



Conservation assessment of the vulnerable species *Capra nubiana* under changing precipitation: a decision- support tool for conservation planning

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Abstract

Over the last century, a significant decline in the population size of the Nubian *Capra nubiana* has been observed across its distribution range. This decline is attributed to the changes in natural resources, including water and foraging site capacity, due to the ongoing climate change. We applied species distribution models (SDMs) to investigate the response of *C. nubiana* to projected climate change in the next decades. We fitted ensemble SDMs with recently developed climate data based on climate models and two different dispersal scenarios to minimize the uncertainty and bias in our SDMs prediction. Our SDMs predicted a significant shrinkage of the distribution range of the *C. nubiana* in the coming decades, where *C. nubiana* may lose ca. 60% of its area of occupancy before 2050, while it may become extinct (lose > 90% of its projected area) before the end of the current century. Our results call for urgent conservation intervention at global and national scales to halt the impact of climate change on one of the remaining top mountain ungulate species in desert ecosystems.

Keywords Nubian ibex · Threatened species · Ensemble modelling · Conservation · Climate change

Introduction

Climate change is one of the most significant factors affecting the potential distribution of species, biodiversity, and ecosystem status (Agudelo-Hz et al. 2019; Díaz et al. 2019). Climate change not only affects the individual species but also has an impact on the interaction between the organisms and their habitats, which makes changes to the structures of the ecosystem and its services to society (Díaz et al. 2019). Climate changes lead to shifts in species ranges and cause

species to lose their habitat, which eventually leads to biodiversity decline (Agudelo-Hz et al. 2019; Ahmadi et al. 2019; Román-Palacios and Wiens 2020). Consequently, that will lead to an increased rate of species extinction (Díaz et al. 2019; Dakhil et al. 2021). However, there are some factors that affect the number of affected species, such as their ecological tolerances and how the species interact with climate change (Urban 2015; Guo et al. 2018).

Mountainous species are particularly at risk of extinction because of climate change due to their restricted distribution and distinctive evolutionary histories (Ahmadi et al. 2019). The Nubian *C. nubiana* (*Capra nubiana*) is one of the mountainous mammals that are considered Vulnerable (VU) species according to the International Union for Conservation of Nature (IUCN) Red List conservation assessment (2020). This is because *C. nubiana* encounters many threats that affect its population and its habitats. These threats include poaching and illegal hunting, habitat degradation, and scarcity of water resources (El Alqamy et al. 2010; Ross et al. 2020). The effect of these threats is accelerated and expanded because of the ongoing climate change (Ross et al. 2020).

The *C. nubiana* lives in rocky, desert mountains with steep slopes and hills, which work as a vital escape route

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(Ross et al. 2020). Also, the animal is found in associated plateaus, canyons, and valleys (Ross et al. 2020). *C. nubiana* is found in North African and Middle East countries such as Egypt, Jordan, Saudi Arabia, Oman, Yemen, and Sudan. Over the last few decades, it has been extirpated from Syria but is currently being reintroduced into Lebanon through a reintroduction project promoted by the Shouf Biosphere Reserve (SBR) (Ross et al. 2020). Currently, limited information is available on its population and its actual distribution. Evidence indicated that the *C. nubiana* populations are particularly rare and in decline in Sudan, Eritrea, and Yemen (Ross et al. 2020). Similarly, its population is declining in Saudi Arabia (Al-Eissa et al. 2012; Barichievsky et al. 2018), Oman, Jordan (Ross et al. 2020), and Egypt (El Alqamy et al. 2010) due to illegal hunting and competition with other animals (Ross et al. 2020).

