Landscape Ecol (2012) 27:869–885
DOI 10.1007/s10980-012-9735-2

RESEARCH ARTICLE

A fuzzy logic method to assess the relationship between landscape patterns and bird richness of the Rolling Pampas

Federico Weyland · Jacques Baudry · Claudio M. Ghersa

Received: 27 October 2011 / Accepted: 21 March 2012 / Published online: 3 April 2012

Abstract The loss of biodiversity in productive ecosystems is a global concern of the last decades. The Rolling Pampas of Argentina is an intensively cropped region that underwent important land use and landscape change, with different impacts on biodiversity of both plants and animals. Land use type and habitat complexity are hypothesized to be the most important factors determining species richness in agro-ecosystems. But it is not easy to define these attributes in an unambiguous fashion, or determine their interactions at different spatial scales. A fuzzy logic approach allows overcoming some of these problems by using linguistic variables and logic rules to relate them and formulate hypothesis. We constructed fuzzy logic models to study how bird species richness in the Rolling Pampas is related to land use and habitat complexity, and how these variables interact at two spatial scales. Results showed that at the local scale, landscape complexity is the most important factor determining species numbers; trees and bodies of water are the most influential complexities. The effect of local scale landscape attributes was modified depending on the context at broader scales, so that agricultural sites were enriched when surrounded by more favorable landscapes. There was a high dispersion in the predicted/observed value relationship, indicating that landscape factors interact in more complex ways than those captured by the models we used. We suggest that the fuzzy logic approach is suitable for working with biological systems, and we discuss the advantages and disadvantages of its use.

Keywords Agroecosystem · Biodiversity · Fuzzy logic · Pampas region · Argentina

Electronic supplementary material The online version of this article (doi:10.1007/s10980-012-9735-2) contains supplementary material, which is available to authorized users.

F. Weyland (✉) · C. M. Ghersa
IFEVA/CONICET, Departamento de Recursos Naturales y Ambiente. Facultad de Agronomía, Universidad de Buenos Aires, Av. San Martín, 4453 (C1417DSE) Buenos Aires, Argentina
e-mail: fweyland@agro.uba.ar

J. Baudry
INRA, SAD Paysage, 65, Rue de Saint Brieuc. CS 84215, 35042 Rennes Cedex, France

Introduction

The loss of biodiversity in agroecosystems led to the recognition of the necessity to develop management tools to counteract this trend (Sala et al. 2000). Management tools applied in EU countries have proven to have an idiosyncratic effect, as their effectiveness depends on landscape context (Tscharntke et al. 2005; Concepción et al. 2008; Batáry et al. 2010). As a consequence, extrapolation of results would not be the best option to develop new management tools for other regions. This is most relevant in novel ecosystems, like the Pampas (Argentina) agro-ecosystem where new combinations of species and abiotic conditions make the outcome of management even less predictable (Hobbs et al. 2006; Seastedt et al. 2008). For that reason, we need to improve our understanding on how landscape factors affect biodiversity in this region.

The most common hypothesis is that land use intensity and landscape heterogeneity are two of the most important factors that determine biodiversity in agroecosystems. Intensive land use, which is related to high levels of disturbance, agrochemicals and human appropriation of net primary production, exerts a negative impact on species (Matson et al. 1997; Flynn et al. 2009). Alternative land uses or managements, such as pastures or organic agriculture, offer better habitat conditions (Bengtsson et al. 2005; Cingolani et al. 2008; Kragten and Snoo 2008). In the argentine Pampas, bird diversity and abundance is generally negatively correlated with the percentage of land used for intensive human activity, in the landscape at local and regional scales (Filloy and Bellocq 2007; Codesido et al. 2008; Schrag et al. 2009; Cerezo et al. 2011). Conversely, habitat heterogeneity or complexity, considered as compositional and configurational heterogeneity rendered by different cover types and elements of the landscape (Fahrig et al. 2011), enhances biodiversity by providing resources and refuge for a wide arrange of species (Benton et al. 2002; Dauber et al. 2003; Bennett et al. 2006).

There is a growing recognition that land use intensity and landscape heterogeneity interact in complex ways at different spatial scales to determine local species numbers (Levin 1992; Beever et al. 2006). For example, intensive farming has a negative effect on weed species numbers, but only in simple landscapes (Roschewitz et al. 2005). A similar pattern was found for vascular plants, butterflies and carabids, in Swedish agro-ecosystems (Weibull and Östman 2003). The larger pool of species of complex landscapes can compensate local management through colonization and mass effects. Mass effects are the occurrence of species outside their core habitats, increasing alpha diversity while decreasing beta diversity (Schmida and Wilson 1985). The interaction between scales should be taken into account in studies that aim at elucidating the relevance of landscape attributes to determine biodiversity.

Assessing the combined effects of land use intensity and landscape complexity also sets a series of methodological challenges. First of all, these terms have to be defined in an unambiguous fashion to facilitate the communication and comparison of results. The myriad of indices used to describe landscape complexity makes this task difficult (Liebhold and Gurevitch 2002; Turner 2005). Moreover, many attributes of the landscapes cannot be combined in a single mathematical index, such as the physiognomic complexity rendered by landscape features like hedgerows, trees, bodies of water and human settlements. When faced with this problem, the most common statistical approach is multivariate analysis like CCA or multiple regression (see for example Cueto and Casenave 1999; Schrag et al. 2009; Cerezo et al. 2011). These methods, though widely accepted and used, have still the problem of integrating and interpreting the results beyond the mathematical formalisms. Instead, the description of landscape complexity by means of its component features is better attained in a natural language for which available indices are not completely suitable.

Even when having a single mathematical index of landscape complexity, ecologists face the problem of discerning different degrees of this attribute. The characterization of landscape heterogeneity by means of metrics leads to a continuum of situations from no heterogeneity (i.e. homogeneity) to high heterogeneity (Li and Reynols 1995) with no clear-cut distinction among them. Is there a point where a landscape stops being simple and starts being complex? As well as for many other landscape attributes, there does not seem to be a threshold that separates different levels of landscape complexity.

The last problem we point out here is that in many cases the information needed to parameterize landscape models is either lacking, scarce, or found as expert knowledge that is not formalized or quantified. Traditional methods are not capable of incorporating the uncertainty and ambiguity of this kind of information.

The problems described so far can be overcome using logic and fuzzy reasoning (Zadeh 1965; Dubois and Prade 1996). Logic rules allow combining statements expressed in a natural language using linguistic variables. This approach allows us to compute the information with words rather than numbers, using a means by which ecologists easily communicate among themselves and transmit knowledge (Zadeh 1996). On the other hand, most ecological states, for instance, sustainability, do not have the properties of classic set theory. That is, where an element belongs to a set with full membership (an element is either A or B, "sustainable" or "not sustainable"). Rather, there is a continuum in the membership to different sets like "low" and "high" sustainability. Fuzzy theory is a methodology capable of taking into account the uncertainty of membership of elements to the different sets, by assigning a partial membership to each set.

Fuzzy logic was developed for control systems in engineering, but proved to be useful as well in soft systems such as biology, sociology and economics (Center and Verma 1998). This approach was successfully applied in sustainability assessment (Ducey and Larson 1999; Phillis and Andriantiatsaholiniaina 2001), landscape description (Liu and Samal 2002; Rocchini and Ricotta 2007) and environmental impact analysis (Ferraro et al. 2003; Lu et al. 2006). The aim of this paper is to explore the influence of landscape use and complexity on bird diversity of Pampas agroecosystems, and their interaction at different scales using a fuzzy logic approach. We will analyze the advantages and limitations of this method compared to more traditional statistical analysis.

The fuzzy inference process

A fuzzy inference process consists of four steps, which we will describe briefly in this section. The reader is advised to consult the available bibliography for deeper explanations on fuzzy set theory and methodology (e.g. Dubois and Prade 1996; Zadeh 1996; Center and Verma 1998).

Definition of input and output variables

The output variable is that over which predictions of the model will be made; for instance, landscape complexity. The input variables represent the physical domain in which elements are measured, and their degree of membership relative to the output variable is determined. For example, two input variables of the output variable "landscape complexity" could be land use richness (measured as number of different land use types) and vegetation physiognomic heterogeneity (measured as number of vegetation strata).

Definition of linguistic values and membership functions

In order to compute with words, variables need to take linguistic values, such as "simple", "medium", "complex" and "very complex" for landscape complexity, "low" and "high" for land use richness and "few" and "many" for vegetation strata. Each of these linguistic values represents a fuzzy set. The membership functions will determine the degree to which an element X belongs to each variable. It is in this step that fuzzy logic differs from crisp logic, in which an element is either a member of the set "low", "medium" or "high". In fuzzy logic, the transition between two sets is gradual, so elements can be members of any set with a difference of degree. This degree of membership is expressed as a 0–1 interval (1 represents full membership). Membership functions, $\mu A(x)$ and $\mu B(x)$, can take any shape depending on the nature of the variable; but when the knowledge of the system is poor, triangular or trapezoidal functions are usually the best choice to reduce overall error (Pedrycz 1994) (Fig. 1). This step is one of the most important and difficult of the fuzzy inference process, as some criterion must be chosen. Fuzzy logic allows incorporating a wide array of information sources—even ambiguous, uncertain or subjective ones. The construction of the membership function then can rely on previous information, empirical data or expert knowledge. The flexibility of fuzzy logic also allows modifying the shape and parameters of the functions as new data or knowledge becomes available.

