Monitoring Large-Scale Regenerative Grazing Using Artificial Intelligence

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Article

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Abstract

Grazing livestock raises greenhouse gas emissions and contributes significantly to climate change. Excessive grazing also causes soil degradation, makes pastures more prone to drought, and renders them unsuitable for long-term usage. However, well-managed regenerative grazing can help combat global warming without jeopardizing food security and livelihoods for millions of people worldwide. With existing manual procedures, traditional regenerative grazing has proven difficult to apply efficiently. In this paper we propose a novel Artificial Intelligence-powered method for monitoring large-scale regenerative grazing. Using deep learning and publicly available ESA Sentinel-2 satellite images, this method first classifies land cover. Then, using machine learning, 18 bioparameters are tracked, providing farmers with recommendations on how to arrange livestock to minimize environmental impacts. We apply this method to a large conservancy in Kenya. Our case study demonstrates that our artificial intelligence-powered method achieves considerable gains in grass regeneration and offers great promise for improving sustainable development.

Keywords: AI, climate change, regenerative grazing, rangeland monitoring, nature-based solutions

Agricultural intensification contributes to climate change by increasing greenhouse gas emissions [1]. Grazing livestock, for example, acquire nutrients from grazing, but because grass is more difficult to digest than grains, the livestock emit more methane, a kind of greenhouse gas with approximately 28 times the warming potential of CO2 [2]. Overgrazing of pastures also deteriorates soil, leading to erosion, hindering regrowth, and making pastures more prone to drought [3]. Nonetheless, well-managed grazing methods can contribute to global warming mitigation without jeopardizing food security or the livelihoods of millions of people worldwide [2]. Well-managed regeneration grazing systems relocate livestock to avoid overgrazing and allow manure to re-enter the soil, permitting sequestering more carbon and encouraging plant regrowth of severely degraded soil [4], thereby contributing to climate change mitigation. As grazing lands continue to experience increased pressure from lower
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rainfall and climate variability, successful regenerative grazing plans through responsible animal husbandry become imperative [5].

Several traditional regeneration grazing methods have been used for centuries to minimize environmental impacts including rotational rest, rotational grazing, and deferment [6]. In contrast to the alleged experience of many grazers, scientific studies have found that these traditional practices make no major improvement on land degradation or overall sustainability [7]. For instance, rotational grazing has been found to be no better than light continuous grazing [8], [9], [10]. In addition to their limited effectiveness, traditional regenerative grazing methods are laborious, conducted manually, without using data-guiding protocols, and at small-scale [7]. Although other adaptive management methods have been developed [11], [12] they are often conducted at small scale [13], [14], [15], [16]. For instance, field monitoring has been used to evaluate rangeland quality and inform herd movements [17]. Although this technique is effective, it grows in complexity as the size of a managed landscape expands. Herders may not frequent all areas that their herds have access to, and unless the landscape is small, field monitoring may not be feasible as it is labour-intensive and time consuming to collect enough data to adequately inform decisions [18]. Livestock grazing occurs predominantly in rangelands which compromise about 70% of global terrestrial area, thus regeneration grazing methods also need to be applicable at large scale [19], [9]. Furthermore, global warming, and the recurrent high risk of droughts across many regions require instead a more adaptive than reactive approach, which can be implemented on a large scale [20].

In this article, we propose a novel artificial intelligence (AI)-powered method which guide grazers on how to effectively allocate their livestock to prevent soil erosion balance damage to the land from wildlife and minimize environmental impacts. This method, which we call, AIREGENERATE, is in practice straightforward to apply. First, the land cover is classified using publicly available ESA Sentinel-2 satellite images. Then, using machine learning, 18 bioparameters are tracked, providing farmers with recommendations on how to arrange livestock. This novel method not only automates the laborious task of traditional regeneration grazing methods, but it is also simple to use on a large scale, and effective in limiting overgrazing dangers.

Livestock grazing is predominantly used by 200 million people in Africa [19], [21]. Another contribution of this article is to show how these traditional communities relying on grazing methods can easily apply our method. To this end, this paper shows an application in a large (4000 acres) community conservancy in Kenya. This case study illustrates that our AI-powered method has significantly increased capacity to monitor the rangeland territories and made land management decisions faster and more efficient.