Even though there are conservation efforts, the *C. nubiana* population is still threatened (Ross et al. 2020). In the last ten years, the *C. nubiana* population has decreased in rate by 30–50% in the last three generations to be close to the endangered classification; in addition, the population of *C. nubiana* is estimated to consist of less than 5000 mature individuals, and it declined over the past decade (Ross et al. 2020). It is difficult to determine the number of the population or individuals at a national scale due to its movement and migration along the elevation gradient. That is why it is listed as Vulnerable under criteria C1 and C2a(i) (Ross et al. 2020). Criterion C expresses the taxa with a small population size and are continuing decline, whereas in criteria C1, the containing decline will be by 10% in 10 years or 3 generations, and C2i also continuing decline and the number of mature individuals in each population will be ≤ 1000 (IUCN 2022). Climate modeling and optimization have significantly advanced in studying climate change scenarios, leading to a better understanding of how biodiversity and ecosystems are affected by climate change (Harris et al. 2014). By applying climate modeling, we gain valuable insights into future climate scenarios and their effects on biodiversity. Species Distribution Models (SDMs) play a crucial role in this process by mapping and monitoring species distribution, offering predictions of future distribution patterns (Khayat et al. 2024). These predictions can guide conservation efforts, helping us address the pressing challenges posed by climate change. Several algorithms have been used to evaluate the possible impact of climate change on species ranges, one of these common tools is species distribution models (SDMs) (Beaumont et al. 2008). Several studies used SDMs in conservation biogeography, such as identifying the environmental niche of species, recognizing the areas of possible invasive species, assisting conservation planning, and assessing the likely impacts of climate change on species distributions (Booth et al. 2014). The SDMs are applied in several studies besides climatic and environmental variables to model and

predict the species distribution (Fitzpatrick et al. 2008). To the best of our knowledge, there is no conservation assessment for *C. nubiana* under the climate change scenarios at a global scale under the modern scenarios of climate change (SSPs), dispersal scenarios, and using the recommended ensemble modelling technique of SDMs and the proper measures of conservation assessment of IUCN Red List criteria. Accordingly, there is an urgent need for a comprehensive study to aid field surveys to identify climatically stable areas for reintroduction and conservation planning. Therefore, our objectives were (1) to predict the potential distributions of *C. nubiana* under current and future climate change and dispersal scenarios, (2) to assess the effect of climate change on habitat suitability and estimate the percentage loss in the area of occupancy (AOO), and (3) to identify the potential changes in conservation status under climate change scenarios and adjustment to the extent of occurrence (EOO).

Materials and methods

Species occurrence data

We used R software version 4.2.0 (R Core Team 2023) for the spatial analysis, data cleaning, multicollinearity test, and SDMs. We obtained 533 occurrence records from the GBIF database using the *rgbif* package (Chamberlain et al. 2017) (<https://doi.org/10.15468/dl.uf8a6p>, accessed on 27 March 2022) in R; then we cleaned and verified the data using *CoordinateCleaner* package (Zizka et al. 2019), to exclude the duplicates and occurrence points on inaccessible areas such as urban, seas, or croplands (Dakhil et al. 2021); and hence this package effectively mitigates the inaccuracies or distortions in the geographical distribution of species occurrence records. These spatial biases can arise due to various factors such as sampling effort, accessibility of locations, or reporting tendencies. This cleaning resulted in 256 verified records.

Bioclimatic predictors and multicollinearity

We obtained the nineteen bioclimatic variables from WorldClim 2.1 at 30 arc-seconds spatial resolution (Fick and Hijmans 2017). To assess the impact of climate change scenarios, we selected two global general circulation models (GCMs): BCC-CSM2-MR (Beijing Climate Centre, Wu et al. 2019), and IPSL-CM6A-LR (The Institut Pierre-Simon Laplace, Boucher et al. 2019). BCC-CSM2-MR is widely used for Asian regions (Wu et al. 2014), and IPSL-CM6A-LR performs well in North Africa compared to other GCMs (Babaousmail et al. 2021). The two selected GCM models are able to capture the observed global warming trends and

reproduce the main patterns of atmospheric temperature and wind, precipitation, land, and sea surface temperature, and predict future climate scenarios with reasonable accuracy (Eyring et al. 2016; Boucher et al. 2019; Wu et al. 2019). We used an ensemble average of the two GCMs to reduce the uncertainty arising from a single GCM (Wang and Chen 2014). We used the raster ensemble average of the outputs of the two GCMs for the near future (2021–2040), and far future (2081–2100) for two shared socioeconomic scenarios pathways (low scenario: SSP126 and high scenario: 585), and this method provides superior results to those obtained from one model (Wang and Chen 2014; Dakhil et al. 2021). The low scenario (SSP126) represents a future with low greenhouse gas emissions, while the high scenario (SSP585) represents a future with high greenhouse gas emissions. These scenarios provide a range of possible futures to help us understand the potential impacts of different emission levels (Khayat et al. 2024). SSPs consider socioeconomic factors such as population growth, which are called Shared Socioeconomic Pathways (Hausfather 2019). We cropped the study area or extent ranged from latitude from 14° N to 39° N and longitude from 20° E to 56° E covering the distribution of *C. nubiana* using the “drawExtent” and “crop” functions of the *raster* package in R (Hijmans et al. 2015) and then resampled all of the bioclimatic raster layers into the required or recommended spatial resolution (2 km × 2 km) for the calculation of AOO to estimate the extinction risk based on the loss percentage in the projected AOO (IUCN 2022). The IUCN (International Union for Conservation of Nature) recommends a spatial resolution of 2 km × 2 km for the calculation of the area of occupancy (AOO) to estimate species extinction risk because it is considered to be an appropriate balance between precision and practicality. The AOO is a key parameter used to assess the conservation status of a species, and it is defined as the area within its geographic range that is occupied by the species. AOO is an important measure of the degree of fragmentation or isolation of a species’ population, and it is a useful