Application of fuzzy rules

The input variables are combined through logic rules to determine a value in a set of the output variable. This is another crucial step in the fuzzy inference process for the same reasons as explained above. Furthermore, in this step, hypotheses and predictions of the models are made explicit and translated in mathematical terms.

A fuzzy rule consists of a precedent part expressed in the form of an "IF…" statement. Many precedents can be combined to give a consequent expressed in the form of a "THEN…" statement. Fuzzy rules must cover all possible combinations of values for the input variables. In our example rules could be as follows:

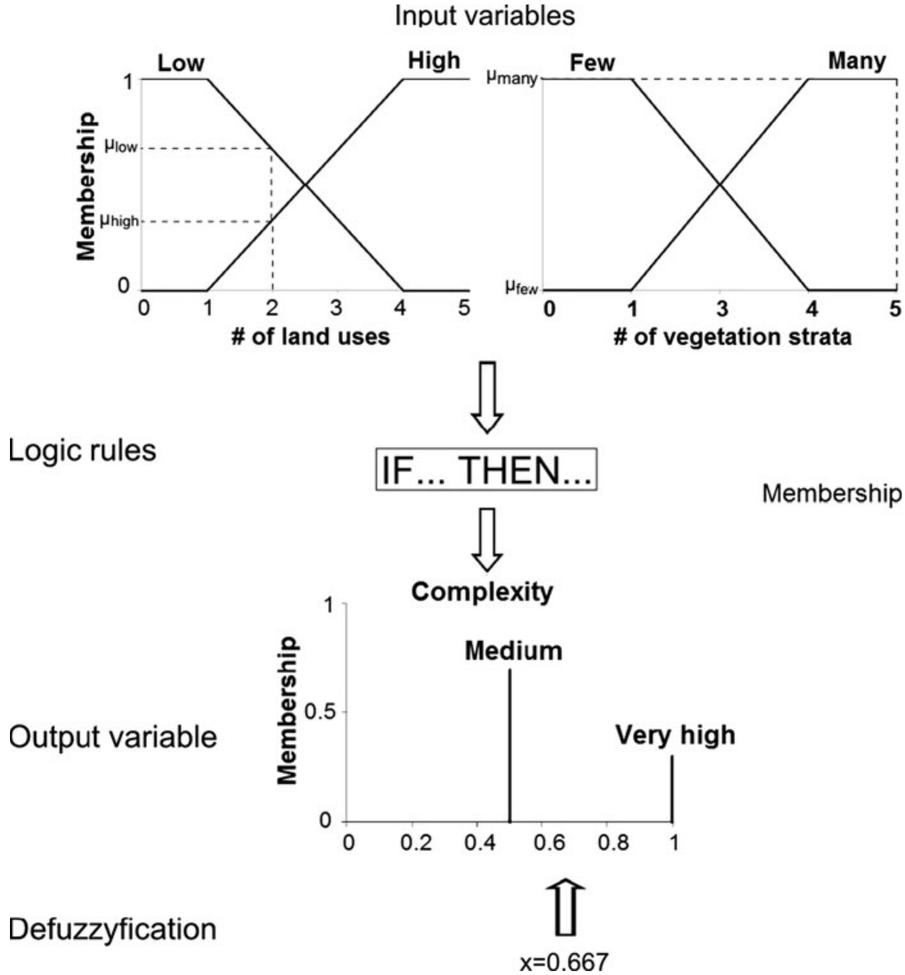


Fig. 1 General method of a fuzzy inference process

(1) IF land use richness is low and IF vegetation strata are few, THEN landscape complexity is low.
(2) IF land use richness is low and IF vegetation strata are many, THEN landscape complexity is medium.
(3) IF land use richness is high and IF vegetation strata are few, THEN landscape complexity is high.
(4) IF land use richness is high and IF vegetation strata are many, THEN landscape complexity is very high.

For a particular measurement the membership values have to be calculated for all rules that are activated. As an example, a landscape, that has two different cover types and five vegetation strata, activates rules 2 and 4 (Fig. 1). The degrees of membership are: land use richness$_{High} = 0.33$, land use richness$_{Low} = 0.66$, vegetation strata$_{Many} = 1$, vegetation strata$_{Few} = 0$. The fuzzy operator "and" is translated as min[$\mu A(x);\mu B(x)$], which represents the truth value of element x for the output set activated by the rule (complex, in this case). The truth value is calculated for all output sets. If two or more rules have the same consequent, the fuzzy operator is max. As a result, we get the partial memberships of the measurement to each output set.

Defuzzification

The membership of an element to multiple and different sets is more realistic than a full membership to any one of them, but it is not useful for subsequent statistical treatment of the data. So the last step of the fuzzy inference process consists in "defuzzifying" the results, to give a single output value (so-called "crisp"

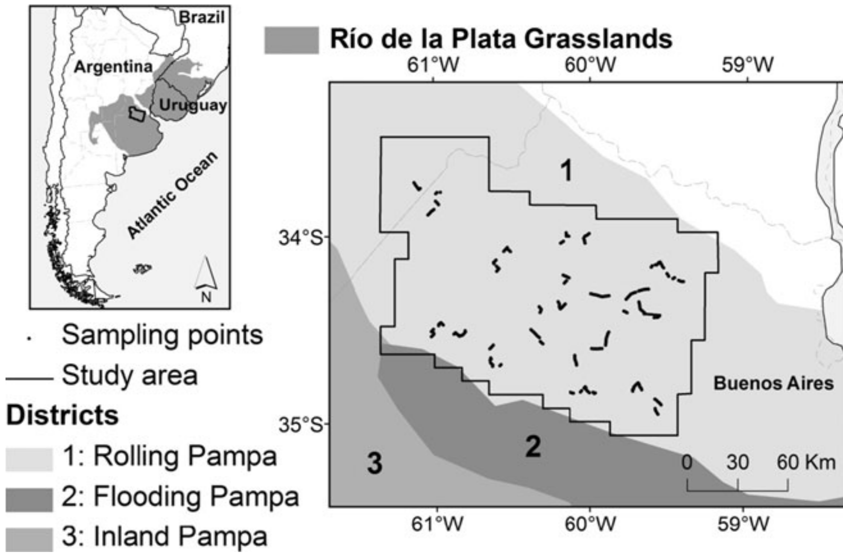


Fig. 2 Study area in the Rio de la Plata Grasslands of South America. This study was carried out in the Rolling Pampas region (*1*)

value). This final value can be used as an input to any traditional statistical analysis like Anova, correlation or multivariate analysis. There are two main defuzzyfication methods, called Mamdani and Sugeno. Here, we used Sugeno, which considers output membership functions as constant, and is recommended because it is better suited for mathematical analysis, and is computationally efficient (Van Leekwijck and Kerre 1999). The final output value is a weighted average of all activated output functions:

$$\text{Final output} = \frac{\sum_{i=1}^{n} x_i \mu_i}{\sum_{i=1}^{n} \mu_i} \quad (1)$$

where x_i is the value in the output variable and μ_i is the membership value for rule i. In this way, the output variable covers the range of 0–1, and the output value can be any number between them. In our example, Landscape complexity is 0.667 (Fig. 1). This represents a situation where the landscape is closer to a definition of complex than simple, but it is not completely one or the other.

Methods

Study area

This study was carried out in a 23.296 km^2 area of the Rolling Pampa (Fig. 2). The Pampas region was originally a temperate, mesic grassland, characterized by the absence of trees and generally flat topography (Soriano 1991). Since the mid 1800's, this region has been severely transformed by agricultural and grazing activities (Ghersa and León 2001). European colonization also introduced changes in the physiognomy of the vegetation. Woody species were planted to provide shade and delimitate properties. Some of these species, like *Gleditsia triacanthos*, *Morus alba*, *Melia azedarach*, *Broussonetia papyrifera* and *Ligustrum lucidum* adapted well to local conditions and invaded roadsides, wastelands and grassland relicts (Ghersa et al. 2002). In the last 20 years, the introduction of no-till cropping systems and GM crops replaced the mixed grazing–cropping system with permanent agriculture with an increase in the soybean area (Baldi and Paruelo 2008). Cattle operations are nowadays restricted mainly to the Flooding Pampas region, where agriculture is restricted by hydrology and soil. Some of the bird species of the region were negatively affected by the reduction in grassland area (Gabelli et al. 2004) or pesticide use (Goldstein et al. 1999), while others colonized from the surrounding ecoregions, favored by the introduction of trees (Comparatore et al. 1996, Sarasola and Negro 2006).

