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Research Article

Hybrid AI-object zoning: Precision conservation planning in Abbas-Abad wildlife refuge

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ABSTRACT- It details the progress of conservation zoning in the Abbas-Abad Wildlife Refuge (AWR) of central Iran through the application of artificial intelligence (AI) with a hybrid pixel- and object-based approach and the Ordered Weighted Averaging (OWA) method. Targeting the pristine conservation zone, Landsat-9 imagery (30 m resolution) was utilized to delineate 229 segments of optimal size from the perspective of ecological accuracy with respect to computational efficiency. Using MaxEnt, habitat suitability for keystone species was modeled, indicating high-elevation zones as critical habitat for biodiversity conservation. Multi-Criteria Decision-Making (MCDM) techniques with OWA in conjunction with AI models (machine learning models) lent themselves to a very precise spatial evaluation. The XGBoost model proved superior, providing a comprehensive accuracy of 0.93 and a Kappa value of 0.91, validated against sixty ground points found to be in strong agreement with the field observations. Suitability maps were rendered reliable due to the low inconsistency coefficient (< 0.1) of the OWA method and the strong emphasis on the fauna criteria. In contrast to classical pixel-based methods, often bearing salt-and-pepper noise, this hybrid approach provides cohesive zoning results toward managing complex arid landscapes. This AI framework represents a scalable conservation-planning model for protected areas that effectively bridges the divide between biodiversity preservation and implementation on the ground. Future studies might feature ever-changing environmental factors paired with climate change, involve local people in MCDM for alignment with socioeconomic viability, and include the exploration of deep learning, that a strong case for redefining paradigms toward sustainable management of the arid environment.

INTRODUCTION

Protected Areas (PAs) are the linchpin for conserving ecosystems on a global scale, and their management is often associated with geographical biases worldwide (Acreman et al., 2020). The literature suggests that PAs assist in mitigating threats to biodiversity from land transformation, environmental degradation, human-induced pressures, and climate change (Geldmann et al., 2019). Wildlife sanctuaries, as a subset of PAs, serve as public assets that deliver ecosystem services for conservation and tourism (Loch et al., 2023). Of all the land on Earth, approximately 44% is needed to maintain global biodiversity (Li et al., 2020), whereas only 15.1% of the Earth's land surface is currently designated as protected. Additionally, for the sustainable management of global biodiversity that is equitably divided among partners, effective management of PAs is equally important as conservation decisions (Gray et al., 2016).

Harmonizing human activity with environmental conservation is an important aspect of designating PAs. Zoning forms the basis of their management and is vital for maintaining this equilibrium (Allen et al., 2023). Land suitability assessment is of utmost importance in providing a positive basis for land use planning and allocation (Xu et al., 2016). Suitability varies according to certain land attribute parameters from region to region, making it pertinent to accommodate and integrate varied sets of quantitative and qualitative data (Pant et al., 2025). Multi-Criteria Decision-Making (MCDM) approaches serve as a good framework for analyzing such heterogeneous data (Talebi et al., 2019).

MCDM methods have been extensively applied across diverse contexts to facilitate spatial decision-making and management processes (Mosadeghi et al., 2015). Compensatory approaches, mainly based on Weighted Linear Combination (WLC) and Ordered Weighted Averaging (OWA) methods, have received particular attention and are regarded as a further extension and generalization of the WLC framework. In contrast to the conventional approaches of the Boolean method, OWA provides the user with the flexibility to adapt the trade-offs and risk levels. The comparison of

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the suitability of the WLC and OWA methods in the same region for a specific purpose has been the subject of many studies (Subandi & Ardiansyah, 2019; Asadi et al., 2022).

Many of the Multi-Criteria Evaluation (MCE) methods employed in land allocation depend on pixel-based approaches (Masoudi et al., 2021; Nguyen et al., 2015). Object-based methods have been efficiently employed in several domains, including mapping volcanic and glacial landforms, urban feature detection, snow cover estimation, vegetation assessment, and classification of garden age categories (Karampour et al., 2024; Stephen and Haldar, 2024; Tong et al., 2024). However, their use in land-use planning is less common. Pixel-based methods in land allocations suffer from limitations because there may be heterogeneous pixels within the same pixel set, and these pixels do not belong to coherent, uniform patches. However, in land-use planning, object-based approaches will allow a more reasonable allocation using various techniques for assigning parcels to alternative uses. These include AI and machine learning techniques such as Boosted Regression Tree (BRT), Artificial Neural Network (ANN), Classification and Regression Tree (CART), eXtreme Gradient Boosting (XGBoost), and Random Forest (RF) (Belgiu et al., 2016; Sang et al., 2019; Lerm et al., 2023; Peykanpour Fard et al., 2025; Zhang et al., 2025).