indicator of the risk of extinction, particularly for species with small and/or restricted ranges (IUCN 2022). Then, we extracted values for multicollinearity analysis to avoid model overfitting; using the *usdm* package (Naimi 2015) to apply the variance inflation factor (VIF) to exclude the highly correlated variables with VIF > 5 and a correlation threshold of 0.75 (Guisan et al. 2017). In the *usdm* package for species distribution modelling, *vifcor* and *vifstep* functions are used for multicollinearity analysis. *vifcor* identifies pairs of variables with high correlation and excludes the ones with a higher Variance Inflation Factor (VIF), repeating this until no highly correlated pairs remain. On the other hand, *vifstep* calculates VIF for all variables and removes the one with the highest VIF, repeating this until all remaining variables have a VIF below the threshold (Naimi 2015; Guisan et al. 2017). This resulted in 7 variables (Table 1) that were used for the distribution modelling.

Ensemble modelling and potential habitat suitability

We used *sdm* package in R (Naimi and Araújo 2016) to apply ensemble modelling of the three common species distribution models (SDMs): generalized linear model (GLM), Boosting Regression Trees (BRT), and random forests (RF), which are characterized by high stability (model’s performance is consistent across different datasets or subsets of the same dataset) and transferability (performs well on new datasets that it has not seen during training), compared to other models such as MaxEnt (Iturbide et al. 2018; Thuiller et al. 2019).

We used 70% as training data and 30% as testing data (Thuiller et al. 2019) for the three numbers of replications. The most effective SDMs require data on both the species presence and pseudo-absence data, so we applied a number of pseudo-absences equal to ten times the number of presences (Barbet-Massin et al. 2012; Dakhil et al. 2021). We used the True Skill Statistic (TSS) to weigh the ensemble

Table 1 Summary of the selected predictor variables explaining the potential distribution of *C. nubiana*

Code	Description of the predictor variable	Response curve relationship	VIF	Current average ± SD	Current range
Bio9	Mean temperature of the driest quarter (°C)	Positive	2.18	26.00 ± 2.20	18.04–34.94
Bio8	Mean temperatures of the wettest quarter (°C)	Negative	2.05	12.17 ± 2.84	6.81–28.38
Bio3	Isothermality (°C) (*100)	Negative	1.77	44.58 ± 2.71	34.52–56.67
Bio18	Precipitation of the warmest quarter (mm)	Positive	1.60	0.15 ± 1.60	0–25
Bio13	Precipitation of the wettest month (mm)	Negative	1.41	39.71 ± 21.77	1–143
Bio14	Precipitation of the driest month (mm)	Positive	1.19	0.00 ± 0.08	0–1
Bio7	Temperature annual range (°C)	Negative	1.18	28.82 ± 1.64	22.52–36.34

Correlated variables with variance inflation factor (VIF) values > 5 and a correlation threshold of 0.75 were removed to avoid multicollinearity problems

models with TSS higher than 0.9. We calculated the area under the receiver-operating characteristic curve (AUC) and TSS to evaluate the accuracy of the models (Guisan et al. 2017).