Landscape classification

We divided the study area with a grid of 8 × 8 km cells (hereafter, facets sensu Zonneveld 1989). We used supervised classified Landsat TM images of four cropping years (2002/03, 2004/05, 2006/07 and 2008/09) following the method described by

Guerschman et al. (2003). This classification identified seven land use types: water, lowlands, pastures, maize, soybean, wheat, and urban. In each facet we measured landscape indices for each land use type: % cover area, number and size (in ha) of patches, effective mesh area (a fragmentation index that simultaneously considers the patch size and the level of dissection, (Jaeger 2000), total border (in km). With these variables we ran a cluster analysis using the Sorensen distance and farthest neighbor group linkage method to classify the landscape at the facet scale. We obtained seven groups, characterized by their main cover type, that were ranked in a landscape transformation level gradient: water, lowlands, pasture, mixed pasture, mixed agriculture, agriculture and urban (Table 1). We randomly selected 39 facets in which we placed field sampling points 1 km apart (3–8 points per facet, $n = 260$) along secondary dirt roads (Fig. 2).

Development of fuzzy models

We developed three fuzzy models to explore the effect of landscape characteristics on bird species numbers. The first two models relate variables at the local scale, while the third explores the interaction of variables at local and facet scales.

The first model was designed to provide a measure of landscape complexity at the local scale. We considered complexity as a structural complexity, rendered by the different cover types and elements present in the landscape. Following this criterion, and based on a literature review and interviews of experts, we defined six input variables potentially relevant to determine bird diversity in agroecosystems at this scale: roadside vegetation complexity, trees as woodlots and tree lines, cover type richness, presence of scattered trees, houses and water bodies (Fig. 3, Appendix 4 in supplementary material). We hypothesized that the landscape complexity rendered by roadsides depends on the contrast between the vegetation and the main land use in the matrix, and whether or not there are similar ecotopes in the landscape (Appendix 1 and 2 Supplementary material). We also considered that the relevance of the roadside would depend on its width. So, we built an intermediate fuzzy rule base to weigh the importance of the width of the roadside and obtained a final variable, which is the complexity rendered by the roadside. The complexity rendered by woody vegetation depends on the combination of presence/absence of tree lines and simple (monospecific) or complex (multispecific with some secondary succession) woodlots. The landscape complexity increases when more of the latter elements are present (Appendix 3 in supplementary material). The last three variables (water bodies, trees and houses) are non fuzzy as they can only take the values 0 (absence) or 1 (presence). But fuzzy logic allows combining fuzzy and crisp variables in a model (Dubois and Prade 1996). Bodies of water are temporary or permanent ponds found across the landscape or in depressed surfaces along roadsides. We considered only inhabited houses and not other buildings like store houses, sheds and silos.

We constructed the fuzzy rule bases and membership functions to relate these variables to the final landscape complexity based on theoretical expectations, and tested them with empirical data.

In order to get this data we carried out field surveys in two consecutive years (2007 and 2008), during the southern hemisphere bird reproductive season (November–December). At each point we measured landscape variables in a 350 m radius (hereafter, local scale) by visual inspection: cover area for each land use type, roadside vegetation condition (spontaneous, grazed, spayed, cultivated, stubble, ploughed, ditch), presence of trees (woodlots, tree lines, scattered trees), bodies of water and inhabited houses. Bird surveys were carried out using the point count method (Ralph et al. 1995). Each point was visited once during the reproductive season of each year. Surveys were done in the first hours after sunrise (6:00–10:30 a.m.) in good weather conditions and all birds seen or heard during 5 min in the 350 m radius were counted. This radius was determined based on the field observer ability to detect individuals and identify the species (Rocha "personal communication"). Species richness was calculated as the number of species detected in the sampling point.

We started with a parsimonious model, having the fewest possible number of membership functions and similar weight of the input variables to determine landscape complexity (the weight was determined by the logic rules). We then correlated the output values with the observed species number.

A second model explored the interaction between landscape complexity and land use (agricultural vs. pasture), to predict species numbers (Appendix 5 in supplementary material). The output variable of model

Table 1 Summary of landscape attributes for each land cover type in each facet (mean±SD). MPS: mean patch size

	Class area (ha)	# of patches	MPS (ha)	Effective mesh size
1. Water				
Water	2,163 ± 486	13.3 ± 11.3	523 ± 687	6,995,592 ± 3,779,878
Lowlands	1,331 ± 388	227 ± 78	6.8 ± 3.6	926,240 ± 1,285,645
Pasture	1,095 ± 302	288 ± 108	4.5 ± 2.9	332,220 ± 340,945
Maize	400 ± 182	70 ± 45	6.5 ± 2.3	155,541 ± 310,553
Soybean	865 ± 341	146 ± 66	7.5 ± 5.3	283,017 ± 268,279
Soybean/wheat	417 ± 187	74 ± 56	7.1 ± 4.0	147,157 ± 266,264
Urban	83 ± 81	107 ± 68	0.7 ± 0.8	3,591 ± 8,995
Agriculture	1,683 ± 543			
Non agriculture	2,426 ± 356			
Total border (km)	676 ± 118			
2. Lowlands				
Water	110.5 ± 360	1.0 ± 1.4	34.1 ± 113	184,507 ± 680,397
Lowlands	3,648 ± 572	154 ± 45	25.8 ± 9.4	16,909,754 ± 6,858,181
Pasture	1,484 ± 572	433 ± 161	3.6 ± 1.4	717,834 ± 1,016,788
Maize	141 ± 216	44 ± 49	3.3 ± 5.1	17,697 ± 40,726
Soybean	574 ± 516	136 ± 66	4.9 ± 4.6	289,541 ± 755,316
Soybean/wheat	347 ± 223	135 ± 78	4.0 ± 4.1	37,570 ± 48,747
Urban	47 ± 77	66 ± 53	0.5 ± 0.6	969 ± 2,631
Agriculture	1,062 ± 817			
Non agriculture	5,132 ± 958			
Total border (km)	751 ± 133			
3. Pasture				
Water	1.9 ± 6	0.5 ± 1	0.8 ± 2.0	48 ± 223
Lowlands	796 ± 489	324 ± 111	2.3 ± 1.1	111,888 ± 283,351
Pasture	4,611 ± 450	80 ± 31	69 ± 33	32,827,172 ± 6,775,194
Maize	215 ± 199	96 ± 49	2.6 ± 1.9	12,141 ± 12,721
Soybean	494 ± 259	91 ± 39	5.7 ± 2.8	63,729 ± 59,051
Soybean/wheat	221 ± 199	65 ± 50	3.1 ± 2.0	46,615 ± 50,646
Urban	62 ± 72	53 ± 47	1.0 ± 0.6	777 ± 1,140
Agriculture	930 ± 423			
Non agriculture	5,407 ± 454			
Total border (km)	608 ± 109			
4. Mixed pasture				
Water	10.0 ± 66	4.3 ± 12.2	0.6 ± 1.8	5,534 ± 63,430
Lowlands	848 ± 466	270 ± 92	3.5 ± 2.4	362,053 ± 804,503
Pasture	2,968 ± 733	174 ± 68	20.7 ± 13.2	7,070,422 ± 6,221,718
Maize	514 ± 296	121 ± 72	5.4 ± 3.8	3,389,308 ± 8,722,125
Soybean	1,427 ± 494	170 ± 99	10.9 ± 6.5	924,929 ± 1,595,829
Soybean/wheat	523 ± 310	98 ± 57	6.3 ± 4.0	237,293 ± 377,813
Urban	87 ± 101	62 ± 52	14.7 ± 64.5	11,970 ± 46,375
Agriculture	2,465 ± 703			
Non agriculture	3,817 ± 749			
Total border (km)	721 ± 108			