Artificial intelligence methods have been widely applied in multiple fields to support climate change mitigation and adaptation [20]. These applications range from peatland monitoring [22], wetland restorations [23], tree cover monitoring and counting of individual trees [24]. Already, rangelands in the western
United States have been evaluated using satellite imagery and the information obtained is being used to inform decisions on a national level, especially in management decisions to restore degraded areas [25]. To our knowledge, artificial intelligence has not been deployed to optimise regenerative grazing at large scale in settings like Africa combining publicly available satellite images and machine learning. Thus, our contribution to the extensive literature of AI is to develop an novel framework that guides livestock farmers restoring the ecosystem services provided by rangelands by sustainably managing their herds and herd movements. With this kind of responsible management within a well-informed grazing plan, livestock can be utilized to rehabilitate degraded rangelands, enhancing the forage available to wildlife and revitalizing carbon sequestration [15], [16].

1 Results: Applying AIREGENERATE

The proposed AIREGENERATE consists of six steps as depicted in Fig.1. AIREGENERATE first identifies the high-level properties of the region to be analysed, crucially the type of landcover. Then, a bioparameter model is used to predict the characteristics of the landcover type. The next stages provide an overview on the existing risks of overgrazing and other anomalies detected on land use. Then our model predicts how to optimally allocate livestock across rangeland territory, and finally this advice is passed to grazers to prevent land degradation and enable grazing regeneration.

Fig. 1 The proposed AIREGENERATE top-down framework

To demonstrate the applicability of AIREGENERATE and its scalability, we analyse grazing patterns in the Enonkishu Conservancy located in the Masai Mara Serengeti region in Kenya (Fig.2). Conservancies provide a habitat for most of the biodiversity in the region which is in a vulnerable state due to extensive overgrazing, among others such as firewood use and charcoal production.
The Enonkishu conservancy comprises 1705 hectares. Since 2013, the conservancy has been monitored by the Masai Mara Training Center, scientists, rangers and volunteers recording 18 bio-monitoring parameters in five 1m quadrats for each sampling site [26] (Fig. 3). This team has also used regenerative grazing in the conservancy eliminating thus far livestock fatalities, in sharp contrast with adjacent rangelands which still experience several hundred of these fatalities. However, monitoring has been very labour intensive and as a result is difficult to scale to the entire Masai Mara Serengeti area comprised of 250,000 hectares.

**Fig. 2** Left panel: map of Enonkishu conservancy; right panel: topological map with overlayed vegetation health.

**Fig. 3** Left panel: map of Enonkishu conservancy; right panel: example of a quadrant for different sampling sites.
To tackle the problem of biomonitoring parameter estimation, we use the top-down approach, as depicted in Fig. 1. This approach first identifies high-level properties of the region that we want to analyse, such as type of landcover, and then uses them as an input to predict measurements (in our case biomonitoring parameters) for each landcover type. Finally, we provide actionable recommendations to farmers on resource optimisation, in this case cattle movement, across rangeland territory and preventing further land degradation from overgrazing.

To categorise land coverage, we first collated the 18 parameters available for the Enonkishu conservancy since 2014 with satellite imagery publicly available for December, 2015. Then we applied our AI algorithm, which surpassed the state-of-the-art model performance. On land cover segmentation task, we achieved 79% accuracy (training loss: 0.32, validation loss: 0.1, test loss: 0.79).\(^1\)

Overgrazing was predicted across all grass and shrub areas creating a binary image of either overgrazed or not overgrazed pixels (Fig. 4). The overgrazing model prediction had an overall accuracy of 84-98\(^%\) \(^2\). This high degree of accuracy is important as overgrazing is one of the most important parameters for conservancy management to guide where to move livestock around the conservancy.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{overgrazing.png}
\caption{Overgrazing prediction on grasslands. Red areas indicate the places with highest degrees of overgrazing.}
\end{figure}

\(^1\)AI algorithm showed some confusion between the agricultural land and bare soil, since for prolonged periods of time crops are harvested on agricultural land bearing land bare.