The prime aim of this study is to demarcate and delineate area for conservation, rehabilitation, tourism, and various other purposes in the Abbas-Abad Wildlife Refuge (AWR), an important Protected Area (PA) in the central desert region of Iran. This site performs a crucial role in sustaining the diverse fauna of these arid ecosystems, hosting high densities of carnivore species like the Persian leopard (*Panthera pardus*), Asiatic cheetah (*Acinonyx jubatus*), wolf (*Canis lupus*), and caracal (*Caracal caracal*), along with large herbivores such as the wild goat (*Capra aegagrus*), wild sheep (*Ovis vignei*), and chinkara (*Gazella bennettii*) (Asadi et al., 2022). Interestingly, AWR plays a vital role a corridor for the Asiatic cheetahs connecting its northern and southern population cores. Besides, AWR stands out as one of the important nature-based tourism destinations, due to its strategic location, access, and array of ecotourism attractions.

This study proposes a spatial assessment as an object-based method due to the limitations of pixel-based spatial allocation methods. We would use a small number of objects instead of an endless pixel arrangement to evaluate the pristine conservation zone within the protected area. To achieve this, we applied the OWA method to recognize and assess the prototype areas of the conservation zone. Zonation by object-based methods was then performed, in which some artificial intelligence techniques, namely BRT, ANN, CART, XGBoost, and RF models, were utilized to assess and indicate the suitability for the conservation zone of each object. The importance of this study lies in its application of new landscape analysis and modeling techniques, particularly the combination of object-based and AI-based methods, which are rarely applied in the environmental management and spatial planning of PAs. Such an approach could provide guidelines for future research and strategies to develop more concrete mechanisms for assessing and managing ecologically pertinent conservation areas.

MATERIALS AND METHODS

Study area

The Abbas-Abad Wildlife Sanctuary (AWR), characterized by a hot and arid climate, is situated in the eastern region of Isfahan Province, central Iran (Fig. 1). Spanning an area of 305854 hectares, the sanctuary features predominantly rugged, mountainous terrain in its central zones. The AWR has an average elevation of approximately 1161 m, with the southern lowlands marking the lowest point at around 714 m and the central and southeastern areas reaching a peak elevation of about 2547 m (Fig. 1). The region experiences an average annual rainfall of roughly 90.4 mm and maintains an average annual temperature of about 18.8 °C (Peykanpour Fard et al., 2025). Serving as a critical habitat for one of Asia's most iconic and endemic large felids, the AWR also supports substantial populations of other rare and threatened species, including the Persian leopard, caracal, sand cat, sand fox, chinkara, wild goat, wild sheep, Iranian ground jay, and houbara (Peykanpour Fard et al., 2025). Furthermore, the sanctuary is home to 25 species of reptiles from 2 orders and 8 families, alongside 197 species of birds from 19 orders and 46 families.

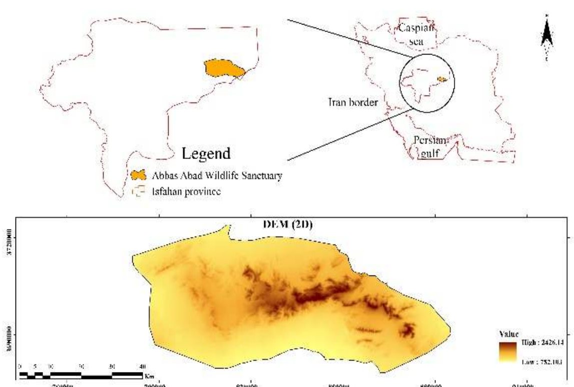

Fig. 1. Geographical position of the Abbas-Abad Wildlife Refuge (AWR) in Isfahan province, Iran.