Table 1 continued

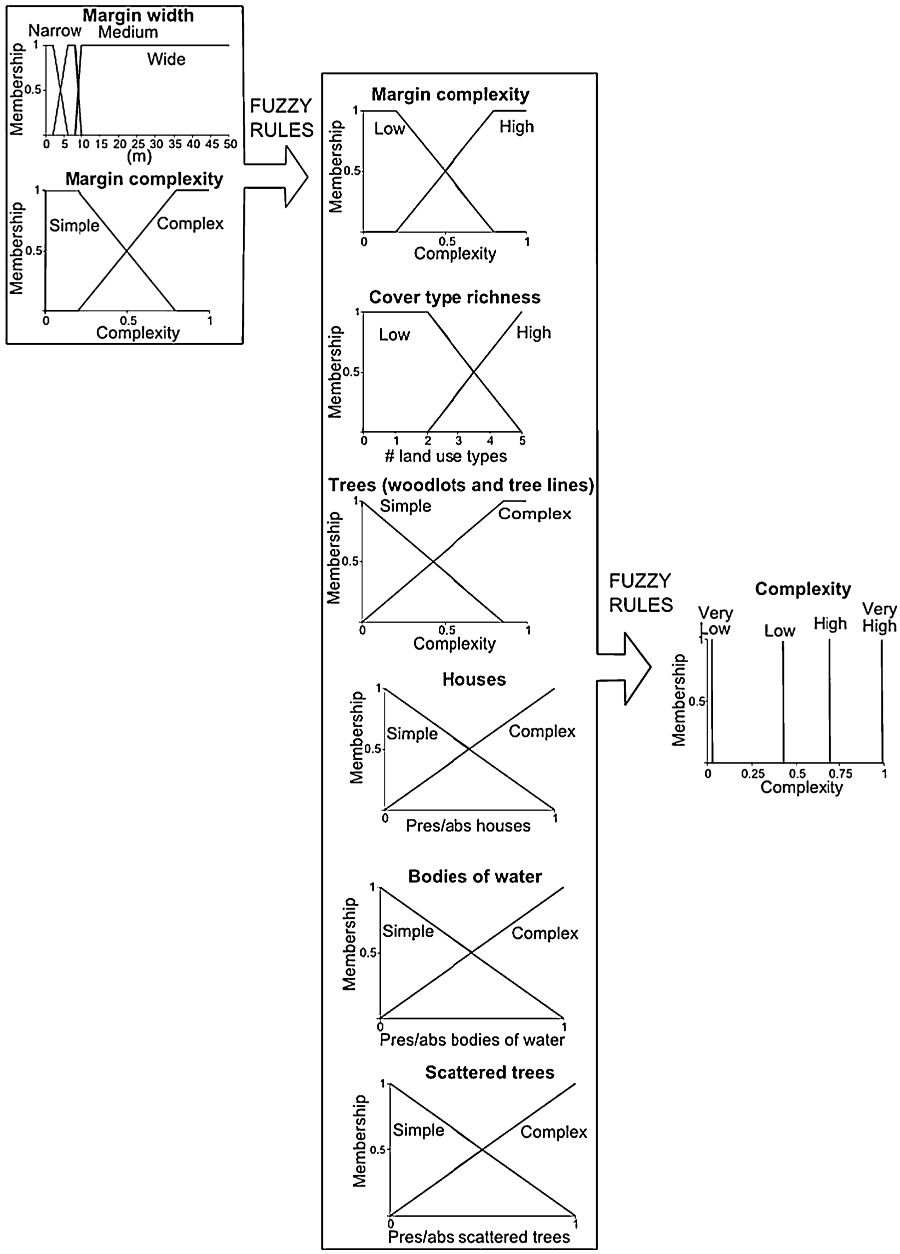
	Class area (ha)	# of patches	MPS (ha)	Effective mesh size
5. Mixed agriculture				
Water	23.9 ± 105	4.5 ± 5.9	3.6 ± 15.9	11,510 ± 80,716
Lowlands	1,122 ± 667	504 ± 137	2.6 ± 2.4	780,621 ± 1,774,489
Pasture	1,405 ± 672	512 ± 163	3.5 ± 3.5	286,577 ± 737,265
Maize	750 ± 340	90 ± 47	9.7 ± 5.7	1,147,589 ± 2,791,670
Soybean	2,016 ± 614	284 ± 74	7.8 ± 3.7	1,959,403 ± 2,274,830
Soybean/wheat	1,023 ± 354	158 ± 63	7.8 ± 4.8	243,541 ± 232,337
Urban	58 ± 115	79 ± 72	5.8 ± 47	10,658 ± 77,149
Agriculture	3,789 ± 964			
Non agriculture	2,527 ± 950			
Total border (km)	941 ± 121			
6. Agriculture				
Water	5.1 ± 23	4.8 ± 17	1.5 ± 13.8	530 ± 5,296
Lowlands	524 ± 425	211 ± 118	2.9 ± 2.8	231,686 ± 626,596
Pasture	1,123 ± 548	267 ± 111	5.1 ± 3.9	543,858 ± 1,078,063
Maize	956 ± 388	108 ± 62	11.2 ± 6.8	258,910 ± 423,685
Soybean	2,740 ± 669	134 ± 60	26.1 ± 20.2	6,581,822 ± 6,531,884
Urban	73 ± 91	60 ± 41	5.1 ± 30.9	8,084 ± 42,709
Agriculture	4,673 ± 707			
Non agriculture	1,648 ± 699			
Total border (km)	653,337 ± 115,829			
7. Urban				
Water	1.9 ± 4	4.4 ± 9.3	0.5 ± 1.5	12 ± 51
Lowlands	961 ± 654	470 ± 189	2.1 ± 1.6	348,131 ± 1,118,584
Pasture	1,603 ± 722	478 ± 221	5.1 ± 6.3	424,292 ± 934,772
Maize	483 ± 289	230 ± 149	2.7 ± 1.9	1,450,120 ± 4,177,949
Soybean	1,911 ± 767	298 ± 154	9.0 ± 7.7	2,059,765 ± 2,963,654
Soybean/wheat	700 ± 319	197 ± 77	3.8 ± 1.7	618,739 ± 2,055,692
Urban	740 ± 587	158 ± 107	127 ± 320	981,403 ± 1,547,663
Agriculture	3,095 ± 983			
Non agriculture	2,563 ± 928			
Total border (km)	1,075 ± 206			

Effective mesh size is calculated as $\frac{1}{A_t}\sum_{i=1}^{n} A_i$ where A_t is total area of the region and A_i is the size of the patch

#1 was used here as an input variable together with % pasture cover (Fig. 4).

In the third model we explored how interactions between land use and landscape complexity are modified in different landscape contexts. We created a variable at the facet scale, which is the landscape transformation intensity, a degree of how much the landscape has been transformed from the original grassland. We assigned a value for each facet class in a landscape transformation level gradient, from 1–7 (Table 1). We then integrated the values of each facet for the 4 years analyzed (Fig. 5). In that way, a value of 28, indicates that the facet was always classified as Urban (value for urban facets = 7) and represents the maximum possible value. A value of 4 indicates a minimum level of transformation, where the facet was classified as water in the 4 years. We integrated the data of 4 years to avoid noise from variations due to climatic conditions, which also augmented the error in the satellite image classification. We averaged the

Fig. 3 Membership functions of the fuzzy model describing landscape complexity at the local scale



species richness for points in the same facets to avoid pseudoreplication. This model then has three input variables, two at local scale and one at the facet scale (Appendix 6 in Supplementary material, Fig. 6). We used Fuzzy Logic Toolbox of Matlab 2006b to construct all the fuzzy models.

We used the field data on bird surveys to validate and at the same time improve the models. In each case, we modified the rule base and membership functions to improve the fit of the output variable. In model #1 we correlated the complexity value with observed species richness and we seek to improve the r of this correlation. In models #2 and #3, the output variable is species richness. To test these models' performance, we used the mean absolute error (MAE), which is a measure of how much predicted values deviate from observed values. The membership functions and rules were modified to reduce as much as possible the MAE of the model. This is a method suitable for model testing (Mayer and Butler 1993) and has been used in

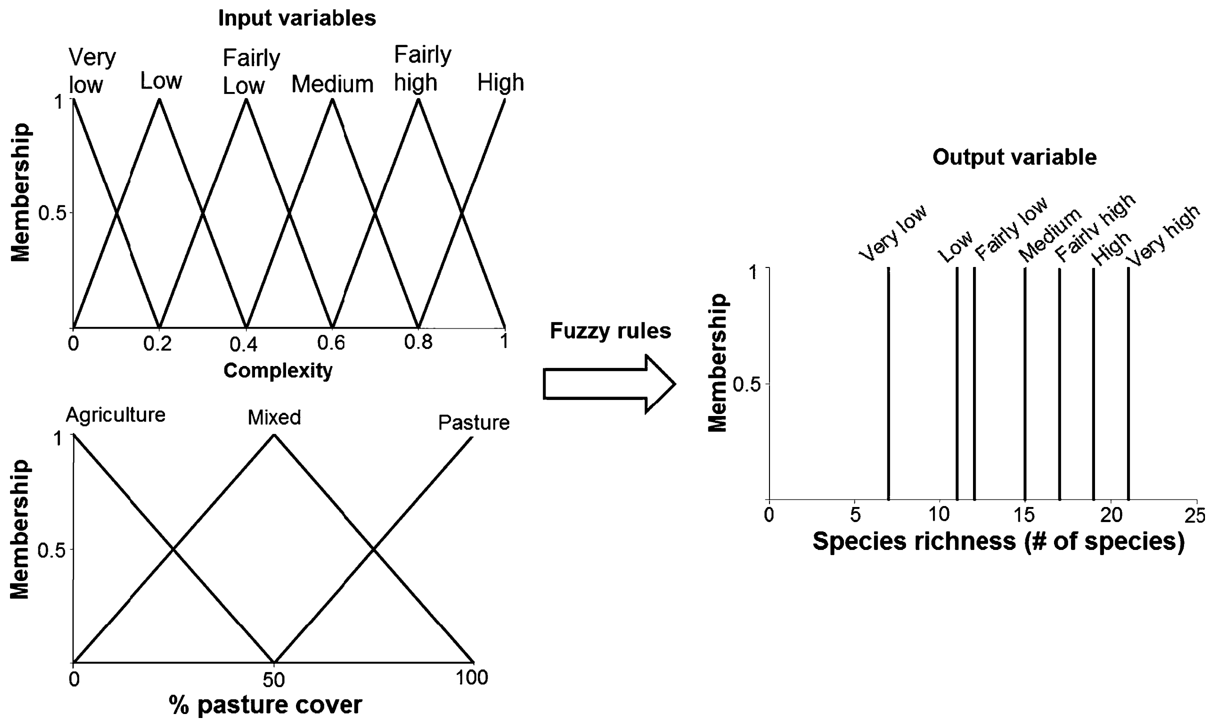


Fig. 4 Membership functions for the fuzzy model relating landscape complexity and land use at the local scale