\(^2\)The training accuracy of 98\% with a validation accuracy of 92\% validates on 5\% of training data. On the testing dataset the model had an overall accuracy of 86\% with 84\% accuracy of over-grazed and 92\% accuracy of non-overgrazed pixels.
The bioparameter model also had a very high accuracy of (98%) for biomass measures that can range from 1000 - 2500. In general, the areas of grassland and shrubland had higher biomass than forest areas so for visualisation these were separated into two separate images (Fig. 6, 5). The parameters which are classified into 0-5 quantiles had varying accuracy depending on the parameter, due to the nature of it being discrete ordinal classes error was generally around 0.5 to 1. Each parameter had a different mean error and error distributions. Plant density estimation parameter is described in Fig. 7.

Fig. 5 Estimation of forest biomass across the rangelands. The colour coding shows the highest biomass as blue and the lowest as red, respectively.

The results of our bioparameter estimation models, provide an interpretable tool with a high degree of accuracy (98%) that the conservancy could use for management and optimal movement of the livestock (Fig. 8). The negligible small margin of error can be solved with minimal managerial decisions on land.

The recommendation and optimization system, built on the top of the parameter bioparameter estimation model, allows identification of the over-grazed area, ground confirmation and moving livestock between different parts of the conservancy.

The model proposed here, AIREGENERATE, outperforms two earlier studies conducted in Africa using the same or lower resolution imagery ([28], [29]). These earlier studies used random forest modelling to determine biomass and thereby guide grazing for livestock. One of these studies achieved 84% of accuracy in determining biomass using high resolution 0.5m Worldview 2 imagery over rangelands in South Africa [28]. A separate study achieved 87% accuracy using Sentinel-2 data on rangelands in Ethiopia [29].
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2 Discussion

With the pressing need to balance natural resources, wildlife conservation and human livelihoods, better monitoring of non-urban areas is critical. We proposed here AIREGENERATE, a novel Artificial Intelligence-powered method
that has the capability of monitoring grazing on a large-scale and guides grazers how to allocate their livestock with 98% accuracy to avoid overgrazing.

**Learning from AIREGENERATE.** This method helps prevent overgrazing, by monitoring and providing rapid and reliable insights into the condition of land, including their suitability for both grazing and nature conservation. Moreover, Masai Mara region has wet seasons during which it is particularly vulnerable in terms for overgrazing: cattle and wildlife can do significant amount of damage to the soil in the rainy season. The proposed system can help to minimize the damage and adjust the recommendations accordingly.

**Application.** Precision monitoring allows for the creation of adaptable grazing regimes. Thus, grazers can alter how long each area is grazed for or which area to move grazing to depending on the condition of an area or the surrounding areas. Grazers can then in turn have informed decisions on whether to maximise the use of an area for conservation or community purposes.

We showed that tools like AIREGENERATE can provide grazers with reliable information on how to allocate livestock at large scale. Our application in the Enonkishu conservancy in Kenya was implemented during the ongoing COVID-19 pandemic. COVID-19, like many other diseases, natural disaster events or episodes of violence, disrupts monitoring of land and agricultural activities in the country.

Our remote monitoring tool provides essential information to enable grazers to substantially decrease manual monitoring, and the costs associated with it, and rely instead on the advice provided by our near-real-life monitoring.

**Prospects.** Many general pasture settings such as meat or dairy cattle could benefit from precision grazing regimes like the one proposed here to
maximize the health of the livestock animals while minimizing the damage to the land. For instance, overgrazing by cattle and goats has caused large-scale erosion of soil and desertification across many regions, particularly Africa [30]. The Sahel region, for instance, on the edge of the Sahara Desert is expanding at an alarming rate every year. While there are actions already being taken to counteract overgrazing [31], such as the green wall initiative [30], there is still a substantial large gap in monitoring and guiding cattle allocation. We showed here, that tools like AIREGENERATE can provide accurate and actionable guidance to grazers on their land and grazing management plans. Beyond Africa there is also much need for large-scale monitoring to prevent deforestation. A clear example is the Amazon rainforest in South America [32], [33]. Satellite data and machine learning are already being used in the Amazon to monitor the rate of deforestation [34], [35]. Nonetheless, there is still need for more advanced tools like the one proposed here to monitor and guide the regeneration of already deforested land.

Agriculture and livestock intensity contribute to global warming and are equally affected by it. Sudden changes in climate and extreme weather events have been shown to have a negative impact on tropical grazing and rangelands, including variability in the livestock market, disease outbreaks, and unreliability of water sources [36], [37]. Higher temperatures combined with drought impair livestock production by negatively impacting on animals’ physiological performance, increasing ectoparasite abundance, and reducing forage quality and quantity [38].

