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Research article

A multi-criteria inference approach for anti-desertification management

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ABSTRACT

We propose an approach for classifying land zones into categories indicating their resilience against desertification. Environmental management support is provided by a multi-criteria inference method that derives a set of value functions compatible with the given classification examples, and applies them to define, for the rest of the zones, their possible classes. In addition, a representative value function is inferred to explain the relative importance of the criteria to the stakeholders. We use the approach for classifying 28 administrative regions of the Khorasan Razavi province in Iran into three equilibrium classes: collapsed, transition, and sustainable zones. The model is parameterized with enhanced vegetation index measurements from 2005 to 2012, and 7 other natural and anthropogenic indicators for the status of the region in 2012. Results indicate that grazing density and land use changes are the main anthropogenic factors affecting desertification in Khorasan Razavi. The inference procedure suggests that the classification model is underdetermined in terms of attributes, but the approach itself is promising for supporting the management of anti-desertification efforts.

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1. Introduction

Desertification is the impoverishment of terrestrial ecosystems under human activities – it is a deterioration process of vulnerable ecosystems that can be caused by reduced biological productivity and biomass, decreased biodiversity and increased frequency of invasive species; accelerated soil deterioration, changes in vegetation patterns, and alterations within the inhabiting human societies including effects such as an ascending trend of immigration and poverty (Dregne, 1977). The term "desertification" is generally used for referring to many different land degradation phenomena, and although there are various studies about desertification (Mainguet, 1991; Bestelmeyer, 2005, 2006; Sepehr et al., 2007; Sepehr and Zucca, 2012; Dregne, 1977; Reynolds and Smith, 2002; Downing and Lüdeke, 2002; Nearing et al., 1994; Nearing, 2003; Morgan, 1995; Rose, 1998; Thornes, 2003; Kirkby et al., 2004; Mulligan and Wainwright, 2003), most of them consider desertification to be according to the UNCCD (1994) definition: "land degradation in vulnerable environments including arid, semi-arid and dry sub-humid areas mainly resulting from excessive human activities and climatic oscillations".

Desertification can be analyzed based on the equilibrium change paradigm which focuses on oscillations in the states of an ecosystem (Scheffer et al., 2009, 2001; Scheffer, 2001; Dakos et al., 2008; Klein et al., 2003). Accordingly, desertification can be defined to mean a change of the equilibrium point of an ecosystem from a "green" state to a desert state due to certain environmental forces. The ability of an ecosystem to endure these environmental perturbations is determined by its resilience range (Gunderson, 2000). In desertification terms, a high resilience range indicates an ecosystem that is sustainable against desertification – such ecosystems are resilient and exhibit an equilibrium state. Fig. 1 illustrates the relationship between the resilience ranges and equilibrium alterations: a perturbation in the environment is increased by the desertification drivers, and this changes the equilibrium points of the system.

This paper develops a methodology for anti-desertification management and presents its application to the Iranian province of Khorasan Razavi (KR). Iran is located in a very arid area of the world and has an average yearly precipitation of a third of the world

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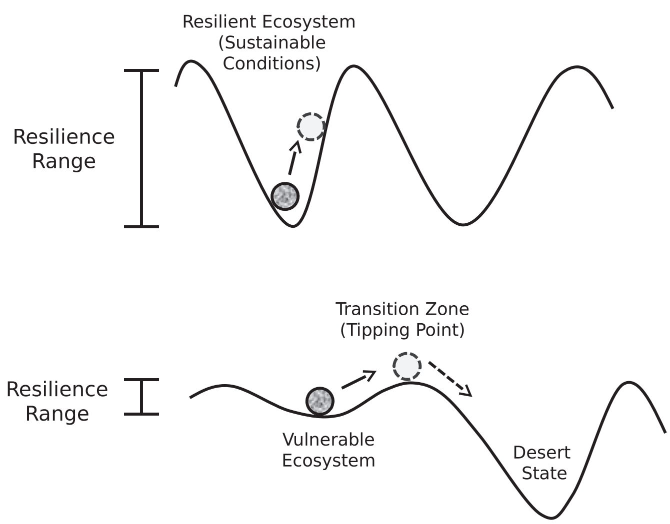

Fig. 1. The alternative stable states of an ecosystem under the influence of disturbance event. For the resilient ecosystems, a high resilience range creates sustainable conditions and high resistance ability against desertification. Conversely, in ecosystems with a low resilience range, a non-equilibrium condition occurs easily – such ecosystems are near to the thresholds points and can transform easily to desert landscapes.

average. Iran's climate ranges from arid or semi-arid (approximately 85% of the Iranian territory) to subtropical along the Caspian coast and the northern forests (see Fig. 2). KR is located in northeastern Iran and it borders North Khorasan province and Turkmenistan in the north, Semnan province in the west, Yazd and South Khorasan provinces in the south and Afghanistan and Turkmenistan in the east. More than 60% of the province includes desert and semi-desert areas. The annual precipitation ranges from 100 mm in the southern parts to 400 mm in the northern parts of the province. The average summer temperatures exceed 38 °C.

KR is a critical zone regarding land degradation and erosion. Urban developments in the recent years have brought overexploitation of natural resources, and many of the region's past pastures and scrublands have been transformed into environmentally degraded areas or settlements. These changes have caused vegetation degradation and the appearance of unvegetated areas with low resilience towards desertification. Based on the UNCCD Agenda (UNCCD, 1994), Iran has prepared a National Action Program (NAP) to combat desertification. The NAP framework involves four components: (i) determining parameters affecting desertification, (ii) soil and water conservation, (iii) rehabilitation and promotion of sustainable livelihoods in the affected areas, and (iv) participating rural communities in decision making and anti-desertification measures. As wide range of Khorasan Razavi areas are covered by Erg lands (sand dune landforms), sand dune stabilization is the main anti-desertification measure in the province. Sand dune stabilization projects have been successful in some parts of Iran (Amiraslani and Dragovich, 2010, 2011), but in the collapsed ecosystems of KR with harsh desert conditions, vegetation and sand dune stabilization is challenging. Some areas of KR have seen past dune stabilization projects with unsatisfactory results. The overall shares of anti-desertification plans implemented in KR from 2005 to 2012 are presented in Table 1.

To combat desertification and to manage national anti-desertification programs, it is deemed necessary to distinguish vulnerable and fragile ecosystems within the regional level. The ecosystems' soil properties, vegetation densities and ecogeomorphic factors determine their resilience ranges. The main hypothesis of this research is that we are able to distinguish ecosystem susceptibility to desertification based on their resilience ranges and biomass alterations. We present a methodology for identifying

Table 1
The most important anti-desertification measures in the Khorasan Razavi Province from 2005 to 2012.