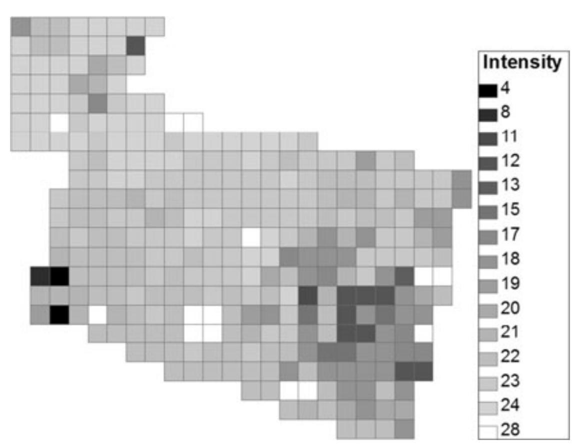


Fig. 5 Landscape transformation intensity in the whole time period analyzed. Values represent the sum of the scores for intensity according to Fig. 2. Low values represent low transformation intensity levels

fuzzy logic (Kampichler et al. 2000). In this paper, we present only the final models after improvements have been made.

To test the performance of the fuzzy logic method we also analyzed our data with a more traditional statistical method. We ran a stepwise multivariate regression analysis using the six input variables for the model of local complexity.

Results

We recorded a total of 107 bird species, which represent approximately 40 % of cited species for the region (Narosky and DiGiacomo 1993). The species recorded correspond to common species found in the area of study (Appendix 7 in Supplementary material).

Bird species numbers correlated positively with landscape complexity at the local scale (Spearman correlation $r = 0.42$; $p < 0.001$). In the best model, trees and bodies of water were the two most important variables to generate a landscape complexity relevant for birds (Appendix 3 in supplementary material). Surprisingly, roadside vegetation did not have a significant effect on species richness, nor in the fuzzy model, or when we correlated species numbers with this single variable (Spearman correlation $r < 0.001$, $p = 0.98$). Still, we kept this variable for the final fuzzy model as it could interact with other variables.

Species numbers correlated positively with % pasture cover at the local scale (Spearman correlation

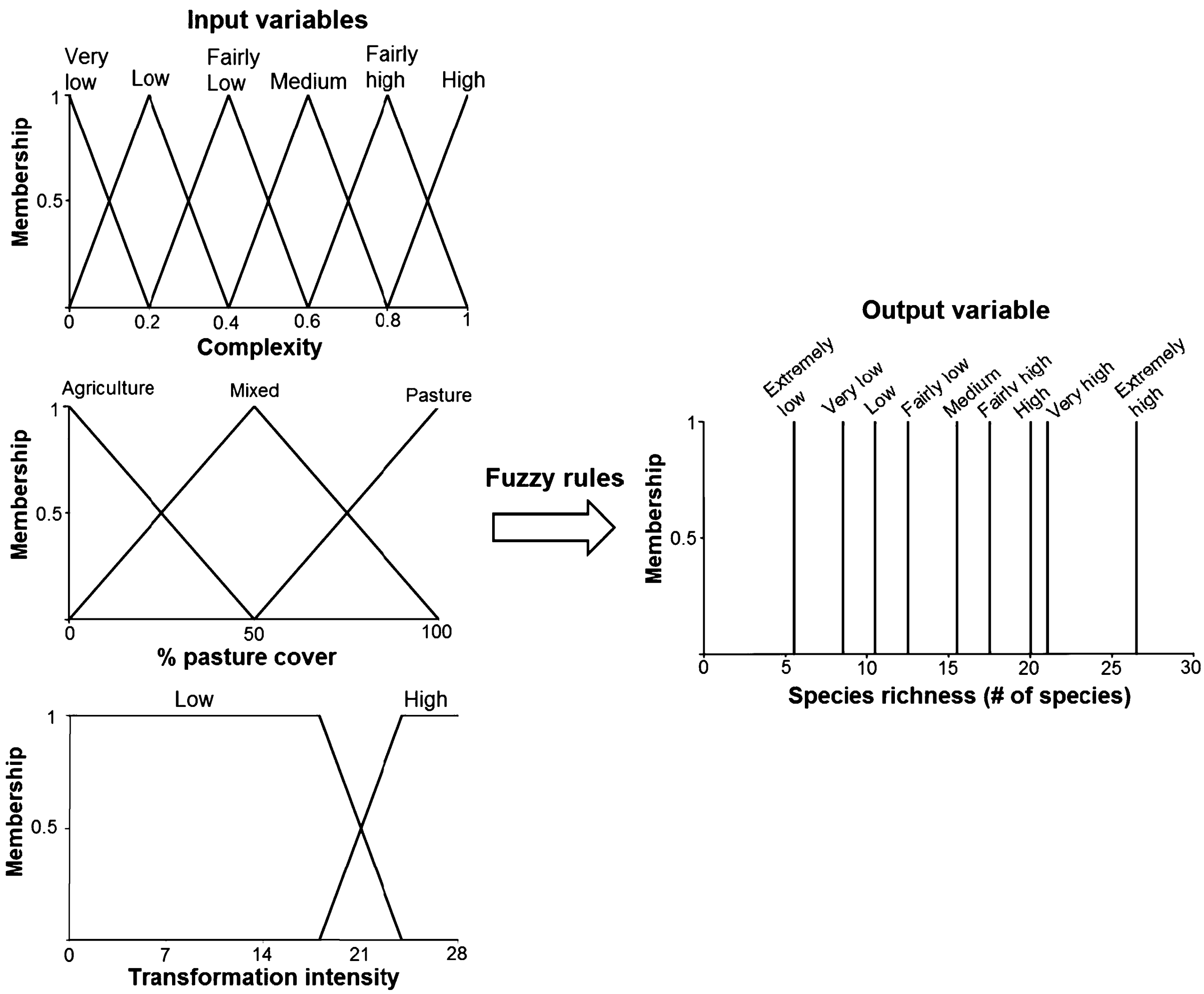


Fig. 6 Membership functions for the fuzzy model relating landscape complexity and land use at the local scale and landscape transformation intensity at the facet scale

$r = 0.36$, $p < 0.001$). The data dispersion for both landscape complexity and % pasture cover was very high. This uncertainty could be reduced by exploring the interaction between these two landscape attributes in a single model.

The best model relating land use type to complexity shows some interactions among these landscape attributes (Fig. 7a). The model predicts that species richness is lowest in simple agricultural landscapes. Departing from this initial landscape type, if pasture cover is increased, species numbers increases as well, but reaches a plateau at intermediate (~50 %) levels of pasture cover. If only complexity is increased by adding trees and bodies of water, species numbers also increases, but at a higher level. The highest number of species is predicted by this model in complex pastoral landscapes. When compared with observed species richness, this model has a MAE of 2.98 and shows a tendency to under estimate species numbers at low predicted values, i.e. simple agricultural landscapes (Fig. 7b).