The field of satellite imagery, incorporating artificial intelligence to upscale existing field monitoring data has vast potential to promote the implementation of sustainable rangeland management and inform decision making across entire landscapes of rangeland [39], [40]. In this paper we showed an application of artificial intelligence that not only can help regenerate grazing, but also has the potential to contribute positively to global climate change and mitigate its effect on livestock and food security.

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Appendix A  Methods and data

AIREGENERATE consists of six steps depicted in Fig.1. First, the land cover is classified. Then, a bioparameter model is used to predict the characteristics of the landcover type. The next stages provide an overview on the existing risks of overgrazing and detects anomalies on land use. Then the decision support model predicts how to allocate livestock. In the last stage, the advice on land and livestock is passed to grazers to prevent land degradation and enable grazing regeneration.
A.1 Landcover classification

This study was performed over the Enonkishu Conservancy in the Masai Mara, Kenya (Fig. 2). The Mara Serengeti ecosystem is in a vulnerable state with the threat of human encroachment and associated activities such as extensive overgrazing and firewood and charcoal production. As the Mara conservancies provide a habitat for most of the biodiversity in the Mara region, it is imperative that areas of severe degradation are rehabilitated to support biodiversity of wildlife and minimise environmental impact due to water run off on bare soil. Since 2013, Enonkishu (1705 hectares) and The Mara Training Center have been conducting intensive monitoring of the vegetation to drive rangeland improvements such as regenerative grazing by livestock.

Whilst adjacent rangelands experience several hundred livestock fatalities annually, Enonkishu’s regenerative grazing strategies have eliminated livestock fatalities. However, monitoring has been very labour intensive and as a result is difficult to scale to the entire Maasai Mara Serengeti region (250,000 hectares). Enonkishu is a research community conservancy with a structured grazing regime to determine sustainable levels of cattle grazing balanced with conservation needs. The area is monitored by a team of scientists, rangers and volunteers who periodically perform transects of areas recording several bio-monitoring parameters in five 1m quadrats for each sampling site [26]. This creates a dataset that has been recording since 2014 with on average one record period per quarter, which was clipped to the date period that satellite imagery is available for (December, 2015). For each block a total of 18 parameters was monitored for 6 years. Table A1 show the most essential parameters.

To tackle the problem of biomonitoring parameter estimation, we use the top-down approach, as depicted in Fig. 1. This approach first identifies high-level properties of the region that we want to analyse, such as type of land cover, and then uses them as an input to predict measurements (in our case biomonitoring parameters) for each landcover type. Finally, we provide actionable recommendations to farmers on resource optimisation, in this case cattle movement, across rangeland territory and preventing further land degradation from overgrazing.

A.2 Habitat classification

In the first step, we classify land into cover types using satellite imagery. This step allows us to understand what kind of analysis should be applied to each part of the rangeland, e.g. shrubland, grassland, forest or bare soil. To detect different types of land cover, a semantic segmentation model is built for habitat classification [41]. Semantic segmentation models allow to detect pixels of the image, which belong to the same class.

For semantic segmentation of land cover, we use a multi-class segmentation U-net model, based on the original architecture, proposed by [41]. Previously, U-net architecture showed good results for landcover classification [24]. The architecture of the U-net model consists of two parts: encoder and decoder.
The encoder consists of the repeating sets of blocks, each of which consists of two convolutional layers, activated by rectified linear unit (ReLU) function, followed by a MaxPooling and Dropout layer. Convolution is a fundamental operation in computer vision. The parameters of the convolution operation are learned during the training of the neural network and further used to define the features that are extracted. The decoder consists of the same blocks, however the convolutional operation is replaced by a transposed convolution operation. At each upsampling level, the output of the corresponding encoder block is concatenated with the corresponding decoder block. We used Softmax activation function in the final activation layer of the model to perform multi-class classification.

**Fig. A1** The proposed U-net architecture consists of an encoder (downsampler) and decoder (upsampler) with a bottleneck in between. The grey arrows correspond to the skip connections that concatenate encoder block outputs to each stage of the decoder. The the number of output channels equals the number of the classes (6 classes: 0 - agriculture, 1-bare soil, 2- forest, 3 - grassland, 4 - shrubland and 5- water).