Methodology

This study used a hybrid approach that combined pixel-based and object-based methods for AWR zoning. A hybrid methodology combining OWA suitability mapping with AI-driven object allocation. The workflow is illustrated in Fig. 2.

1) Pixel-based phase: OWA method with Best-Worst Method (BWM) weighting using the LINGO 18 software.
2) Factor selection: Different environmental variables (elevation, slope, Normalized Difference Vegetation Index (NDVI), distance to water, etc.) were identified through literature review and expert surveys.

3) Object-based phase: Multi-Resolution Segmentation (MRS) of Landsat-9 imagery, creating 229 objects
4) AI classification: BRT, ANN, CART, XGBoost, and RF models implemented in R software with 10-fold cross-validation
5) Main objective: Identifying optimal pristine conservation zones

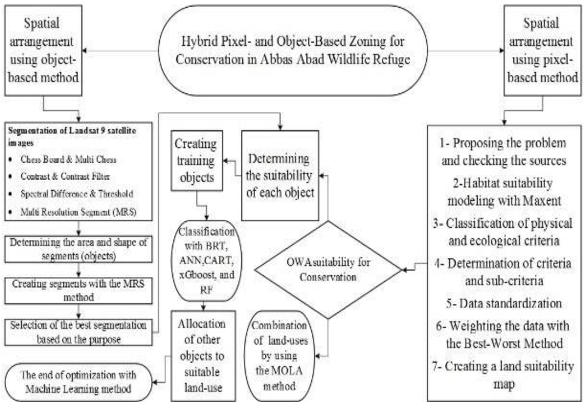

Fig. 2. Flowchart of wildlife sanctuary zoning using a hybrid pixel-based and object-based approach.

Standards and subcategories

Every indicator, criterion, subcategory, and suitability threshold for AWR protected area zoning was determined through a scientific literature review, expert surveys, field observations, and wildlife habitat suitability modeling. For the conservation zone, biological factors included habitat suitability maps for focal species (Persian leopard, Asiatic cheetah, and wild goat) generated by the MaxEnt model using approximately 500 occurrence points from field surveys (2020-2024) and different environmental variables (elevation, slope, NDVI, distance to water, and prey density). Physical factors (elevation and slope) and infrastructural factors (distance to roads and settlements) were also considered. All criteria were prepared in ArcMap 10.5 with a consistent extent, 30 m pixel size, and UTM Zone 40N coordinate system. All layers were standardized using linear fuzzy models, with values ranging from 0 (least suitable) to 1 (most suitable).

All layers were standardized using linear fuzzy membership functions that converted crisp input values into continuous suitability scores ranging from 0 (completely unsuitable) to 1 (perfectly suitable). This fuzzification process ensured effective aggregation using the OWA method. The threshold values for each criterion were determined based on ecological requirements and expert judgment, maintaining compatibility across all thematic layers for multi-criteria decision analysis.

Model weighting

The BWM was used to assign weights to environmental and topographic factors to assess the pristine conservation zone in the AWR. The process involved: 1) identifying the best and worst criteria, 2) performing pairwise comparisons, and 3) solving the optimization model using LINGO 18 software to derive the final weights (Rezaei, 2015). The consistency ratio (CR < 0.1) confirmed reliable comparison.

OWA-driven utility map

The OWA method was used for the aggregation of environmental and topographic criteria to evaluate the pristine conservation zone in the AWR with the incorporation of ranks and weight assignments (Asadi et al., 2022). One major benefit is the production of different outcomes through varying weight distributions (Kang et al., 2018), thereby better dealing with criterion dependency and uncertainty. OWA can model decision-making approaches, ranging from conservative (risk-averse) to optimistic (risk-seeking), for conservation zoning. The adjustment of these ranges occurs through expert judgment or pairwise comparison, allowing for trade-off analysis among the criteria (Peykanpour Fard et al., 2023). The OWA method is mathematically defined as Eq. (1).

$$Max\ H(w) = -\sum_{i=1}^{n} w_i \ln w_i \quad s.t.\ orness(w) = \sum_{i=1}^{n} \frac{n-i}{n-1} w_i = a, \qquad Eq.(1)$$

$$0 \le a \le 1 \quad \sum_{i=1}^{n} w_i = 1,\ w_i \in [0,1], \quad i = (1, 2, \dots, n)$$

where Max h(w): Maximum entropy, Wi: Weight of i factor, n: Total number of Factors, i: i factor, and *a*: Risk rate (Kang et al., 2018).