Landscape transformation intensity correlated negatively with bird species numbers ($r = -0.55$, $p < 0.01$). The fuzzy model that included this variable along with the variables at local scale (fuzzy model #3), predicts that only at very high levels of intensity is there a negative effect on local species numbers (Fig. 8a). This effect is only evident in agricultural landscapes, while in pastures bird species number is high regardless of the landscape context. The MAE of this model is 3.07, meaning that there is not an overall improvement in the fit of predicted versus observed

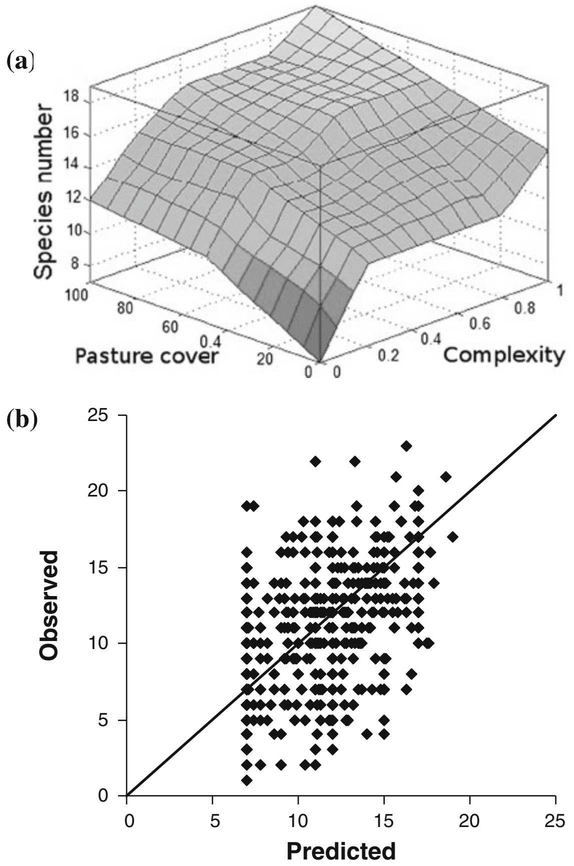


Fig. 7 **a** Response surface of predicted species numbers for the fuzzy model relating local landscape complexity and use (% pasture cover). **b** Predicted vs observed species numbers of the model. The *line* represents a 1:1 slope, where all predicted and observed values should coincide

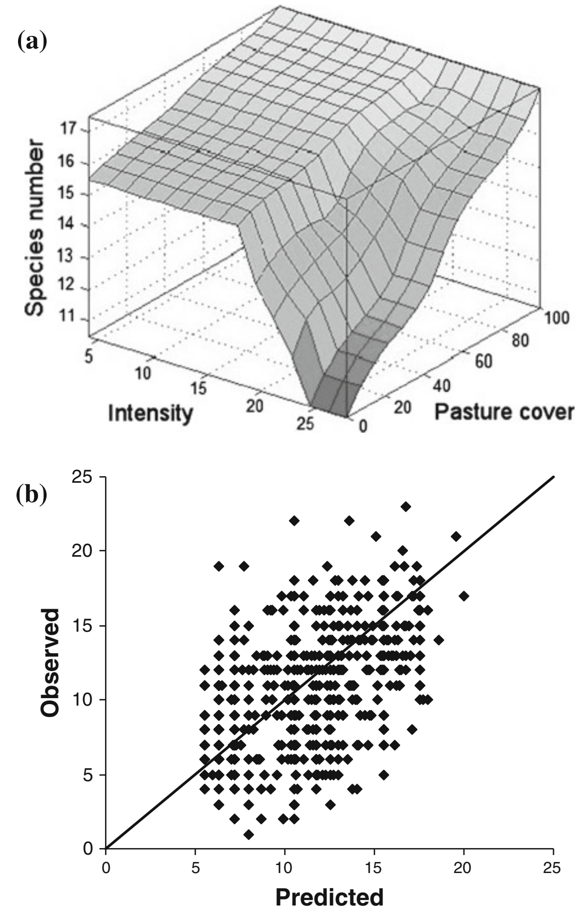


Fig. 8 **a** Response surface of predicted species numbers for the fuzzy model relating the landscape attributes at the two spatial scales analyzed. Percent pasture cover is at the local scale. **b** Predicted versus observed species number of the model. The *line* represents a 1:1 slope, where all predicted and observed values should coincide

values with respect to the local scale model (Fig. 8b). However, predictions were slightly improved for low richness values.

The stepwise multiple regression for the model of local complexity kept all the variables except roadside complexity (species richness = 1.68*[trees (element)] + 3.07*[trees (ecotope)] + 0.4*(land use richness) + 3.14*(water) + 1.41*(houses).

Discussion

Suitability of the method

Recent advances in landscape ecology have improved the ability of metrics to describe landscape attributes (Wu et al. 2002; Li and Wu 2004; Fahrig et al. 2011). The focus in future research should not be put on developing new metrics, but in trying to understand their behavior in relation to relevant ecological processes in real landscapes (Li et al. 2005; Cushman et al. 2008). In order to do that, there are still methodological issues that must be faced when working with the existing indices and information available. In this discussion, we will review some of these problems and show how fuzzy logic and decision rules can overcome them as seen in our study of pampas agroecosystems.

The first issue is the nature of the landscape attributes under consideration. Many of these attributes, as well as many ecological concepts, do not behave as binary variables with mutually exclusive states. It is not simple to set arbitrary cutting points in order to determine different levels of metrics, like patch shape index, border width or fractal dimension. Rather, continuity between different states is a more realistic situation. Landscape complexity is clearly one of these concepts. A conventional statistical design would force us to define different states (e.g. simple, complex) for which there is no clear cutting point. This uncertainty is a problem in traditional approaches, but is explicitly incorporated in fuzzy logic. The ambiguity in the definition of the variable states can be expressed mathematically through membership functions to give a concrete answer (Phillis and Andriantiatsaholiniaina 2001). At the same time, fuzzy logic is flexible enough so that binary variables can be incorporated as well. In our study, we used a combination of fuzzy and binary variables, depending on which approach was more appropriate, according to their nature. In that way, we treated the complexity of roadside vegetation as a continuum from simple to complex. On the other hand, we considered that the effect of inhabited houses would be better attained by a binary (presence/absence) variable, since we restricted our study sites to rural areas and did not evaluate a gradient of urbanization. In developing fields like sustainability assessment or environmental impact analysis, where these concepts cannot be defined unambiguously, fuzzy set theory may also be particularly useful. Prato (2005) for example, used fuzzy logic to define different levels of regional income, biodiversity and water quality that determine ecosystem sustainability. Setting thresholds for the input variables would have been unrealistic, and could lead to specific conclusions about management decisions that do not take into account the ambiguity and uncertainty of the input variables.

The information available to study landscape attributes and metrics and build predictive models is usually imprecise and incomplete. This is also very usual in developing fields or in novel landscapes. In these cases, expert knowledge and citizen science (knowledge and data produced by non scientists) become valuable (Chen and Mynett 2003; Yamada et al. 2003; Dickinson et al. 2010). This information must be managed by methods that reproduce natural reasoning processes and incorporate vagueness and imprecision. Decision rules and fuzzy inference are probably the best way to deal with expert knowledge. They are based in natural language, the way knowledge is transmitted among ecologists and to the lay person and decision makers. Experts do not need to express their propositions with complex mathematical formalisms that are sometimes beyond their capacity but with words used in everyday communication. This can be done with structured or semi-structured questionnaires and interviews (Yamada et al. 2003; Azadi et al. 2009). It is the modeler who then translates these propositions in a mathematical formalism for analysis. By computing with words, it is also easier to integrate dissimilar information in a single output variable. In this aspect, multivariate methods cannot fully achieve the possibilities of fuzzy logic and decision rules. Although multivariate regression can deal with several variables at a time, dropping non significant variables and keeping informative ones, the output is a mathematical formalism that may still be difficult to interpret. In our study, we compared the performance of the first fuzzy model (local complexity) with a multivariate regression using the same input variables. Results did not vary with the method used since both are congruent in their results, as they give similar weights to the input variables as determinants of the output variable, and both show that roadside complexity was not relevant.

Fuzzy inference is a predictive method, which represents an important advantage over some multivariate methods that are exploratory and non predictive in essence, like redundance analysis or canonical correspondence analysis (Legendre and Legendre 1998). Hypotheses and predictions of the fuzzy models are made explicit through IF–THEN rules and membership functions. In this way, a fuzzy inference process allows controlling the relationship between the input and output variables to suit the knowledge of the system. Even more, in fuzzy logic both an exploratory and a predictive approach can be applied. The usual method is first to construct a model and then modify and validate it with empirical data or new information from experts (see for example Chen and Mynett 2003; Adriaenssens et al. 2006). In our study, we constructed a simple initial model with predictions based on previous studies on the Pampas' agroecosystem and informal interviews to experts. The models were validated with data collected in the field, and by modifying the parameters until the maximum explanation was reached we obtained a final model. As with any modeling method, there is a compromise between precision and generalization, or precision and ecological interpretability. In fuzzy logic, the modeler has control over the fitting process and can stop at any time he/she considers it appropriate. The alternative methods do not allow this process to be done.