We used He weight initialisation [42] and Tversky loss [43] as a loss function used during training, which deals better with class imbalance in segmentation compared to the common classification loss.

To classify landcover in our application to the Enonkishu Conservancy located in Kenya we used the freely available Sentinel-2 satellite imagery from December 2016 until July 2020. These images were then filtered to remove cloudy images, leaving a dataset of 123 images. Atmospheric correction was then applied to produce images ready for data processing. The images, which were taken during the flooding period, were masked out. To fill in the gaps in the time series, linear interpolation techniques were used to interpolate between preceding and consequent time slices. From two patches, randomly
sampled patches of 64x64 pixels, including all 12 bands went into the input. Fig. A2 shows a few examples of such classification. We performed habitat classification using a U-net model, trained on labelled habitat masks [41]. As input data, we use 12 bands of Sentinel-2 images at 10-m spatial resolution and added an additional NDVI (normalised difference vegetation index) layer to increase the classification accuracy of the vegetation.

Trees and shrublands in Kenya stand out as objects with a high NDVI value — in contrast to their surroundings, which have low NDVI values in the dry season. We manually delineated and annotated all the vegetation types across the conservancy to construct the labels (or masks) for the supervised learning algorithm. The resulting mask contained a total of 6 classes: agriculture, bare soil, forest, grassland, shrubland and water. For convenience, the data was split into two patches, with a separate mask for each patch. Therefore, there were two masks for each class, with 1 mask for water, since it was present only in 1 patch, but not the other, which resulted in a total of 11 masks. We formed the NDVI from every image from the pansharpened red and near-infrared bands.

![Habitat classification with semantic segmentation](image)

**Fig. A2** Habitat classification with semantic segmentation

### A.3 Biomonitoring parameter estimation

After classifying landcover and habitat for each pixel in the rangeland, AIRE-GENERATE moves to the next stage. This consists of evaluating available biomonitoring parameters using historical data for each land cover type. For each bio-monitoring parameter we build a random-forest model [44], taking as an input the three vegetation indices which best correlate to that parameter, the habitat type, and the season. We split data into train and testing data (80-20 split). Once the models are trained and validated, the vegetation and habitat values from the entire conservation area are extracted from the satellite image and predicted on. The resulting prediction was then reshaped back
into the shape of the conservancy providing a predicted map across the entire area of interest.

In contrast with the most of parameters, biomass is calculated as a numeric value, measured in the units of kilograms of dry matter per hectare. We used historical data on grass height measurements, and a formula to calculate the biomass yield from this data. To predict biomass from the satellite imagery, we used a linear regression model during each season, the habitat type (U-net model output) and three vegetation indices as inputs (normalised difference vegetation index (NDVI), normalized difference water index (NDWI), and renormalised difference vegetation index (RDVI)). The model performance was extremely good, and reached an accuracy of 98% and a mean error of 38.

Plant density was measured in a 0-5 scale which corresponds to the % of plants in a given square. To predict plant density from the satellite imagery, we similarly used a linear regression model taking the season, the habitat type and four vegetation indices as inputs (TCARI, TDVI2, NLI, NDVI). The model had an error of 0.64 on the 0-5 scale with a standard deviation on 0.59.

To predict these parameters across the map, we use the historical data, collected on the ground by the Enonkishu conservancy team and ESA Sentinel imagery data, downloaded for the same period as described above. The conservancy has been monitored since 2013 by a team of scientists, rangers and volunteers that have monitored 18 parameters over 6 years, shown in Table A1.

Next, we used linear regression to make predictions and the outputs were displayed as model outputs over the map per each pixel. We calculate 20 different vegetation and moisture indices for each image. For every sampling date from the bio-monitoring dataset we find the closest satellite image and calculate the pixel values of all vegetation indices at the sampling locations.