Anti-desertification measure	Share of all measures
Education of rural communities	21%
Stabilizing sand dunes	32%
Culturing of Halophyte species	26%
Improving agricultural irrigation	9%
Implementing watershed management	12%

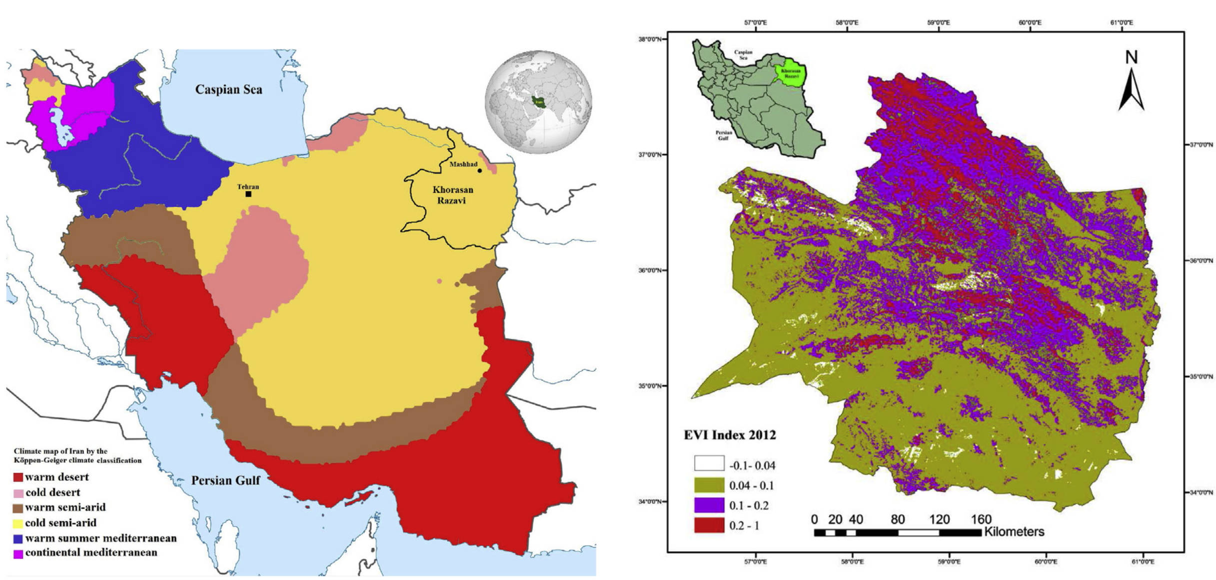

Fig. 2. The research has been done for Khorasan Razavi province located in northeastern Iran. The ecosystems of this region are susceptible to desertification processes. The right-hand image visualizes the region's EVI, an index of vegetation cover extracted by MODIS imagery data, for June 2012. According to this image only less than 15% of the study area contains higher vegetation cover density than 40%, which indicates presence of highly fragile ecosystems.

resilient and vulnerable zones in KR based on the equilibrium paradigm and by using vegetation density changes from 2005 to 2012 as a proxy measure for resiliency oscillations. We propose a new approach for classifying administrative zones by applying a multi-criteria classification method which infers a set of compatible models using a number of classification examples, and uses the inferred models to deduce class ranges for the remaining zones. In addition, the method derives a central model that explains the factors important for the classification.

Several authors have proposed assessment methods for desertification (Kosmas et al., 1999, 2000; Okin et al., 2001; Sepehr et al., 2007; Giannini et al., 2008; Costantini et al., 2009; Geist and Lambin, 2004; Grunblatt et al., 1992; Liu et al., 2003; Mouat et al., 1997), and although a number of desertification assessment studies have been developed for Iran in the previous years (see e.g. Ekhtesasi and Ahmadi, 1995; Jafari and Bakhshandehmehr, 2013; Sepehr et al., 2007), up to our best knowledge, the current study is the first one to develop a fully quantitative multi-criteria inference approach for anti-desertification management, in Iran or elsewhere. The advantage of the inference approach over say, regression models, is that it derives not only the relative importances of the individual desertification criteria, but also part-worths of the indicator levels within them. Furthermore, although we use vegetation density changes as an indication of the zones' resiliency against desertification, the approach is usable also in cases where measurements for such a dependent variable are not available (e.g. for technical reasons or due to prohibitive costs of measurement). The robust inference procedure applies expert opinion for assigning a subset of all zones to resiliency classes, and to derive possible classifications with all compatible models for the other zones. Applying all compatible models instead of only a single one allows to derive robust classification recommendations and nullifies the need for an extended sensitivity analysis. Goals of the approach are to identify the main desertification factors, and to provide decision support for managing anti-desertification activities at a regional level.

2. Material and methods

2.1. Study area

The Khorasan Razavi province contains the second most populous metropolitan area of Iran, Mashhad, and is one of the erosion and soil degradation centers of the country. The province covers a land area of about 128,430 km^2 situated approximately within the longitudes 59° 19 and 61° 16 east, and latitudes 33° 52 and 37° 42 north (Fig. 2). More than 60 percent of the province can be classified as desert or semi-desert. Thirteen cities are partially or completely located within these desert areas. Some desert areas have difficult living conditions due to very low rainfall and lack of vegetation. In general, the conditions within the province cause high wind and water erosion, which leads to many areas being prone to soil erosion and desertification. The political-administrative zones of the KR province are shown in Fig. 3. In order to support ecological management, we will use the administrative division for forming zones that are classified with the multi-criteria model.

2.2. Inference-based multi-criteria classification

We apply a multi-criteria sorting (ordinal classification) method in which $A = \{a_1,\ldots,a_i,\ldots,a_n\}$, a finite set of n zones are evaluated in terms of $G = \{g_1,\ldots,g_j,\ldots,g_m\}$ criteria. $X_j = \{g_j(a_i), a_i \in A\}$ is the set of evaluations on g_j. To model the desertification potential, we apply additive value functions, which are constructed as the sums of marginal value functions associated with specific criteria

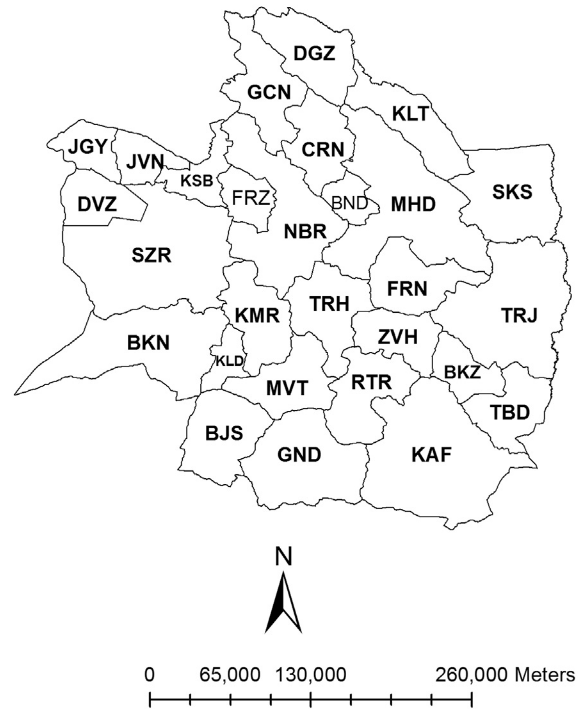

Fig. 3. The administrative zones of the Khorasan Razavi province.

characterizing the zones. The additive value function is formally defined as:

$$U(a) = \sum_{j=1}^{m} u_j(a), \tag{1}$$

where the marginal value functions u_j are expected to be monotonic and normalized so that the comprehensive value (1) is bound within interval [0,1]. The additive value function not only provides an overall value for an alternative, but through the marginal value functions u_j it also gives thorough insight into values associated with the specific evaluations. The latter is crucial for answering our research questions.