Some problems in the methodological approach were also evident and worth noting. In a fuzzy reasoning process, the number of rules grows exponentially with the number of variables and membership functions (Chen and Mynett 2003). This is a general drawback of the method and was particularly evident in this study, in which the number of rules ($n = 164$) was very high. This complicated the process of tracking the most relevant variables and tuning the membership functions to improve the fit of the models. In our case, predicted values were restricted in the lower bound, but enlarging the range by modifying models' parameters would have worsened their fit. Some of the existing software to help to automate the construction of the rule base and membership functions, like neuro-fuzzy systems (Jang 1993; Salski and Holsten 2006), is not well developed enough for input variables such as those used here. As an alternative, intermediate models can be constructed, reducing total number of rules (Kampichler et al. 2000). These limitations prevented us from exploring more complex relationships among variables and improving the fit of the fuzzy models developed. In spite of these disadvantages, fuzzy logic reasoning permitted us to study a poorly explored system and elucidate some of the important issues that should be taken into account for management of the Rolling Pampas' agroecosystem.

To conclude, fuzzy logic, as applied in our study, is a method that is suitable to obtain an objective measure of landscape complexity integrating and dealing with vague and ambiguous information. It does not add a new metric of landscape characterization, but instead works with existing indices with a natural reasoning process. Neither has it necessarily improved the performance of traditional statistical techniques. In fact, we could use it alongside with traditional statistical methods, when the information was not suited to them. Fuzzy logic is a promising methodology in landscape ecology which is increasingly being applied in several areas (Ducey and Larson 1999; Ferraro et al. 2003; Lu et al. 2006; Rocchini and Ricotta 2007).

Ecological insights

Bird species richness of the Pampas' agroecosystem was negatively affected by the high proportion of annual crops in the landscape at the local scale, which coincided with other studies in the same region (Filloy and Bellocq 2007; Codesido et al. 2008; Cerezo et al. 2011). Landscape complexity proved to be a more important factor to determine species richness, though. Contrary to our predictions, roadside vegetation did not enhance bird species richness, though several authors (Lakhani 1994; Goijman and Zaccagnini 2008; Di Giacomo and López de Casenave 2010) conclude that hedgerows and non cultivated field margins are important for providing habitat for birds in agroecosystems. This may have been because we considered the contribution of roadside vegetation to complexity, but there may be only particular vegetation conditions that favor bird species, like spontaneously vegetated roadsides. In the Rolling Pampas, these kind of roadsides are being removed for cultivation before their effect on birds is evaluated. This calls for a further and urgent focus on this aspect in future studies.

Landscape complexity can compensate the negative effect of agricultural land use, showing that different alternatives can be applied as management policies for the region. In spite of this, in the Pampas' agroecosystems much focus has been put in land use, and little attention is given to the landscape elements that can generate complexity, like trees and bodies of water. Future research should study with more detail these landscape elements and determine their conservation value by evaluating which species are benefited.

Models showed that landscape transformation intensity at the facet scale was the most important factor in determining species richness. It is not surprising that coarser scales exert the highest effect since species are affected by landscape characteristics at the scale they perceive it (With 1994). As highly mobile organisms, it is expected that birds are affected primarily by coarse scales. Furthermore, the level of transformation intensity modified the response of birds to the local scale factors. Agricultural sites were enriched when surrounded by a facet of low transformation intensity. This was probably due to colonization of species from the regional pool through mass effects (Schmida and Wilson 1985). The effect of landscape transformation intensity was only evident at very high intensity levels. This may be due to the fact that at intermediate levels, landscapes where heterogeneous enough to provide a suitable habitat for bird species. The interaction between different spatial scales is a very important issue that should be taken into account when designing management tools to conserve biodiversity. Local management actions will not have the same effect in different landscape contexts (Tscharntke et al. 2005; Concepción et al. 2008). To our knowledge, there are no studies in the Pampas that have considered the interaction between scales. There is an urgent need to include this aspect in order to design and apply effective conservation tools in a rapidly changing agricultural landscape.

The overall predictive power of the coarse-scale fuzzy model did not improve compared to the model at the local scale. This was the result of a balance between improvements in the predictions for certain situations with the worsening in others, with no clear general pattern. This rather surprised us, as there is a growing recognition that analysis of landscape effects on biodiversity at different spatial scales improves the variance explained in biodiversity patterns (Levin 1992; Beever et al. 2006). It is possible that other biodiversity attributes rather than species numbers are affected by landscape context. For instance, the composition of bird assemblages could vary in different landscape contexts while keeping total species numbers constant (Weyland et al. “in preparation”). The outcome of different landscape attributes combinations may not be the same and be relevant for conservation purposes.

Acknowledgments This paper is a result of FW Ph.D thesis, he was financed by a fellowship of the CONICET and the FONCYT. The ECOS-SECYT A07B04 grant permitted the exchanges between France and Argentina. The final stay in France of FW was made possible through a grant from the French Embassy and the Ministry of Education of Argentina. G. Rocha and P. Moreyra assisted in bird field surveys. Satellite images where provided by the Laboratory of Regional Analysis and Teledetection (LART-FAUBA).

References

Adriaenssens V, Goethals PLM, Pauw ND (2006) Fuzzy knowledge-based models for prediction of Asellus and Gammarus in watercourses in Flanders (Belgium). Ecol Model 195:3–10

Azadi H, Jvd Berg, Shahvali M, Hosseininia G (2009) Sustainable rangeland management using fuzzy logic: a case study in Southwest Iran. Agric Ecosyst Environ 131:193–200

Baldi G, Paruelo JM (2008) Land-use and land cover dynamics in South American temperate grasslands. Ecol Soc 13(2), Article no 6. http://www.ecologyandsociety.org/vol13/iss2/art6/ES-2008-2481.pdf

Batáry P, Matthiesen T, Tscharntke T (2010) Landscape-moderated importance of hedges in conserving farmland bird diversity of organic vs. conventional croplands and grasslands. Biol Conserv 143:2020–2027

Beever EA, Swihart RK, Bestelmeyer BT (2006) Linking the concept of scale to studies of biological diversity: evolving approaches and tools. Divers Distrib 12:229–235

Bengtsson J, AhnströM J, Weibull AC (2005) The effects of organic agriculture on biodiversity and abundance: a meta-analysis. J Appl Ecol 42:261–269

Bennett AB, Radford JQ, Haslem A (2006) Properties of land mosaics: implications for nature conservation in agricultural environments. Biol Conserv 133:250–264

Benton TG, Vickery JA, Wilson JD (2002) Farmland biodiversity: is habitat heterogeneity the key? Trends Ecol Evol 18:182–188

BirdLife International (2011) The BirdLife checklist of the birds of the world, with conservation status and taxonomic sources. Version 4. Downloaded from http://www.birdlife.info/im/species/checklist.zip

Center B, Verma BP (1998) Fuzzy logic for biological and agricultural systems. Artif Intell Rev 12:213–225

Cerezo A, Conde MC, Poggio S (2011) Pasture area and landscape heterogeneity are key determinants of bird diversity in intensively managed farmland. Biodivers Conserv 20:2649–2667

Chen Q, Mynett AE (2003) Integration of data mining techniques and heuristic knowledge in fuzzy logic modelling of eutrophication in Taihu Lake. Ecol Model 162:55–67

Cingolani AM, Noy-Meir I, Renison DD, Cabido M (2008) La ganadería extensiva, ¿es compatible con la conservación de la biodiversidad y los suelos? Ecol Aust 18:253–271

Codesido M, Fischer CG, Bilenca D (2008) Asociaciones entre diferentes patrones de uso de la tierra y ensambles de aves en agroecosistemas de la Región Pampeana, Argentina. Ornitol Neotrop 19:575–585

Comparatore VM, Martínez MM, Vassallo AI, Barg M, Isacch JP (1996) Abundancia y relaciones con el hábitat de aves y mamíferos en pastizales de *Paspalum quadrifarium* (paja colorada) manejados con fuego (provincia de Buenos Aires, Argentina). Interciencia 21:228–237

Concepción ED, Díaz M, Baquero RA (2008) Effects of landscape complexity on the ecological effectiveness of agri-environment schemes. Landscape Ecol 23:135–148

Cueto VR, Casenave JLd (1999) Determinants of bird species richness: role of climate and vegetation structure at a regional scale. J Biogeogr 26:487–492

Cushman SA, McGarigal K, Neel MC (2008) Parsimony in landscape metrics: strength, universality, and consistency. Ecol Indic 8:691–703

Dauber J, Hirsch M, Simmering D, Waldhardt R, Otte A, Wolters V (2003) Landscape structure as an indicator of biodiversity: matrix effects on species richness. Agric Ecosyst Environ 98:321–329

Di Giacomo AS, López de Casenave J (2010) Use and importance of crop and field-margin habitats for birds in a neotropical agricultural ecosystem. Condor 112: 283–293

Dickinson JL, Zuckerberg B, Bonter DN (2010) Citizen science as an ecological research tool: challenges and benefits. Annu Rev Ecol Evol Syst 41:149–172

Dubois D, Prade H (1996) What are fuzzy rules and how to use them. Fuzzy Set Syst 84:169–185

