbacks or loops.*

In order to arrive at good predictions of the target variable based on the given input data, ANN have to be trained. To find the best predicting net a number of properties has to be systematically varied. First, the best training (or 'learning') algorithm has to be determined, i.e. the rule set determining how the initially random weights of the links between neurons are updated in reaction to the net's prediction performance in each teaching step. Second, the appropriate number of hidden neurons for the particular prediction task has to be found. Unfortunately, there is no general recipe describing how to calculate the best suited number of hidden neurons, so this has to be done exploratively. Third, the optimal number of teaching steps or 'lessons repetitions' has to be determined. Lessons which are too short result in poor predictions while lessons too long can result in the effect of 'over-generalisation' or 'overfitting', i.e. networks performing excellently on 'known' case data from the training set while failing when being confronted with new case data, i.e. data which was not part of the training set. To prevent over-generalisation, the prediction performance of trained networks is systematically validated by evaluating their prediction performance using case data which was not used during training and is thus completely 'unknown' to the networks.

For this study, 10 different splits of the data were split into training (~80% of the data) and test sets (~20% of the data):

| | *Split name* | *Criterion: Ensure that training and test set are balanced regarding...* |
|---|---|---|
| 1 | BAL | ... the distribution of a variable stating the overall balance of regeneration and withdrawal from the resource. |
| 2 | MEAN | ... no variable – rather introduce some artificial biases (a technical test: we expected this split to be counterproductive). |
| 3 | FIRI | ... the number of irrigation and fishery cases and success. |
| 4 | FISH | ... success (but only use fishery cases, n = 44+12). |
| 5 | IRRI | ... success (but only use irrigation cases, n = 52+14). |
| 6 | RANDOM | ... everything (by just picking test cases out randomly). |
| 7 | SIZE | ... the distribution of smaller and larger resources. |
| 8 | SOCCAP | ... the distribution of social capital. |
| 9 | SUCCESS | ... success (use all cases, n = 100+22). |
| 10 | TYPERES | ... the distribution of a variable stating what the original coder's intuitive evaluation of the performance of the resource was. |

Table 2: Data splits for training and test sets

Using these 10 different training and test sets we ran a total of more than 39,000 different training sessions varying

a) net architecture (number of hidden neurons, 29 variations, 1 to 29 hidden neurons),

b) learning algorithm (3 variations, resilient, standard and backpropagation with momentum), and

c) training length (15 variations, ranging from 50 to 1,500 lesson repetitions).

Each configuration was run three times to test the stability of the results. The results stated in the next section (Results) were all obtained during the validation phase, i.e. the predictions were obtained for cases which networks had not encountered during training.

# D RESULTS

The results of the more than 39,000 training sessions runs are summarised in Table 3.

| Split | SUCCESS | IRRI | FIRI | FISH | SOCCAP | RANDOM | SIZE | MEAN | BAL | TYPERES |
|---|---|---|---|---|---|---|---|---|---|---|
| Best $R^2$ reached by a net | 0.80 | 0.78 | 0.76 | 0.76 | 0.69 | 0.68 | 0.63 | 0.55 | 0.50 | 0.36 |
| Best MSE reached by a net | 0.01 | 0.02 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 | 0.03 | 0.03 | 0.04 |
| Stable results? | YES | YES | YES | NO | NO | YES | YES | NO | NO | NO |

Table 3: Summary of training session results. MSE = Mean squared error; Results are labelled 'stable' if the well predicting nets did not show too much variance in prediction over the three independent training sessions.

Nets learned best on data splits balancing for success (SUCCESS, IRRI, FIRI and FISH) and among those the data split balancing only for success did best. The network with the single best prediction performance has 18 hidden neurons, used resilient propagation (RPROP) for learning and a training length of 1,500 repetitions. This net reached an $R^2$ of 0.80 (MSE = 0.01) in one of its training sessions. In the two repetitions using the same configuration it performed poorer, reaching only $R^2$ values of 0.55 and 0.47. In contrast, the best predicting robust net – the one with the best

performance overall (averaged over all three runs) – has 11 hidden neurons, also uses RPROP and 500 repetitions training. It reached an average $R^2$ of 0.68 (average MSE = 0.02).

In order to have a benchmark these nets' performance, we set up a standard multivariate linear regression model and fit it to the same data that the NN had been using to learn (training set of SUCCESS split). We then used that model to predict the data from the respective test set. The multivariate linear regression model only predicted with an $R^2$ of 0.45 (MSE = 0.04).