We assign land zones into p classes $C_1,\ldots,C_p$ ordered so, that C_{h+1} is preferred to C_h, $h = 1,\ldots,p-1$. We employ the threshold-based classification procedure in which the limits between consecutive classes are defined by thresholds on the value scale $\mathbf{b} = \{b_0,\ldots,b_p\}$ (Greco et al., 2010; Zopounidis and Doumpos, 2000; Kadziński and Tervonen, 2013). Precisely, given a value function U and its associated thresholds b_h, $h = 0,\ldots,p$, zone $a \in A$ is assigned to class C_h, denoted as $a \rightarrow C_h$, iff $U(a) \in [b_{h-1}, b_h[$, where b_{h-1} and b_h are, respectively, the minimum and maximum values for an alternative to be assigned to class C_h. We set $b_0 = 0$, i.e., the lower threshold for class C_1 is the worst possible value, and $b_p > 1$ so that all zones have comprehensive values worse than b_p. Moreover, we impose $b_{h-1} < b_h$ for $h = 1,\ldots,p$. The threshold-based classification procedure is presented graphically in Fig. 4.

An outline of the method we use in the study is given in Fig. 5. In Step 1, we establish the exemplary assignments of a subset of the zones (these are called reference zones), $A^R = \{a^*, b^*,\ldots\} \subseteq A$. The desired assignments are denoted with

$$a^* \rightarrow \left[C_{L_{DM}(a^*)}, C_{R_{DM}(a^*)}\right],$$

where $[C_{L_{DM}(a^*)}, C_{R_{DM}(a^*)}]$ is an interval of contiguous classes $C_{L_{DM}(a^*)}$,

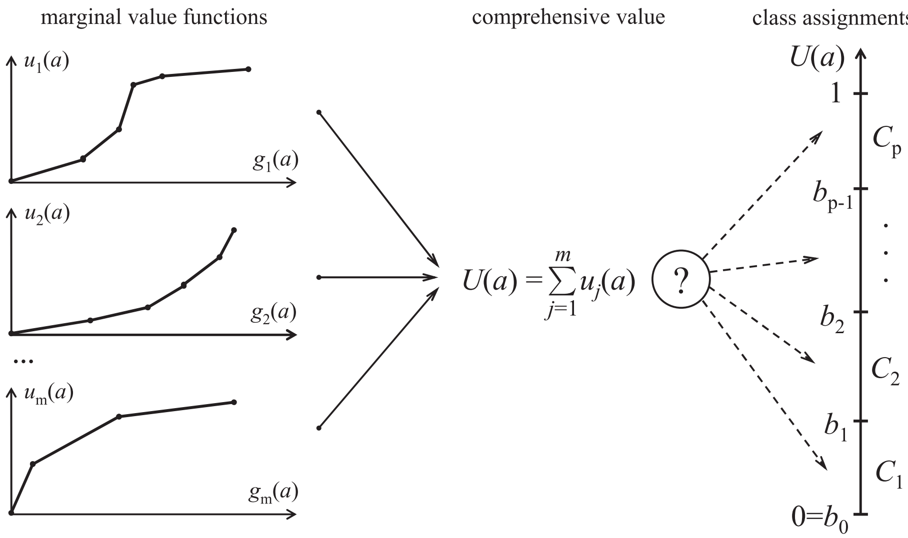

Fig. 4. Threshold-based multiple criteria sorting.

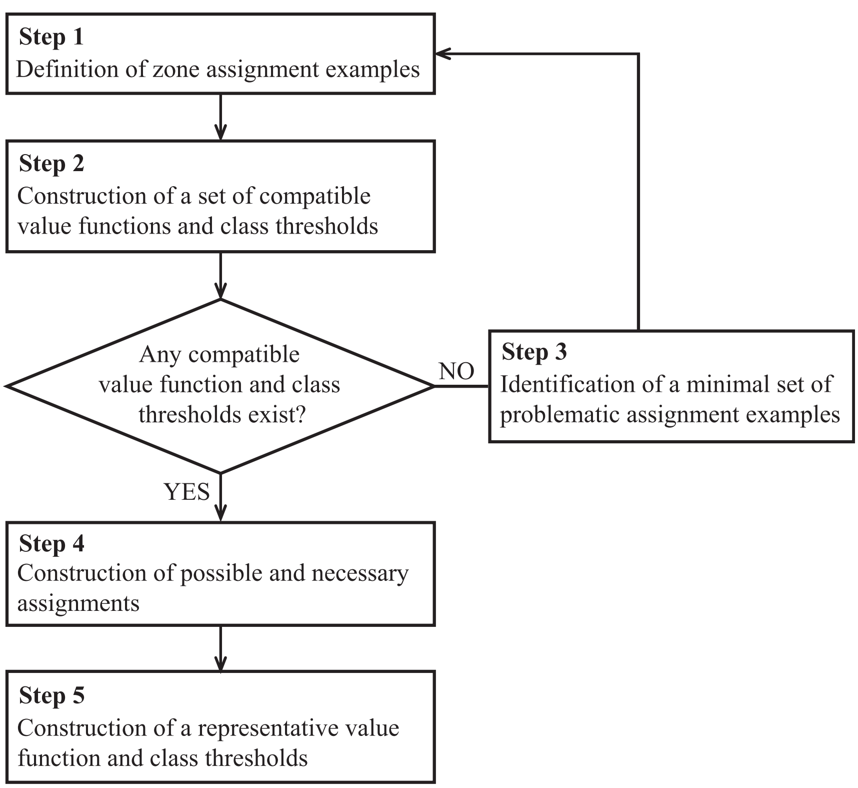

Fig. 5. General outline of the multiple criteria sorting method used in the study.

$C_{L_{DM}(a^*)+1}, \ldots, C_{R_{DM}(a^*)}$. An assignment example is said to be precise if $L_{DM}(a^*) = R_{DM}(a^*)$ and imprecise otherwise. In our study, all assignment examples are precise.

Subsequent computations conducted with the method are divided to four steps (marked as Steps 2–5 in Fig. 5) that involve solving different Linear Programming (LP) models (for detailed description of the models, see Appendix A). In Step 2, we need to construct all pairs (U,**b**) consisting of an additive value function U and a vector **b** of thresholds delimiting the classes that are consistent with the provided assignment examples. This is achieved by solving a model with linear constraints representing the class information. Each of these pairs is a compatible model, and can be applied to assess other zones that are not included in the reference set. The set of all pairs (U,**b**) compatible with the provided assignment examples is denoted by $(\mathcal{U}, \mathbf{b})^R$.

If the model has no solution (i.e., no compatible value function and class thresholds exist), the method indicates that the assignment examples cannot be represented by an additive model, that is, the assignments are incompatible with each other regarding the additivity and monotonicity conditions. In such cases, we are able to identify reasons for the incompatibility by proceeding to Step 3. In this step, Mixed-Integer Linear Programming (MILP) models are solved for identifying a minimal set of constraints that need to be removed from the model constructed in Step 2, so that at least one compatible value function and respective class thresholds can be found (Mousseau et al., 2006; Greco et al., 2011). The identified constraints establish problematic assignment examples that need to be removed or revised. Then, we return to Step 2.

If Step 2 terminates successfully (i.e., at least one compatible value function and class thresholds have been found), we proceed with Step 4 where the necessary $C_N(a)$ and possible $C_P(a)$ assignments are constructed, as in the UTADIS^{GMS} method (Greco et al., 2010). The necessary results are supported by all compatible value functions and class thresholds $(\mathscr{U}, \mathbf{b})^R$ obtained in Step 2. Thus, they can be considered as the most certain recommendation. The possible results are supported by at least one compatible pair in $(\mathscr{U}, \mathbf{b})^R$. All these outcomes are established by solving another LP models.