Defining the area

For this research, a pure Landsat-9 satellite image from April 2024 was segmented specifically to spatially assess the immaculate conservation area within the AWR. Landsat-9 images with a resolution of 30 m were processed with bands in the blue, green, red, near-infrared, and short-wave infrared regions. All bands were assigned a weighting equivalent to unit 1. Seven distinct segmentation algorithms were incorporated. The criterion for selecting among them is that the MRS outputs closely match real-world features. Thus, for the dimensions of the study area under consideration, the scale parameter (SP) has a minimum range of 92 hectares (0.3 of the area) to a maximum range of 5305 hectares (1.7 of the area). Weights were assigned as follows: spectral shape, 0.4; compactness, 0.6.

Artificial Intelligence-based allocation

The pristine conservation zone in the AWR was classified using the BRT, ANN, CART, XGBoost, and RF machine learning algorithms for object allocation. These models were trained using 30 objects (13% of the 229 total objects) selected based on optimal OWA suitability scores. Each training object contained 10-20 field-sampled validation points collected during extensive ground surveys, providing a robust representation rather than a single-point sampling per object. This multipoint sampling approach ensured sufficient data density (300-600 total points) for reliable model training and generalization in object-based classification.

Models were built in R using the ‘gbm’, ‘nnet’, ‘rpart’, ‘xgboost’, and ‘randomForest’ (Belgiu & Drăgu, 2016; Ripley et al., 2016; Sang et al., 2019; Ding et al., 2024; Peykanpour Fard et al., 2025; Zhang et al., 2025) packages, coupled with 10-fold cross-validation. Their effectiveness was tested using 60 ground points collected during field surveys and classified by conservation zone experts. Comparing the predicted and observed assignments in a pixel-based manner utilized a confusion matrix, overall accuracy, and kappa coefficient.

RESULTS AND DISCUSSION

Weights of criteria

The OWA implied an inconsistency of less than 0.1 for significant results in the ordered weighted averaging method. For the pristine conservation zone in the AWR, the OWA method achieved a coefficient below 0.1, confirming a robust model. Table 1 indicates that fauna contributed the highest weight in the suitability map, indicating high biodiversity in AWR, whereas roads had the least importance since they conflicted with the goal of conservation. In contrast to Peykanpour Fard (2023), who used OWA for land use planning, this study focused on the conservation zone solely based on a pixel approach. Unlike pixel-based studies, such as Dornik et al. (2018), which can miss spatial relationships, our OWA-based model presents a promising framework for conservation zones in similar arid regions.

Zoning suitability map

OWA was employed to develop the suitability map of the conservation zone in its pristine state of the AWR, quantified in values ranging between 0 and 1 (Fig. 3). The OWA suitability score was 0.82 for the conservation zone, with trade-off and risk levels of 0.7. These results were used for spatial assessment via a hybrid pixel- and object-based approach, which proved to be very effective in identifying potential areas for conservation zoning. The findings validate the OWA method as successful for conservation zoning and offer a solid tool for spatial assessment in ecologically fragile areas such as AWR. Similar to Asadi et al. (2022), who demonstrated the success of community-based wildlife conservancies in enhancing biodiversity, our study shows the possibilities that OWA may confer for conservation tailored to local needs. By integrating MCDM methods such as OWA, local communities can decide on land-use options that mediate between ecological sustainability and socio-economic interests (Chi et al., 2020). This participatory approach enhances sustainable wildlife management for both biodiversity and local livelihoods.

Optimal segmentation method selection

For this research, a pure Landsat-9 satellite image from April 2024 was segmented for the spatial assessment of the pristine conservation area within the AWR. Images from Landsat-9 (30 m resolution) were processed using bands 2-6 (blue, green, red, near-infrared, and short-wave infrared) with equal weighting (1.0). The MRS algorithm was applied with scale parameter ranging from 92-5305 hectares (0.3-1.7% of study area), shape weight of 0.4, compactness weight of 0.6, color weight of 0.6, and smoothness weight of 0.4, resulting in 229 optimally sized segments that aligned with natural landscape features while balancing computational efficiency and ecological precision (Fig. 4).