### Table A1 Biomonitoring parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass</td>
<td>A measure of the total amount of harvestable grass</td>
<td>Cont.distr.</td>
</tr>
<tr>
<td>Plant Density</td>
<td>The percentage of a sample that is plant matter</td>
<td>0-5 Quantiles</td>
</tr>
<tr>
<td>Plant Height</td>
<td>The height of the plant out of max. possible height</td>
<td>0-5 Quantiles</td>
</tr>
<tr>
<td>Leaf Area</td>
<td>The area of the sample which is leaves</td>
<td>0-5 Quantiles</td>
</tr>
<tr>
<td>Plant Young</td>
<td>The percentage of the area consisting of young plants</td>
<td>0-5 Quantiles</td>
</tr>
<tr>
<td>Plant Mature</td>
<td>The percentage coverage of mature plants</td>
<td>0-5 Quantiles</td>
</tr>
<tr>
<td>Overgrazing</td>
<td>Whether an area is overgrazed or not</td>
<td>Binary (0/1)</td>
</tr>
</tbody>
</table>

### A.4 Overgrazing

In the third stage of AIREGENERATE, we estimated the extent of overgrazing using the same dataset as in the earlier step. For our application in the Enonkishu conservancy to provide a prediction of overgrazing we used a time series of four images. Then the overgrazing is estimated using a deep learning model with an LSTM auto-encoder structure [45]. The input of this model is
a single pixel from the image corresponding to the 20 vegetation indices plus the season that image was taken in and the habitat type of the pixel; four of these corresponding to the four most recent images are stacked and the time series is the input of the LSTM at each step. This architecture was chosen due to the specific properties of the area (overgrazed areas being a minority class, seasonal differences in the vegetation, specific to Masai Mara Valley, etc.) and might need to be adjusted slightly for other areas depending on the local properties of the vegetation.

Due to overgrazing being a rare event it was a minority class in the binary classification model making up 15% of observations. To prevent over-fitting to the majority class synthetic data of the minority class was generated using Synthetic Minority Oversampling Technique (SMOTE) within the training data to bring it up to a 0.5 ratio \[46\]. The model was then trained on this dataset until binary cross-entropy error had converged and then tested on 20% of the data to determine accuracy.

### A.5 Anomaly detection

Then, AIREGENERATION detects anomalies using the time series of vegetation indices, described earlier. To this end, we first filter out the images, containing clouds and then used the remaining images to form the time-series data. For our application in the Enonkishu conservancy we used an isolation forest model, which is an unsupervised machine learning algorithm that identifies anomalies by isolating outliers in the data.

The isolation Forest algorithm used calculates the anomaly score of each sample \[47\]. This algorithm isolates the outliers by randomly selecting a feature from the given set of features. Then it randomly selects a split value between the max and min values of that feature. This random partitioning of features produces shorter paths in trees for the anomalous data points, thus distinguishing them from the rest of the data.

### A.6 Resource optimization

In the fifth stage of AIREGENERATE, a summarising model uses all the calculated parameters to predict the optimal movements of livestock to stimulate regenerative grazing in the analysed rangeland. This model provides grazing managers with concrete information to decide whether to move livestock between the blocks and if so, where to move it every few weeks.

To provide meaningful prediction of livestock movement over a time frame, the model requires input with relevant time data. A wide variety of models have been proposed to analyse similar allocation of resources over time, from dynamic programming \[48\], \[49\] to graph neural networks \[49\]. However, due to the restricted amount of data available from satellite images, we utilize a fuzzy logic approach to resource allocation \[50\].

For our application in the Enonkishu conservancy we did not have access to historical data on cattle movement, but we had access to expert opinion and
current parameter measurements. Thus, we use two fuzzy models to assess the suitability of rangeland for grazing. The first model is a set of fuzzy production expert rules, based on fuzzy linguistic estimates of the initial set of parameters (in our case, the predicted 18 biomonitoring parameters). The model uses Mamdani fuzzy inference system \[27\] as a method to create a prognosis system to estimate the rangeland suitability by synthesizing a set of linguistic control rules obtained from experienced human operators. The expert creates 27 fuzzy production rules, i.e. Rule 7: If (grass biomass is small) and (shrubland biomass is large) and (overgrazing is small), then (rangeland quality is small). A part of these rules is shown in Fig. A3.