In Step 5, we construct a representative value function and class thresholds on the basis of all pairs $(\mathscr{U}, \mathbf{b})^R$ from Step 2, and the so-called assignment-based preference relations (Greco et al., 2011; Kadziński et al., 2013). The resulting representative value function defines a central model that can be used for interpreting the importances of different criteria levels for the classification of assignment examples.

2.3. Classification criteria

The main environmental problem in KR is the high degree of soil erodibility as many parts of the province are arid or semi-arid. In these vulnerable ecosystems, human activities such as grazing and overexploitation of water and soil resources have caused a high susceptibility to desertification phenomena. Thus, the main criteria affecting desertification are related to human activities such as land use alterations and overexploitations, and to inherent desertification potentials of the ecosystems such as soil erodibility and climate erosivity. Our key assumption in this study is that it is possible to categorize the ecosystem's susceptibility to desertification based on these criteria using additive classification models.

To choose the criteria for the multi-criteria inference model, we applied the Delphi methodology to elicit opinions from the scientific members of the desert division of the Iranian Research Institute of Forest and Rangelands (www.rifr-ac.ir). In addition, we collected opinions from the scientific members of the KR Natural Resources Organization (frw.org.ir). Based on the responses, we formed 7 criteria presented in Table 2 for assessing the natural and anthropogenic factors affecting desertification. The natural factors indicate the ecosystems potential for resisting environmental perturbations, and the anthropogenic factors model the human caused perturbations.

The **soil** erodibility criterion has been calculated based on the physical properties of the soil including texture, depth and surface cover regarding the stoniness percentage. According to the expert opinions and quality measurements on these indicators, the soil erodibility was categorized in three quality classes involving low, moderate and high intensity in the study zones. The role of the **climate** was estimated with the rainfall's ability to erode soil. For this, we applied the Fournier index of erosivity:

$$FI = \sum_{i=1}^{12} P_i^2 \Big/ P, \tag{2}$$

where P_i is the total precipitation fall in month i (mm) and P the annual average amount of precipitation (mm). We used an **Aridity** Index (AI) for evidence of drought and estimated it with

$$AI = P/ETP, \tag{3}$$

where P is annual mean precipitation and ETP is the annual mean evapotranspiration. To incorporate land use changes, land cover alteration was considered as evidence for **land use** changes. The land cover alteration was calculated based on land cover changes between the years 1992 and 2012 using ETM$^+$ satellite imagery data. Based on the observed changes and the increase in non-protected areas, a qualitative degree (low–moderate–high) was assigned for each zone. Fig. 6 shows the change in protected areas between the years 1992 and 2012. There is an ascending trend in the amount of non-protected areas, which indicates a general descending trend in the ecosystem's resilience against desertification. High **grazing** density and **groundwater** over-exploitation were categorized in three quality classes based on reports from the water organization of the province, and the reports from the natural resource organization of the region.

The **land abandonment** was determined based on qualitative estimates of the agricultural organization of KR between the years 1992 and 2012. Accordingly, many parts of the province show mismanagement of cultivated lands, rangelands and pastures. Using this information, qualitative classes low, moderate and high were determined for the zones' measurements on this criterion.

Enhanced Vegetation Index (EVI) was measured with MODIS (Moderate Resolution Imaging Spectro-radiometer), which is a 36 band spectrometer providing a global data set every 1–2 days with a 16-day repeat cycle. The spatial resolution of MODIS (pixel size at nadir) is 250 m for channel 1 and 2 (0.64–0.9 μm), 500 m for channel 3 to 7 (0.4–2.1 μm) and 1000 m for channel 8 to 36 (0.4–14.4 μm), respectively. For more information, see the NASA MODIS website (modis.gsfc.nasa.gov). EVI is an alternative index to NDVI (Normalized Difference Vegetation Index), which measures land biomass based on the observed differences of ratios between near infrared and red reflectances ($NDVI = (NIRRed)/(NIR+Red)$), and is more sensitive to changes in areas with high biomass (a serious shortcoming of NDVI). EVI reduces the influence of atmospheric conditions on vegetation index values, and also corrects for canopy background signals. Furthermore, EVI tends to be more sensitive to plant canopy differences like leaf area index, canopy structure, and plant phenology and stress than NDVI, which generally responds just to the amount of chlorophyll present. The EVI is computed from the MODIS measurements as follows:

$$EVI = 2.5*(NIR - Red)/(NIR + C_1*Red - C_2*Blue + L), \tag{4}$$

where NIR, Red, and $Blue$ are atmospherically-corrected (or partially atmospherically-corrected) surface reflectance, and C_1, C_2, and L are coefficients to correct for atmospheric condition (i.e., aerosol resistance). For the standard MODIS EVI product, $L = 1$, $C_1 = 6$, and $C_2 = 7.5$.

Investigation of drought periods for the study area shows an extreme drought for the year 2004, and to account for the drought effects, we measured the EVI for 2000, 2005 as wet year and 2012.

Table 2
The factors affecting desertification, and the corresponding evaluation criteria used for assessing the zones.

Factor	Criterion	Criterion abbreviation
Natural	Soil erodibility	Soil
	Climate erosivity	Climate
	Drought	Aridity
Anthropogenic	Land use alterations	Land use
	High grazing density	Grazing
	Land abandonment	Land aband
	Groundwater exploitation	Water

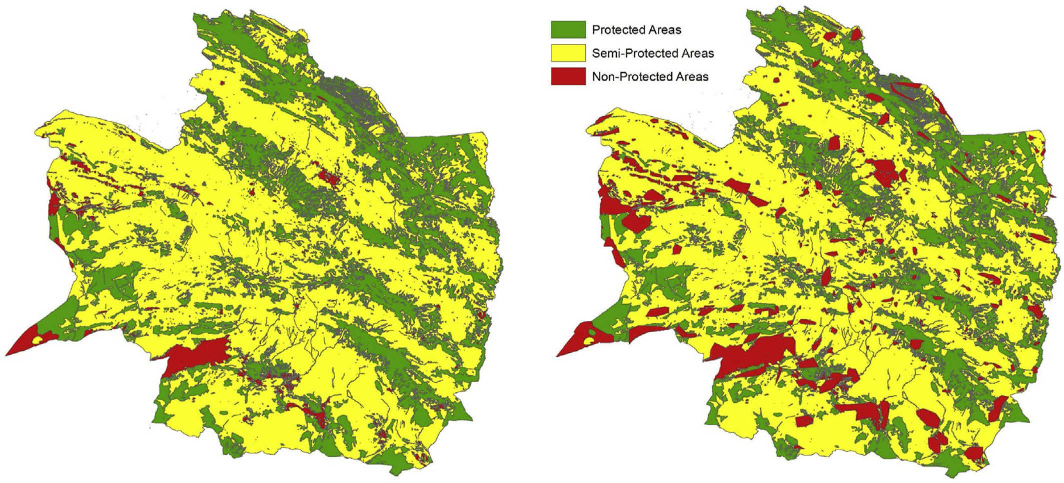

Fig. 6. Change of protected areas in KR between the years 1992 (left) and 2012 (right). An ascending trend in the amount of non-protected areas indicates a descending trend in the ecosystem's resilience against desertification.