With the limited data set at hand (n = 122 cases) and regarding its imperfect nature (~15% of data had imputed at one stage), we must refrain from drawing any ultimate conclusions here. Still, we think that our results yield at least some tentative support for our hypotheses.

*Hypothesis 1:* A statistical tool suited to cope with nonlinearities in the data performs better than multivariate linear regressions (MLR) in predicting real-world SES data.

Here, however, we have so far only made one particular 'fluke' by finding a net with $R^2 = 0.80$ by chance. Our more reliably successful nets performed at an average $R^2$ of 0.68. This is quite a bit better than MLR prediction and NN should outperform MLR even more clearly, once larger SES data sets are available.

*Hypothesis 2:* The finding that the best split does not specifically balance cases from the two sectors (fishery and irrigation cases) in the data set supports hypothesis 2 rather strongly. It turned out to be most important for nets' prediction performance that training and test set were balanced regarding the dependent variable 'ecological success of SES'. However, whether nets were trained on sets consisting purely of fishery or irrigation cases or a mix of both did not influence performance much.

Although not too big, this data set is one of the few bigger ones available for SES performance and we appreciate the generosity of Lin Ostrom† allowing us to use it. Although we have to keep this limitation in mind, we think our results can encourage the use of more sophisticated tools in SES research in order to cope with their complexity.

# E DISCUSSION

We hope to have shown that a relatively precise quantitative model can be developed using a database of 122 case studies (irrigation and fisheries). Given that data from such data sources, with appropriate recoding, can be analysed by virtually any data mining or statistical method, it is unfortunate that such large-N sources are still rare (Poteete, Janssen, and Ostrom 2010; Poteete and Ostrom 2008).

It can be argued, therefore, that research on SESs has a great potential to go forward if three deficiencies are overcome. First, producing larger data sets should be made a priority in research. This would allow comparisons across cases or even sectors, enable the construction of general models, and much more. For this, a comprising joint SES database would be of extraordinary use. A suitable database design must facilitate approaches that come from different disciplines, hence should be general. A further desirable feature would be a data structure that is easily alterable in order to answer different research questions. Consequently, this would enable researchers to compare cases across countries, user groups or in fact any attribute that is in the data.

A second obstacle in SES research is the lack of rigorous definitions of its concepts (e.g. group boundaries) and their relationship among each other. A promising way are *ontologies* that formalize entities and their relationships in a logically consistent way. They could be based on existing frameworks. To move forward in SES research, a third problem, namely that concepts should be measured in a more consistent way using the same or at least similar indicators must be overcome as well. This is in fact a precondition for building up databases (see first problem). Such an operationalisation would in turn help to clear up inconsistencies when constructing ontologies or databases (second problem).

It therefore seems to be the time to develop a more complete framework than existing ones whose logical consistency could be tested e.g. by transforming it into an ontology. These theoretical considerations could then be used to develop a database with concepts on different levels of abstraction. Data collection (either by direct data entry into such a database via a browser-based interface over the internet or from fieldwork) could be facilitated enormously by a consistent, and general guiding framework.

The bottom levels of such a database would be operationalised indicators. These could easily be transformed or even taken as they are to build questionnaire items that make it possible to collect data on a large scale.

# F CONCLUSION

We analysed a database of 122 irrigation and fishery case studies in order to find general patterns of ecological success. For this, 222 variables are assigned to 24 system attributes in a highly structured coding and combining process. These system attributes then served as input for artificial neural networks that are able to find non-linear connections and general patterns in highly complex data sets. Despite the small number of cases, our best implicit model is able to predict success or failure of irrigation and fishery case studies with a rather high accuracy of $R^2 = 0.80$. A more robust model still performs at $R^2 = 0.68$. In comparison, a conventional multivariate linear regression reaches only $R^2 = 0.45$ for the same data.

In combination with other databases that have been analysed with neural networks (Frey and Rusch, forthcoming), it becomes possible to construct sector-specific and sector-independent models of SESs. This allows answering a long-standing discussion whether attributes like social capital or group boundaries are sector-independent or are important across resource types. In addition, quantitative models, and NN models with their ability to cope with non-linearities in particular, are able to predict ecological success for each case individually, enabling researchers and stakeholders alike to use a general model for the particular case they are interested in with its unique combination of attribute values.

We see a further use in the area of policy-advice. Advice can be based on such a model since it allows the manipulation of each individual attribute in order to see immediately the impacts on the particular system in question (e.g. improved rule-compliance, etc.). This should prove especially useful before taking major investment infrastructure decisions or changes in the rule system.

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