Ducey MJ, Larson BC (1999) A fuzzy set approach to the problem of sustainability. For Ecol Manage 115:29–40

Fahrig L, Baudry J, Brotons L, Burel F, Crist TO (2011) Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. Ecol Lett 14:101–112

Ferraro DO, Ghersa CM, Sznaider GA (2003) Evaluation of environmental impact indicators using fuzzy logic to assess the mixed cropping systems of the Inland Pampa, Argentina. Agric Ecosyst Environ 96:1–18

Filloy J, Bellocq MI (2007) Patterns of bird abundance along the agricultural gradient of the Pampean region. Agric Ecosyst Environ 120:291–298

Flynn DFB, Gogol-Prokurat M, Nogeire T, Molinari N, Richers BT, Lin BB, Simpson N, Mayfield MM, De Clerck F (2009) Loss of functional diversity under land use intensification across multiple taxa. Ecol Lett 12:22–33

Gabelli FB, Fernández GJ, Ferretti V, Posse G, Coconier E, Gavieiro HJ, Llambías PE, Peláez PI, Vallés ML, Tubaro PL (2004) Range contraction of the pampas meadowlark *Sturnella defilippii* in the southern pampas grasslands of Argentina. Oryx 38:1–7

Ghersa CM, León RJC (2001) Ecología del paisaje pampeano: consideraciones para su manejo y conservación. In: Naveh Z, Lieberman AS (eds) Ecología de Paisajes. Editorial Facultad de Agronomía, Buenos Aires, pp 471–512

Ghersa CM, de la Fuente E, Suarez S, Leon RJC (2002) Woody species invasion in the Rolling Pampa grasslands, Argentina. Agric Ecosyst Environ 88:271–278

Goijman A, Zaccagnini ME (2008) The effect of habitat heterogeneity on avian density and richness in soybean fields in Entre Ríos, Argentina. Hornero 23:67–76

Goldstein MI, Lacher TE, Woodbridge B, Bechard MJ, Canavelli SB, Zaccagnini ME, Cobb GP, Scollon EJ, Tribolet R, Hooper MJ (1999) Monocrotophos-induced mass mortality of Swainson's hawks in Argentina, 1995–96. Ecotoxicology 8:201–214

Guerschman JP, Paruelo JM, Di Bella C, Giallorenzi MC, Pacin F (2003) Land cover classification in the Argentine Pampas using multi-temporal Landsat TM data. Int J Remote Sens 24:3381–3402

Hobbs RJ, Arico S, Aronson J, Baron JS, Bridgewater P, Cramer VA, Epstein PR, Ewel JJ, Klink CA, Lugo AE, Norton D, Ojima D, Richardson DM, Sanderson EW, Valladares F, Vilà M, Zamora R, Zobel M (2006) Novel ecosystems: theoretical and management aspects of the new ecological world order. Glob Ecol Biogeogr 15:1–7

Jaeger JAG (2000) Landscape division, splitting index, and effective mesh size: new measures of landscape fragmentation. Landscape Ecol 15:115–130

Jang JSR (1993) ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans Syst Man Cybern 23:665–685

Kampichler C, Barthel J, Wieland R (2000) Species density of foliage-dwelling spiders in field margins: a simple, fuzzy rule-based model. Ecol Model 129:87–99

Kragten S, Snoo GRd (2008) Field-breeding birds on organic and conventional arable farms in the Netherlands. Agric Ecosyst Environ 126:270–274

Lakhani KH (1994) The importance of field margin atributes to birds. En field margins: integrating agriculture and conservation. Monograph 58. Surrey, BCPC, pp 77–84

Legendre P, Legendre L (1998) Numerical ecology. Elsvier, Amsterdam, p 844

Levin SA (1992) The problem of pattern and scale in ecology: the Robert H MacArthur Award lecture. Ecology 73: 1943–1967

Li H, Reynols JF (1995) On definition and quantification of heterogeneity. Oikos 73:280–284

Li H, Wu J (2004) Use and misuse of landscape indices. Landscape Ecol 19:389–399

Li X, He HS, Bu R, Wen Q, Chang Y, Hu Y, Li Y (2005) The adequacy of different landscape metrics for various landscape patterns. Pattern Recognit 38:2626–2638

Liebhold AM, Gurevitch J (2002) Integrating the statistical analysis of spatial data in ecology. Ecography 25:553–557

Liu M, Samal S (2002) A fuzzy clustering approach to delineate agroecozones. Ecol Model 149:215–228

Lu Y, Fu B, Chen L, Ouyang Z, Xu J (2006) Resolving the conflicts between biodiversity conservation and socioeconomic development in China: fuzzy clustering approach. Biodivers Conserv 15:2813–2827

Matson PA, Parton WJ, Power AG, Swift MJ (1997) Agricultural intensification and ecosystem properties. Science 277:504–509

Mayer DG, Butler DG (1993) Statistical validation. Ecol Model 68:21–32

Narosky T, DiGiacomo AG (1993) Las aves de la Provincia de Buenos Aires: distribución y estatus. Asoc. Ornitológica del Plata, Vázquez Mazzini Ed. y L.O.L.A., Buenos Aires

Pedrycz W (1994) Why triangular membership functions? Fuzzy Set Syst 64:21–30

Phillis YA, Andriantiatsaholiniaina LA (2001) Sustainability: an ill-defined concept and its assessment using fuzzy logic. Ecol Econ 37:435–456

Prato T (2005) A fuzzy logic approach for evaluating ecosystem sustainability. Ecol Model 187:361–368

Ralph CJ, Sauer JR, Droege S (1995) Monitoring bird populations by point counts. Gen. Tech. Rep. PSW-GTR-149. Pacific Southwest Research Station, Fores Service, US Department of Agriculture, Albany

Rocchini D, Ricotta C (2007) Are landscapes as crisp as we may think? Ecol Model 204:535–539

Roschewitz I, Gabriel D, Tscharntke T, Thies C (2005) The effects of landscape complexity on arable weed species diversity in organic and conventional farming. J Appl Ecol 42:873–882

Sala OE, Chapin FS, Armesto JJ, Berlow E, Bloomfield J, Dirzo R, Huber-Sanwald E, Huenneke LF, Jackson RB, Kinzig A, Leemans R, Lodge DM, Mooney HA, Oesterheld M, Poff NL, Sykes MT, Walker BH, Walker M, Wall DH (2000) Global biodiversity scenarios for the year 2100. Nature 287:1170–1174

Salski A, Holsten B (2006) A fuzzy and neuro-fuzzy approach to modelling cattle grazing on pastures with low stocking rates in Central Europe. Ecol Inform 1:269–276

Sarasola H, Negro JJ (2006) Role of exotic tree stands on the current distribution and social behaviour of Swainson's hawk, *Buteo swainsoni* in the Argentine Pampas. J Biogeogr 33:1096–1101

Schmida A, Wilson MV (1985) Biological determinants of species diversity. J Biogeogr 12:1–20

Schrag AM, Zaccagnini ME, Calamari N, Canavelli S (2009) Climate and land-use influences on avifauna in central Argentina: broad-scale patterns and implications of agricultural conversion for biodiversity. Agric Ecosyst Environ 132:135–142

Seastedt TR, Hobbs RJ, Suding KN (2008) Management of novel ecosystems: are novel approaches required? Front Ecol Environ 6:547–553

Soriano A (1991) Rio de la Plata grasslands. In: Coupland RT (ed) Introduction and western hemisphere. Elsevier, Amsterdam, pp 367–407

Tscharntke T, Klein AM, Kruess A, Steffan-Dewenter I, Thies C (2005) Landscape perspectives on agricultural intensification and biodiversity—ecosystem service management. Ecol Lett 8:857–874

Turner MG (2005) Landscape ecology: what is the state of the science? Annu Rev Ecol Evol Syst 36:319–344

Van Leekwijck W, Kerre EE (1999) Defuzzication: criteria and classification. Fuzzy Set Syst 108:159–178

Weibull AC, Östman O (2003) Species composition in agroecosystems: the effect of landscape, habitat, and farm management. Basic Appl Ecol 4:349–361

With KA (1994) Using fractal analysis to assess how species perceive landscape structure. Landscape Ecol 9:25–36

Wu J, Shen W, Sun W, Tueller PT (2002) Empirical patterns of the effects of changing scale on landscape metrics. Landscape Ecol 17:761–782

Yamada K, Elith J, McCarthy M, Zerger A (2003) Eliciting and integrating expert knowledge for wildlife habitat modelling. Ecol Model 165:251–264

Zadeh LA (1965) Fuzzy sets. Inform Control 8:338–353

Zadeh LA (1996) Fuzzy logic = computing with words. IEEE Trans Fuzzy Syst 4:103–111

Zonneveld IS (1989) The land unit—a fundamental concept in landscape ecology, and its applications. Landscape Ecol 3:67–86