As the EVI changes can be evidence for vegetation cover changes to determine ecosystem resilience alterations, the value changes in this index are considered indicative for the zones' susceptibility to desertification. A positive EVI indicates an increasing vegetation cover density and a negative amount a decreasing one. Fig. 7 illustrates the EVI changes for the study area from 2005 to 2012.

All zones' measurements on the seven desertification criteria and the EVI indices are presented in Table 3. Based on the resilience paradigm described earlier, we classify the zones into three classes that indicate their resilience against the chosen desertification drivers. EVI changes corresponding to the three classes are presented in Table 4. Note that these classes were constructed solely based on our own expert opinion, whereas the criteria were selected using the Delphi method with external experts. The lack of a formal method for constructing the classes is certainly a limitation of the current study. In other studies that apply the proposed method, the classes could be formed in collaboration with the relevant decision makers to ensure their subsequent commitment for applying the results in planning of the anti-desertification activities.

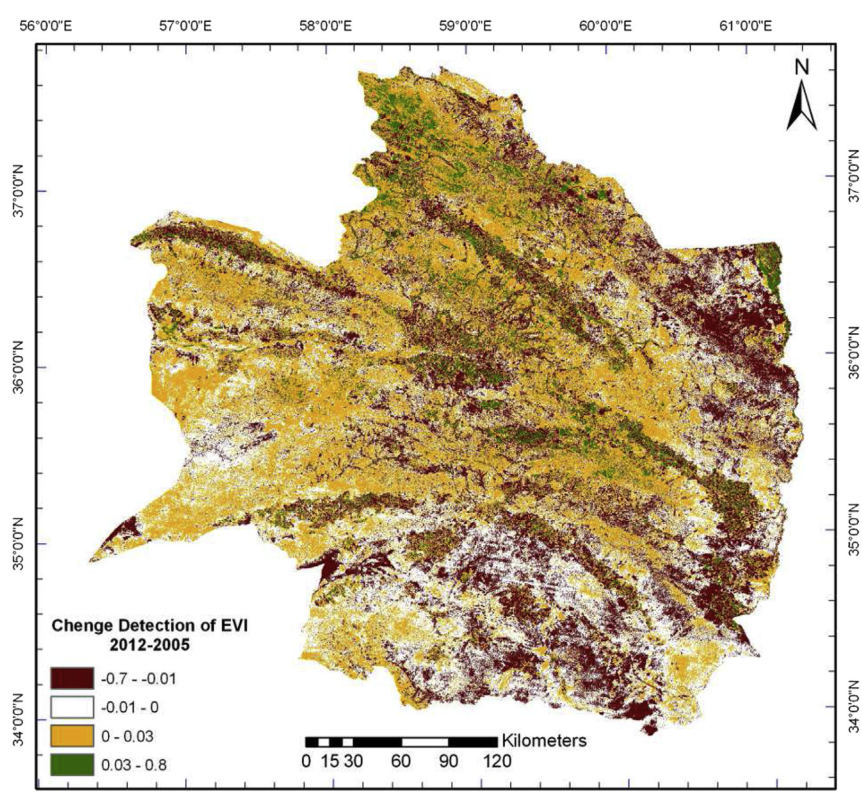

Fig. 7. Change detection of EVI between years 2005 and 2012. Many areas of province shows a descending trend in vegetation cover density which arises from land use alterations and urban development.

Table 3
The EVI differences and the qualitative and quantitative criteria measurements used for classifying the study zones. For EVI_{diff}, higher values indicate more resilient zones. The preference direction for the criteria are so, that for Aridity, higher values indicate more resilient zones, whereas for the other criteria higher values indicate less resilient zones.

Zone	EVI_{diff}	Soil	Climate	Aridity	Land use	Grazing	Land aband	Water
Preference	↑	↓	↓	↑	↓	↓	↓	↓
BKZ	−0.005	High	122	0.07	Moderate	Moderate	High	Moderate
BKN	−0.001	High	144	0.25	High	High	Moderate	Moderate
BND	0.003	Moderate	153	0.63	Moderate	High	Low	High
CRN	0.008	Moderate	159	0.51	High	High	Low	High
DGZ	0.005	High	145	0.69	High	Moderate	Low	High
FRN	0.007	Moderate	140	0.50	Moderate	High	Moderate	High
FRZ	0.002	Moderate	121	0.64	High	High	Moderate	High
GCN	0.013	High	170	0.65	Moderate	High	Moderate	High
GND	−0.006	Moderate	102	0.08	High	High	High	Moderate
JGY	0.000	High	163	0.60	High	Moderate	High	High
JVN	−0.001	High	161	0.57	High	Moderate	Low	Moderate
KLT	−0.002	High	149	0.69	High	Moderate	Low	High
KMR	−0.003	Moderate	178	0.42	High	High	Moderate	High
KAF	−0.007	Moderate	118	0.05	High	High	High	Moderate
KLD	−0.001	Moderate	141	0.25	High	Low	High	High
KSB	−0.001	High	135	0.52	High	Moderate	Moderate	Moderate
MVT	−0.007	Moderate	152	0.18	High	Moderate	Moderate	High
MHD	0.000	Moderate	235	0.55	High	High	Low	High
NBR	0.003	Moderate	250	0.64	High	High	Low	High
RTR	−0.010	Low	150	0.15	High	High	High	Moderate
SZR	0.002	Moderate	155	0.45	High	High	Moderate	High
SKS	−0.007	Moderate	151	0.57	Moderate	High	Moderate	High
TBD	−0.011	High	72	0.06	High	Moderate	High	High
TRH	−0.001	High	265	0.43	High	High	High	High
TRJ	−0.004	Moderate	133	0.40	Moderate	Moderate	High	Moderate
ZVH	0.001	High	140	0.49	Moderate	Moderate	High	Moderate
DVZ	0.016	Moderate	172	0.50	High	Low	High	High
BJS	−0.003	High	94	0.12	High	High	Moderate	Moderate

Table 4
Description of the categories used for classifying the administrative zones of the KR province.

Category	EVI difference boundaries	Description
C_1	$EVI_{diff} < -0.003$	Collapsed ecosystem
C_2	$-0.003 \leq EVI_{diff} < 0.001$	Transition zone
C_3	$EVI_{diff} \geq 0.001$	Sustainable ecosystem

3. Results

By using all zones as assignment examples we could derive no compatible classification models. This is due to too restrictive assignments that are partly caused by dominating alternatives being assigned to worse classes than the corresponding dominated ones. Fig. 8 illustrates the zone classes and the pair-wise dominance relation. Inconsistency analysis indicated a minimal set of assignment examples that need to be removed so that there existed at least one compatible classification model:

$$S = \{KSB \rightarrow C_2,\ SKS \rightarrow C_1\}.$$

Indeed, the desired assignment for SKS was C_1, while it was dominating zones assigned to both C_2 (e.g., KMR) and C_3 (e.g., SZR). With the remaining 26 assignment examples (7 ones for C_1, 9 for C_2, and 10 for C_3) the set of classification models is non-empty − we call this set of classification models our final model. Note that the observed inconsistencies are likely to be due to model underspecification, i.e., having too little attributes or too low discrimination in the qualitative attributes (such as land use alterations). Another explanation is that the EVI classes might not be specified appropriately, or that the EVI measurements are imprecise, or inappropriate altogether for establishing the desertification classes. Model underspecification is the most likely explanation due to the dominance relations (Fig. 8).