<table>
<thead>
<tr>
<th>Rule</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>1.</td>
<td>If (grass biomass is small) and (shrubland biomass is small) and (overgrazing is small) then (rangeland quality is very small)</td>
</tr>
<tr>
<td>2.</td>
<td>If (grass biomass is small) and (shrubland biomass is small) and (overgrazing is middle) then (rangeland quality is extremely small)</td>
</tr>
<tr>
<td>3.</td>
<td>If (grass biomass is small) and (shrubland biomass is small) and (overgrazing is large) then (rangeland quality is extremely small)</td>
</tr>
<tr>
<td>4.</td>
<td>If (grass biomass is small) and (shrubland biomass is middle) and (overgrazing is small) then (rangeland quality is small)</td>
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<tr>
<td>5.</td>
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<tr>
<td>6.</td>
<td>If (grass biomass is small) and (shrubland biomass is middle) and (overgrazing is large) then (rangeland quality is extremely small)</td>
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<tr>
<td>7.</td>
<td>If (grass biomass is small) and (shrubland biomass is large) and (overgrazing is small) then (rangeland quality is middle)</td>
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<tr>
<td>8.</td>
<td>If (grass biomass is small) and (shrubland biomass is large) and (overgrazing is middle) then (rangeland quality is small)</td>
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<td>10.</td>
<td>If (grass biomass is middle) and (shrubland biomass is small) and (overgrazing is small) then (rangeland quality is small)</td>
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<td>11.</td>
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<td>13.</td>
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<td>17.</td>
<td>If (grass biomass is middle) and (overgrazing is middle) then (rangeland quality is large)</td>
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<td>18.</td>
<td>If (grass biomass is large) and (shrubland biomass is small) and (overgrazing is small) then (rangeland quality is large)</td>
</tr>
<tr>
<td>19.</td>
<td>If (grass biomass is large) and (shrubland biomass is small) and (overgrazing is middle) then (rangeland quality is small)</td>
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<tr>
<td>20.</td>
<td>If (grass biomass is large) and (shrubland biomass is small) and (overgrazing is large) then (rangeland quality is small)</td>
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<tr>
<td>21.</td>
<td>If (grass biomass is large) and (shrubland biomass is small) and (overgrazing is small) then (rangeland quality is very small)</td>
</tr>
</tbody>
</table>

Fig. A3 Example of fuzzy rules, created by an expert based on fuzzy linguistic estimates of the initial set of 18 biomonitoring parameters.

The resulting rules help to assess the suitability of a particular zone of the reserve for rangeland. The three projections (functions on two variables) of the decision surface of the Mamdani inference system for rangeland of quality effect function depending on grass, bushes and overgrazing (function on three variables) are presented in the 1st row of Fig. 8.

For the second model, we used an adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system, based on the Takagi–Sugeno fuzzy inference system \[51\], \[52\]. This method integrates both neural networks and fuzzy logic principles and has potential to capture the benefits of both in a single framework. It’s inference system also corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions.

Table A2 shows an example training sample for three parameters - the presence of grass and shrubs, with the help of which we create rules and a surface for assessing the quality of the pasture. The second row in Fig. 8 shows the three projections (functions on two variables) of the decision surface of the Takagi–Sugeno neuro-fuzzy inference system for prediction of rangeland
Table A2  Expert estimation of rangeland quality (column 4) depending of grassland (1) shrubland (2) biomass and overgrazing conditions (3)

<table>
<thead>
<tr>
<th>Grass Biomass</th>
<th>Shrubland biomass</th>
<th>Overgrazing</th>
<th>Rangeland quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>1</td>
<td>0</td>
<td>0.9</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>0</td>
<td>0.7</td>
</tr>
<tr>
<td>5</td>
<td>0.3</td>
<td>0</td>
<td>0.5</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0</td>
<td>0.8</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>1</td>
<td>0.1</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

quality effect function depending on grass, bushes and overgrazing (function on three variables).

A.7 AIREGENERATE recommendations

In the sixth and last stage of AIREGENERATE, grazer managers are offered advice on land and livestock to prevent land degradation and enable grazing regeneration. All the recommendations are displayed on the online portal dashboard, showing current prediction for each stage of the proposed AIREGENERATE framework and recommended blocks for the next herd movement with the highest predicted grazing quality.

References


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116(3) (391–396)


[38] Polley, H.W., Bailey, D.W., Nowak, R.S., Stafford-Smith, M.: In: Briske,
Monitoring Large-Scale Regenerative Grazing Using Artificial Intelligence


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