Table 1. Assigned weights for criteria across four land use classifications

Conservation

#	Sub-criteria	OWA*
1	Fauna	0.254
2	Flora	0.196
3	Water sources (springs)	0.151
4	Climate (drought)	0.116
5	Activities (mines)	0.089
6	Watering place	0.069
7	Water catchment levels	0.053
8	Settlements	0.014
9	Roads	0.031

Tourism

#	Sub-criteria	OWA
1	Natural attraction	0.201
2	Historical and cultural attraction	0.164
3	Tourism weather evaluate	0.134
4	Dust	0.109
5	Settlements	0.089
6	Oases	0.073
7	Roads	0.06
8	Mines	0.049
9	Agriculture	0.04
10	Aspect	0.033
11	Slope	0.226
12	Wind erosion	0.021

Multilateral

#	Sub-criteria	OWA
1	Fauna	0.396
2	Agriculture	0.257
3	Water (well and aqueduct)	0.167
4	Activities (mines)	0.109
5	Facilities (Human settlements)	0.071

Rehabilitation

#	Sub-criteria	OWA
1	Habitats affected by drought	0.461
2	Changes in water catchment	0.276
3	Biodiversity hotspots	0.165
4	Activities (mines)	0.098

* The Ordered Weighted Averaging (OWA) method integrates weights obtained from the Best-Worst Method (BWM) with those based on ranked positions.

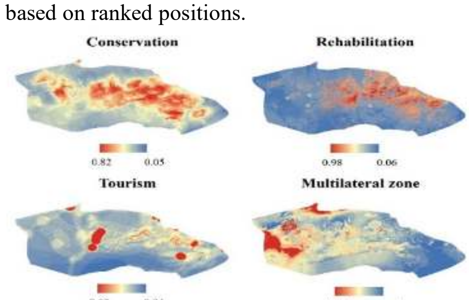

Fig. 3. Suitability map for four land use categories developed using the OWA approach.

The segmentation exercise in Landsat-9 would continue in accordance with very viable field applicability for spatially analyzing conservation zoning exercises, especially for the AWR, which is ecologically sensitive. At 30 m resolution, Landsat-9 had the best number of segments (229) suited to detail the critical ecological features without the over-fragmentation that is often the case in high-resolution datasets such as Sentinel-2, as this greatly complicates the analysis greatly (Bui et al., 2021). Above all, with coarser datasets such as Sentinel-3, natural boundaries for conservation zones are much better defined using those segments of Landsat-9. This is in agreement with studies such as Peykanpour Fard et al. (2025), who pointed out the effectiveness of 30 m resolution images to achieve a better scope from the ecological aspect and computational efficiency in planning PAs. Combining this Landsat-9 segmentation with the OWA will enhance strong conservation zoning that could be applied to other arid ecosystems with similar environmental limitations.

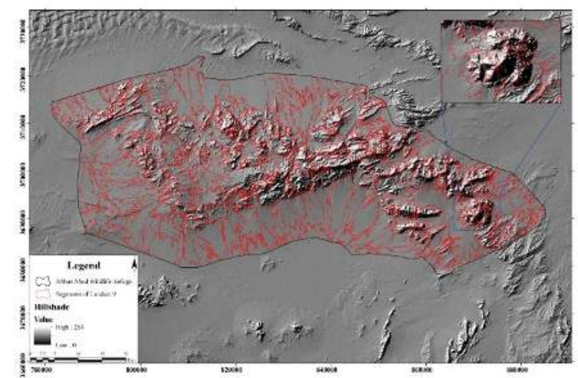

Fig. 4. Predicted segmentation with Landsat 9.

Zone assignment using object-oriented techniques and machine learning

The object-based image classification for the pristine conservation area of the AWR was based on segments generated from the Landsat-9 images. These were then drilled using artificial intelligence methods such as BRT, ANN, CART, and RF. The zonation results from object-based classification indicated a good classification accuracy when compared with observed and predicted zone type models, validated by 60 ground points. The highest performance among all models was achieved with the XGBoost model, which produced a total precision of 0.93 and a kappa index of 0.91. The spatial distribution from five AI-driven classifications saw the conservation zone factor mentioned in Table 2.