The final model assigns two zones into classes that differ from the classes derived using the EVI indices. They are both assigned to C_3 instead of C_2 for KSB and C_1 for SKS. Thus, all zones are necessarily assigned to a single class by the final model. Such unanimity indicates that the space of classification models compatible with the 26 assignment examples is relatively small. All the assignment classes are presented in Table 5.

Fig. 9 illustrates the representative marginal value functions. They form an intuitive representation of the output of the ordinal regression method. Note that the characteristic points of the marginal value functions correspond to evaluations of the different zones. However, for clarity, we marked only the points in which the function's slope changes. Inference of the non-convex and non-concave per-criterion valuation functions is a major difference between the robust multi-criteria inference procedure and other classification methods that mostly assume parameterized shapes for the classification functions.

The greatest maximal share in the comprehensive values corresponds to aridity (0.34) and climate (0.19), while the least maximal share corresponds to water (0.01) and land use (0.08). The variation of marginal values differs significantly from one criterion to another. The two criteria with numerical evaluation scales (climate and aridity) have nearly sinusoidal marginal value function shapes. The greatest difference of marginal values for climate is between 144 and 141, while for aridity it is between 0.40 and 0.42. Another three criteria (soil, land use, and water) have linear marginal value functions. Finally, for grazing and land abandonment the shapes of the marginal value functions are, respectively, concave and convex. For the previous, it is important to have low grazing, whereas for the latter it is valuable to have at most moderate land abandonment. The analysis of both shares in the comprehensive value as well as the shapes of the marginal value functions indicate the factors important for classification of the assignment examples.

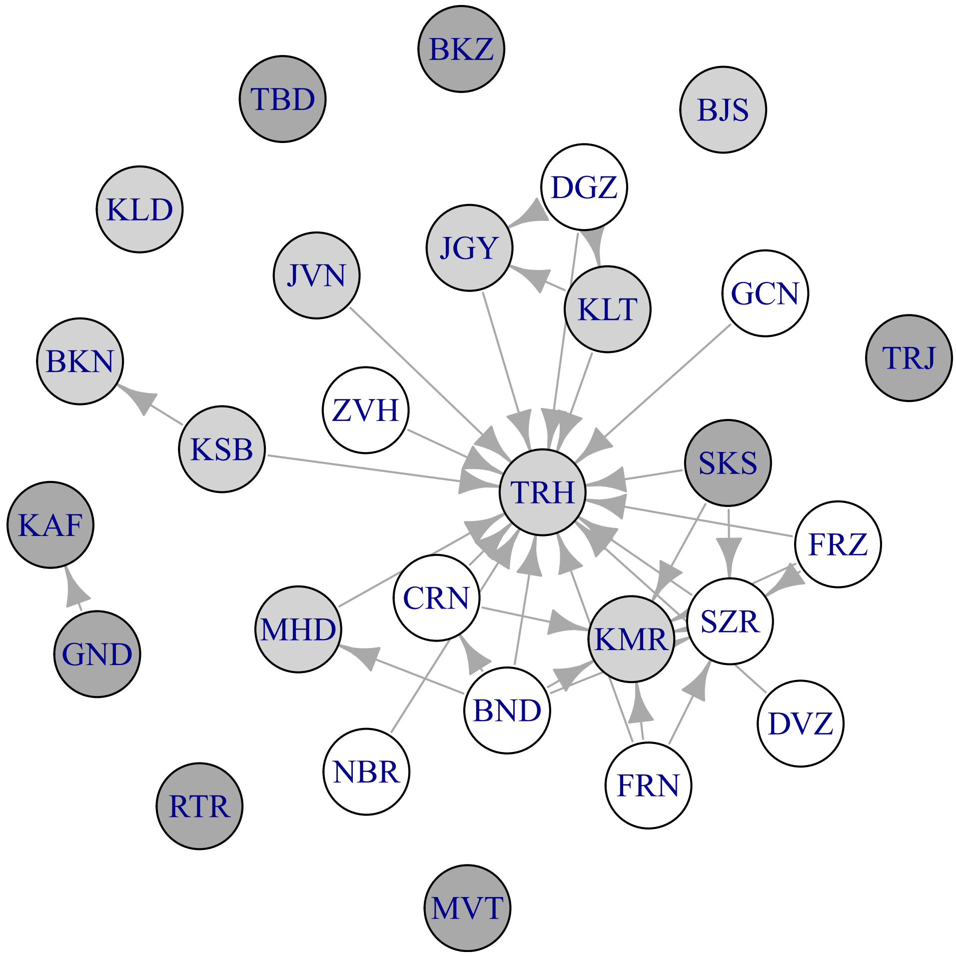

Fig. 8. Dominance graph for the considered zones. An edge (a,b) means that a dominates b. The node colors indicate zone classes derived from the EVI indices: dark-gray = C_1, light gray = C_2, white = C_3. Inconsistency analysis indicates that SKS and KSB need to be removed from the assignment examples.

The comprehensive values of the zones obtained with the representative value function U^{REP} are presented in Table 5. The range of variation of comprehensive values for zones assigned to C_1 is between 0.18 for TBD and 0.28 for TRJ, for C_2 – between 0.31 for BKN and 0.51 for KLT, for C_3 – between 0.53 for GCN and 0.71 for FRN. The value thresholds b_1 and b_2 separating the three classes are, respectively, 0.295 and 0.52.

Since the space of compatible value functions and class thresholds defined with 26 assignment examples is relatively small, even for the representative model, being the most discriminant one, some zones have comprehensive values close to the class thresholds. Let us emphasize, however, that these thresholds are not pre-defined, but rather obtained from the solutions of the respective LP. Consequently, they need to be interpreted jointly with the comprehensive values of the zones, and $U(a) \in [b_{h-1}, b_h[$ justifies $a \rightarrow C_h$ irrespective of the distances between $U(a)$ and the class thresholds b_{h-1} and b_h.

4. Discussion

The resilience ranges of the study zones were estimated based on their rates of vegetation degradation as measured with EVI. A region with a non-marginal increase ($\geq$0.001) of EVI over 2005–2012 was assumed to be resilient towards environmental factors of desertification. The inference model showed that the chosen 7 natural and anthropogenic factors were indicative for the resilience classes formed through EVI ranges, even though the initial model could not re-produce all the assignment examples and therefore it was most probably underdetermined in terms of attributes. However, the minimum set of two conflicting assignments could be discovered in an automated manner, and therefore the approach seems promising for developing classification models for use in similar environmental management problems.

The main difference between the current study and other, more traditional classification approaches is that the classification function we infer is not composed of partial functions of certain parametric shapes. This enables us to discover scale ranges where high value gains can be achieved with moderate measurement improvements. For example, the representative value function inferred in our study indicated that higher zone resilience is associated with having at most moderate grazing and land abandonment, and an aridity index of at most ~0.4, and the climate index measurement of less than ~145. Whereas other factors are also important, their relation with the comprehensive value is more linear. Furthermore, the maximum partial values define the factors' relative importances. For example, aridity seems to be very important for defining the zones' resilience, whereas groundwater exploitation is of marginal importance. Such results could be used for priority-setting in managing anti-desertification efforts by, for example, trying to decrease land abandonment in vulnerable zones where the factor is currently high.

The results indicated that grazing density and land use

Table 5
Possible assignments with the final model and representative comprehensive values of the zones. Star (*) in column EVI class indicates that the recommendation obtained with the final model is different than the EVI class.

	C_1	C_2	C_3	EVI class	$U^{REP}(a)$
BKZ	X			1	0.22
BKN		X		2	0.31
BND			X	3	0.60
CRN			X	3	0.55
DGZ			X	3	0.60
FRN			X	3	0.71
FRZ			X	3	0.71
GCN			X	3	0.53
GND	X			1	0.26
JGY		X		2	0.35
JVN		X		2	0.47
KLT		X		2	0.51
KMR		X		2	0.50
KAF	X			1	0.24
KLD		X		2	0.38
KSB			X	2*	0.62
MVT	X			1	0.24
MHD		X		2	0.48
NBR			X	3	0.53
RTR	X			1	0.18
SZR			X	3	0.53
SKS			X	1*	0.59
TBD	X			1	0.18
TRH		X		2	0.31
TRJ	X			1	0.28
ZVH			X	3	0.53
DVZ			X	3	0.53
BJS		X		2	0.32

management have a large effect in the desertification of Khorasan Razavi. This is in line with other studies that have found overgrazing to be one of the main desertification drivers around the globe (see e.g. Salinas and Mendieta, 2013b). Salinas and Mendieta (2013a) suggest that in areas heavily degraded by overgrazing, the most effective strategies are those oriented to obtain a permanent vegetation cover on degraded soils. In the Khorasan Razavi region, such strategies should be directed towards areas whose grazing density is deemed to be in the 'low' quality class.

The natural factors of the model measure effects that cannot easily be changed with anti-desertification strategies, but the inferred model can still be used for predicting changes in the ecosystems and for planning appropriate measures. Drought and erosivity intensity can be sudden events that impact the vulnerability of the province, and lower the zones' resilience ranges. Interestingly, the level of vulnerability and resilience characterizing the KR landscape appears to be progressively decoupled from the biophysical factors originally associated with the anthropogenic factors, grazing density and land use changes, which not only decrease the land productivity, but also imply natural resource depletion, landscape simplification and fragmentation, as well as soil deterioration. Thus, the representative value function we inferred seems to show good correspondence with how desertification proceeds in the province.

Fortunately, most of the study zones are in sustainable states, but on other hand, many zones are very close to a vulnerability threshold as implied by belonging to the transition class (BKN, JGY, JVN, KLT, KMR, MHD, TRH and BJS). The spatial distribution of environmental resilience and consequences of vulnerability to desertification in the KR province have considerably changed during the last decades and, particularly, evolved from relatively easily understandable to more complex processes. During the last years the drought period and erosion intensity in relation to soil erodibility and climate erosivity have reflected resilience of the KR ecosystems. Our inference approach quantified these effects in a manner that enables usable decision support for priority setting in management of regional anti-desertification efforts.

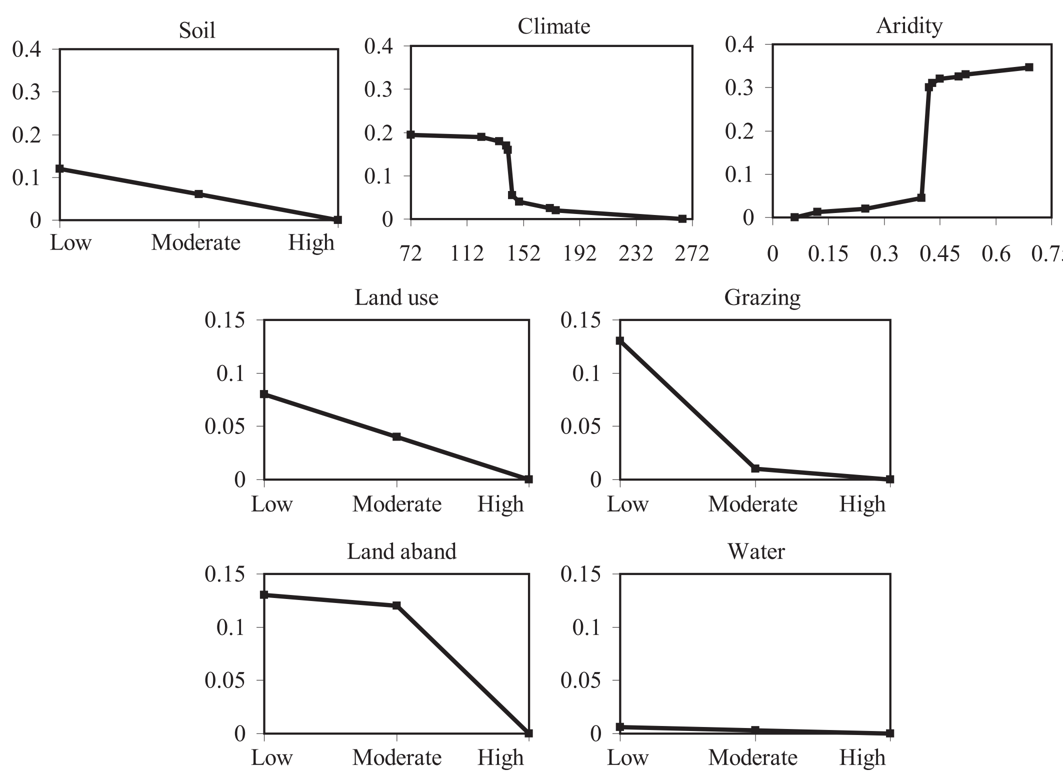

Fig. 9. Representative marginal value functions.

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Appendix A. Mathematical models

We describe here the mathematical models used in the method discussed in the methodology-section and applied in the case study. For clarity of presentation, and without loss of generality, we assume that all criteria have an increasing direction of preference, i.e., the greater $g_j(a_i)$, the better a_i on g_j. The ordered values of X_j, $x_j^k < x_j^{k+1}, k = 1, \ldots, n_j(A) - 1$, where $n_j(A) = |X_j|$ and $n_j(A) \le n$, are denoted with $x_j^1, \ldots, x_j^{n_j(A)}$. Consequently, $X = \prod_{j=1}^{m} X_j$ is the criteria evaluation space.

Appendix A.1. Model used in Step 2

The set of pairs $(\mathscr{U}, \mathbf{b})^R$ compatible with the provided assignment examples is defined with the following constraints (Greco et al., 2010):

$$\left.\left.\begin{array}{l} U(a) = \sum\limits_{j=1}^{m} u_j(a), \forall a \in A, \\ u_j\left(x_j^k\right) - u_j\left(x_j^{(k-1)}\right) \ge 0,\ j \in J,\ k = 2, \ldots, n_j(A), \\ u_j\left(x_j^1\right) = 0,\ j \in J,\ \sum\limits_{j=1}^{m} u_j\left(x_j^{n_j(A)}\right) = 1, \\ b_1 \ge \varepsilon,\ b_{p-1} \le 1 - \varepsilon, \\ b_h - b_{h-1} \ge \varepsilon,\ h = 2, \ldots, p-1, \end{array}\right\} E^{BASE} \\ \begin{array}{l} U(a^*) \ge b_{L_{DM}(a^*)-1},\ U(a^*) + \varepsilon \le b_{R_{DM}(a^*)},\ \forall a^* \in A^R. \end{array}\right\} E\left(A^R\right)$$

To verify that the set $(\mathscr{U}, \mathbf{b})^R$ is not empty, it is sufficient to check whether $E(A^R)$ is feasible and $\max \varepsilon$ s.t. $E(A^R)$ has an optimal value $\varepsilon^* > 0$. Otherwise, if $E(A^R)$ is infeasible or $\varepsilon^* \le 0$, $(\mathscr{U}, \mathbf{b})^R$ is empty and some assignment examples need to be removed or revised.