In the present study, a hybrid approach combining pixel-based and object-based methods integrated with the OWA method was used to assess the pristine conservation zone in the AWR. This study confirmed that the object-based method appreciably enhances management capabilities in favor of conservation zoning. The XGBoost model presented a higher overall accuracy and kappa than the other models (Fig. 5). The pixel-based method is advantageous because of its ease of application in multi-criteria zoning, incorporating indices without high complexity in statistical modeling. However, the main drawback of the pixel-based method is that it obtains heterogeneous pixels closely adjacent to pixels representing a homogenous class. This leads to impulse noise in the results. However, the object-based method fits much better in dealing with such ambiguity, especially in association with high-performance classifiers such as XGBoost. Peykanpour Fard et al. (2023) showed that using pixel-based Multi-Objective Land Allocation (MOLA) introduced impulse noise into the results. Therefore, the methods adopted for mapping ecological zones do not highlight their suitability for conservation planning in a complex landscape such as the AWR.

The object-based approach significantly outperformed the pixel-based methods in AWR zoning. Unlike pixel-based methods, which produce impulse noise (salt-and-pepper effect) due to heterogeneous adjacent pixels (Peykanpour Fard et al., 2023), the 229 MRS segments maintained spatial coherence and aligned with natural habitat boundaries critical for species conservation (Fig. 5). This ecological relevance and reduced boundary errors resulted in 93% accuracy with XGBoost (best performing) compared to 82% accuracy with CART (least accurate).

XGBoost demonstrated superior suitability for AWR conservation zoning, achieving the highest accuracy (overall accuracy: 0.93; kappa: 0.91). This performance is attributed to its ability to handle the complex environmental heterogeneity of the region, including steep elevation gradients and variable arid vegetation patterns. XGBoost effectively ranked fauna habitat suitability (32% importance) and elevation (28% importance) as primary predictors, aligning with the ecological requirements of focal species such as the Persian leopard and Asiatic cheetah. Additionally, its robustness with limited training data (only 30 objects, 13% of the total) makes it particularly suitable for data-scarce protected areas, while its resistance to overfitting ensures reliable conservation zoning in complex arid landscapes.

In the best-performing XGBoost model, feature importance analysis revealed that fauna habitat suitability had the highest relative importance, followed by elevation and distance to roads (15%). These rankings align with the BWM weights in Table 1, confirming the model's ecological validity. The dominance of fauna habitat suitability reflects AWR's role as a critical corridor for the Persian leopard and Asiatic cheetah, while the high importance of elevation corresponds to the species' preference for rugged mountainous terrain. The moderate importance of distance to roads underscores the negative impact of infrastructure on conservation zones. This feature importance analysis validated the model's ability to prioritize ecologically critical factors for pristine conservation zoning.

Temporal dynamics and their influence

This study primarily used static data from April 2024 Landsat-9 imagery and MaxEnt models based on occurrence data collected between 2020-2024. While this approach provides a robust snapshot of conservation zoning, the temporal dynamics of key variables influence the results. The NDVI values from spring 2024 may vary seasonally. MaxEnt habitat models incorporating four years of occurrence data

(2020-2024) reflect the recent population trends of the focal species. Precipitation variability (annual average 90.4 mm) affects water availability, which is critical for species distribution. Future implementations should incorporate multi-temporal satellite imagery and seasonal field surveys to account for these dynamics and enhance zoning adaptability to environmental change.

Limitations

Although this study demonstrates the effectiveness of hybrid AI-object zoning for AWR conservation planning, several limitations should be acknowledged. First, the analysis relies on Landsat-9 imagery (30 m resolution), which may miss fine-scale habitat features that are important for some species. Second, training with 30 objects, although justified by object-based standards, represents a relatively small sample that could benefit from expansion in future research. Third, the MaxEnt habitat models depend on the quality of occurrence data, and while 500 points provide robust sampling, spatial bias in field surveys may influence the results. Finally, the static nature of this zoning requires periodic updates to account for environmental changes and species population dynamics. Future research should incorporate higher-resolution imagery, expanded training datasets, and dynamic monitoring protocols to enhance the accuracy of conservation zoning.