Appendix A.2. Model used in Step 3

When using the threshold-based sorting procedure, we need to solve the following MILP to identify the minimal subset of assignment examples that need to be removed so that $(\mathscr{U}, \mathbf{b})^R$ is non-empty (Greco et al., 2011):

$$\text{Minimize } f = \sum_{a^* \in A^R} v_{a^*},\ \text{s.t. } E'\left(A^R\right),$$

where $E'(A^R)$ is defined as follows:

$$\left.\begin{array}{l} E^{BASE}, \\ \left.\begin{array}{l} U(a^*) + v(a^*) \ge b_{L_{DM}(a^*)-1}, \\ U(a^*) + \varepsilon - v(a^*) \le b_{R_{DM}(a^*)}, \\ v(a^*) \in \{0,1\}. \end{array}\right\} \forall a^* \in A^R \end{array}\right\} E'\left(A^R\right)$$

Let f^* be the optimal value of the objective function and $v^*(a^*)$ the values of the binary variables at the optimum. Then, $S = \{a^* \in A^R : v^*(a^*) = 1\}$ is the subset of assignment examples that have to be removed. Subsequently, Steps 4 and 5 need to be conducted with respect to the set of pairs $(\mathscr{U}, \mathbf{b})^R$ compatible with the assignment examples for $a^* \in A^R \backslash S$, and not $a^* \in A^R$. This procedure is inspired by the general scheme for dealing with incompatibility presented by Mousseau et al. (2006).

Appendix A.3. Models used in Step 4

Let us denote the assignment of a with pair $(U,\mathbf{b})$ by $C^{(U,\mathbf{b})}(a)$. Given a set of compatible pairs $(\mathscr{U}, \mathbf{b})^R$, the possible assignment $C_P(a)$ for $a \in A$ is defined as the set of indices of classes C_h for which there exists at least one compatible pair in $(\mathscr{U}, \mathbf{b})^R$ assigning a to C_h, i.e. (Köksalan and Bilgin Özpeynirci, 2009; Greco et al., 2010):

$$C_P(a) = \{h \in H : \exists (U, \mathbf{b}) \in (\mathscr{U}, \mathbf{b})^R,\ C^{(U,\mathbf{b})}(a) = h\}.$$

The possible assignment of $a \in A$ can be computed with Theorem 1 (Köksalan and Bilgin Özpeynirci, 2009; Kadziński and Tervonen, 2013).

Theorem 1. *$\forall a \in A, \forall h \in H, \exists (U,\mathbf{b}) \in (\mathscr{U}, \mathbf{b})^R : C^{(U,\mathbf{b})}(a) = h$, i.e. $a \to^P C_h$ iff $E(a \to^P C_h)$ given below is feasible and $\varepsilon^* = \max \varepsilon$ s.t. $E(a \to^P C_h) > 0$.*

$$\left.\begin{array}{ll} U(a) \ge b_{h-1}, & \text{if } h \ge 1, \\ U(a) + \varepsilon \le b_h, & \text{if } h \le p-1, \\ E(A^R). & \end{array}\right\} E\left(a \to^P C_h\right)$$

Note that instead of solving p LP problems to identify $C_P(a)$, alternatively we can refer to the procedure proposed by Greco et al. (2010) that requires considering $2p$ less problems.

The necessary ($\succsim^{\to,N}$) assignment-based weak preference relation holds for a pair $(a,b) \in A \times A$ if a is assigned to a class at least as good as b for all compatible pairs in $(\mathscr{U}, \mathbf{b})^R$, i.e. (Kadziński and Tervonen, 2013):

$$a \succsim^{\to,N} b \Leftrightarrow \forall (U, \mathbf{b}) \in (\mathscr{U}, \mathbf{b})^R : C^{(U,\mathbf{b})}(a) \ge C^{(U,\mathbf{b})}(b),$$

Its truth can be verified by considering Theorem 2 (Greco et al., 2011).

Theorem 2. *$\forall a, b \in A : a \succsim^{\to,N} b$ iff $\forall h \in \{1,\ldots,p-1\}$: $E_h(a \succsim^{\to,N} b)$ given below is infeasible or $\varepsilon^* = \max \varepsilon$ s.t. $E_h(a \succsim^{\to,N} b) \le 0$.*

$$\left.\begin{array}{l} U(b) \ge b_h, \\ U(a) + \varepsilon \le b_h, \\ E(A^R). \end{array}\right\} E_h\left(a \succsim^{\to,N} b\right). \tag{A.1}$$

Then, the necessary strict preference ($\succ^{\to,N}$), indifference ($\sim^{\to,N}$), and incomparability ($R^{\to,N}$) are computed in a usual way:

$$a \succ^{\to,N} b \Leftrightarrow a \succsim^{\to,N} b \text{ and } not\left(b \succsim^{\to,N} a\right),$$

$$a \sim^{\to,N} b \Leftrightarrow a \succsim^{\to,N} b \text{ and } b \succsim^{\to,N} a,$$

$$a R^{\to,N} b \Leftrightarrow not\left(a \succsim^{\to,N} b\right) \text{ and } not\left(b \succsim^{\to,N} a\right).$$

Appendix A.4. Model used in Step 5

The following procedure selects a representative value function (Greco et al., 2011; Kadziński et al., 2013):

1. For all $a,b \in A$, such that $a \succ^{\to,N} b$, add the following constraints to the set of constraints $E(A^R)$:

$$U(a) - U(b) \ge \gamma.$$

2. Maximize γ, subject to the set of LP constraints from point 1, i.e. maximize the minimal intensity of preference for pairs (a,b), such that $a \succ^{\rightarrow,N} b$. When using such a maximin rule, the obtained results can be easily interpreted, i.e. we can observe what is the minimal intensity of preference for pairs of alternatives satisfying the conditions.
3. Add the constraint $\gamma = \gamma^*$, with $\gamma^* = \max \gamma$ from the previous point, to the set of LP constraints considered in point 1. This maintains the differences of values of pairs of alternatives considered in point 1 at their optimized levels.
4. For all $c,d \in A$, such that $c \sim^{\rightarrow,N} d$ or $cR^{\rightarrow,N} d$, add the following constraints to the set of constraints from point 3:

$$\left.\begin{array}{l} U(c) - U(d) \leq \delta, \\ U(d) - U(c) \leq \delta. \end{array}\right\}$$

5. Minimize δ, subject to the set of LP constraints from point 4, i.e. minimize the maximal intensity of preference for pairs $c,d \in A$, such that $c \sim^{\rightarrow,N} d$ or $cR^{\rightarrow,N} d$.
6. Read off the representative comprehensive values $U^{REP}(a)$, corresponding marginal values and class thresholds from the solution of the LP problem considered in point 5.

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