Table 2. AI-driven zoning: spatial distribution and predictive accuracy

CART	RF	ANN	BRT	XGBoost	
0.82	0.87	0.90	0.91	0.93	Overall accuracy
0.76	0.83	0.87	0.88	0.91	Kappa coefficient

* Classification and Regression Tree (CART), Random Forest (RF), Artificial neural network (ANN), Boosted Regression Tree (BRT), and eXtreme Gradient Boosting (XGBoost)

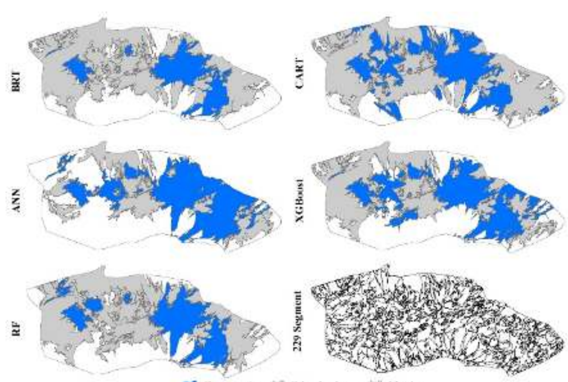

Fig. 5. Allocation of conservation zone with object-based method ((Classification and Regression Tree (CART), Random Forest (RF), Artificial neural network (ANN), Boosted Regression Tree (BRT), and eXtreme Gradient Boosting (XGBoost)).

CONCLUSION

This hybrid AI-object zoning approach identified 21,847 hectares (7.1% of AWR) as optimal pristine conservation zones in the central-southern mountainous regions (elevation > 2000 m). The XGBoost model achieved an overall accuracy of 93% (Kappa: 0.91), confirming these areas as critical habitats for the Persian leopard, Asiatic cheetah, and associated biodiversity.

The object-based methodology proved superior by eliminating the impulse noise characteristic of pixel-based approaches. The 229 MRS segments from Landsat-9 imagery were aligned precisely with the ecological boundaries. OWA-BWM integration (consistency ratio < 0.1) provided robust multi-criteria suitability mapping, with fauna habitat suitability as the dominant criterion (highest BWM weight). For AWR management, these results recommend immediate legal protection of the 21,847 hectares pristine conservation zone, tourism exclusion from high-conservation value areas, enhanced monitoring using annual AI-based re-zoning, and infrastructure restriction within identified core zones.

This zoning enhances connectivity between northern and southern Asiatic cheetah populations, protecting 32% of the high-value fauna habitat and 28% of the elevation-driven biodiversity hotspots. The hybrid AI framework provides a replicable model for conservation planning across other wildlife refuges and similar arid protected areas worldwide. This serves as a replicable framework for the management of ecologically sensitive areas, integrating the preservation of biodiversity with pragmatic implementation, and informing future conservation strategies in similar PAs.

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CRediT AUTHORSHIP CONTRIBUTION STATEMENT

Conceptualization: Reza Peykanpour Fard and Alireza Soffianian; Methodology: Reza Peykanpour Fard and Alireza Soffianian; Software: Reza Peykanpour Fard and Alireza Soffianian; Validation: Reza Peykanpour Fard and Alireza Soffianian; Formal analysis: Reza Peykanpour Fard and Alireza Soffianian; Investigation: Reza Peykanpour Fard and Alireza Soffianian; Resources: Reza Peykanpour Fard and Alireza Soffianian; Data curation: Reza Peykanpour Fard and Alireza Soffianian; Writing—original draft preparation: Reza Peykanpour Fard and Alireza Soffianian; Writing—review and editing: Reza Peykanpour Fard and Alireza Soffianian; Visualization: Reza Peykanpour Fard and Alireza Soffianian; Supervision: Reza Peykanpour Fard and Alireza Soffianian; Project administration: Reza Peykanpour Fard and Alireza Soffianian.

DECLARATION OF COMPETING INTEREST

The authors declare no conflicts of interest.

ETHICAL STATEMENT

The Ethics Committee of Isfahan University of Technology granted approval. This study did not involve human or animal subjects.

DATA AVAILABILITY

The data can be obtained from the corresponding author upon a reasonable request.

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