We transformed the continuous maps (Fig. S1, supplementary materials) of the current and future habitat suitability into binary maps (presence/absence) based on the maximum training sensitivity plus specificity (MTSS) threshold (Liu et al. 2016). To visualize the changes in habitat (loss, gain, and stable areas), firstly, after generating binary maps from the continuous maps (with suitability 0.4–6.0) for the current and future (0: absence/1: presence), we multiplied the future binary maps by 2, so resulted in grid cells with values of (0/2). Then we subtracted the current binary maps (0/1) from the future (0/2), and this resulted in new grid cells representing the four classes: gain class of grid cells with the value of 2, stable class of grid cells with the value of 1, loss class of grid cells with the value of -1 and finally the unsuitable class of grid cells with value 0. Then we adjusted the suitability maps to the mosaic ten classes of the global land cover map (Kobayashi et al. 2017) using *raster* package in R to exclude the inaccessible areas such as cropland and urban. We reclassified the potential habitat suitability generated under the current climate into three classes: low ($= < 0.4$), moderate ($> 4.0 < 6.0$), and high suitability (> 6.0) in ArcGIS 10.5.1 (ESRI 2015).

Assessment of extinction risk under climate change and dispersal scenarios

It has been recommended for conservation studies under climate change to include land use, and dispersal scenarios, along with IUCN guidelines (Dakhil et al. 2021; IUCN 2022), to provide a holistic approach for conservation assessment and smart conservation planning. Accordingly, the area of occupancy (AOO) is a proper measure of extinction risks IUCN 2022. Firstly, we adjusted the model prediction outputs of current and future to the global land cover map to exclude the inaccessible areas. Then, we used *ConR* package in R (Dauby et al. 2017) to compute the extent of occurrence (EOO) using the convex hull method, which involves drawing a polygon around the outermost points of a species' distribution and calculating the area within that polygon in. After that, we used the EOO shapefile to crop the suitable habitats on the current and future outputs to address the EOO's scenarios. Since dispersal scenarios are an important aspect of conservation planning (Thuiller et al. 2019), we applied the full dispersal scenario, which considers the gained grid cells in the calculation of AOO, and the limited dispersal scenario, which does not consider the gained grid cells (Dakhil et al. 2021). In the case of limited dispersal, any predicted grid cells that appeared in new areas in the future were not considered suitable. However, in the case

of full dispersal, we assumed that the species had unlimited dispersal capacity and any suitable grid cells that were not part of the current predicted range were included in the future distribution (Kaky and Gilbert 2019; Dakhil et al. 2021). The AOOs were calculated under the four different scenarios. To assess species extinction risk, we used the relative loss percentage in the projected AOOs according to the IUCN's Red List Criterion A3(c) as follows: Vulnerable (loss $> 30\%$), Endangered (loss $> 50\%$), Critically Endangered (loss $> 80\%$), and Extinct (100% loss) (Kaky and Gilbert 2019; IUCN 2022).

Results

Model performance and potential response to bioclimatic variables

Multicollinearity analysis of the total 19 bioclimatic variables resulted in seven uncorrelated variables with $VIF < 5$ (Table 1), which had been used in the ensemble modelling. Ensemble models of GLM, BRT, and RF showed high accuracy and excellent performance with an average AUC and TSS of > 0.95 (Fig. 1). Temperature annual range (Bio7), precipitation of the warmest quarter (Bio18), and precipitation of the driest month (Bio14) were the most important variables explaining the potential distribution of *C. nubiana* with contribution higher than 5% up to 65% (Fig. 1). The relative variable importance falls in the order: Bio18 $>$ Bio14 $>$ Bio7 $>$ Bio3 $>$ Bio9 $>$ Bio8 $>$ Bio13.

Potential suitability and projected area of occupancy (AOO) under climate change scenarios and dispersal scenarios

The potential suitable habitat under the current climate along with the distribution records of the *C. nubiana* is shown at (Fig. 2). The potential changes in habitat suitability and the percentage of loss in AOO were slightly similar under both dispersal scenarios and all climate change scenarios except the highest scenario of the far future (SSP585_2081-2100), which showed a higher loss in AOO with a percent more than 90% (Table 2). Dispersal scenarios showed similar outputs for both full and limited dispersal (Table 2), and this indicates that the gain areas in the future were very small areas (Fig. 3a–d).

Under the low climate change scenarios (SSP126) for both near and far futures, the climatically stable areas (green colors) were found in the mountainous areas of the eastern desert of Egypt close to the Red Sea coastal areas and in both south and north Sinai (Fig. 3a and b). Similarly, stable climatic areas were also found in Palestine, the middle of Jordan, and mountainous areas located in the northwestern

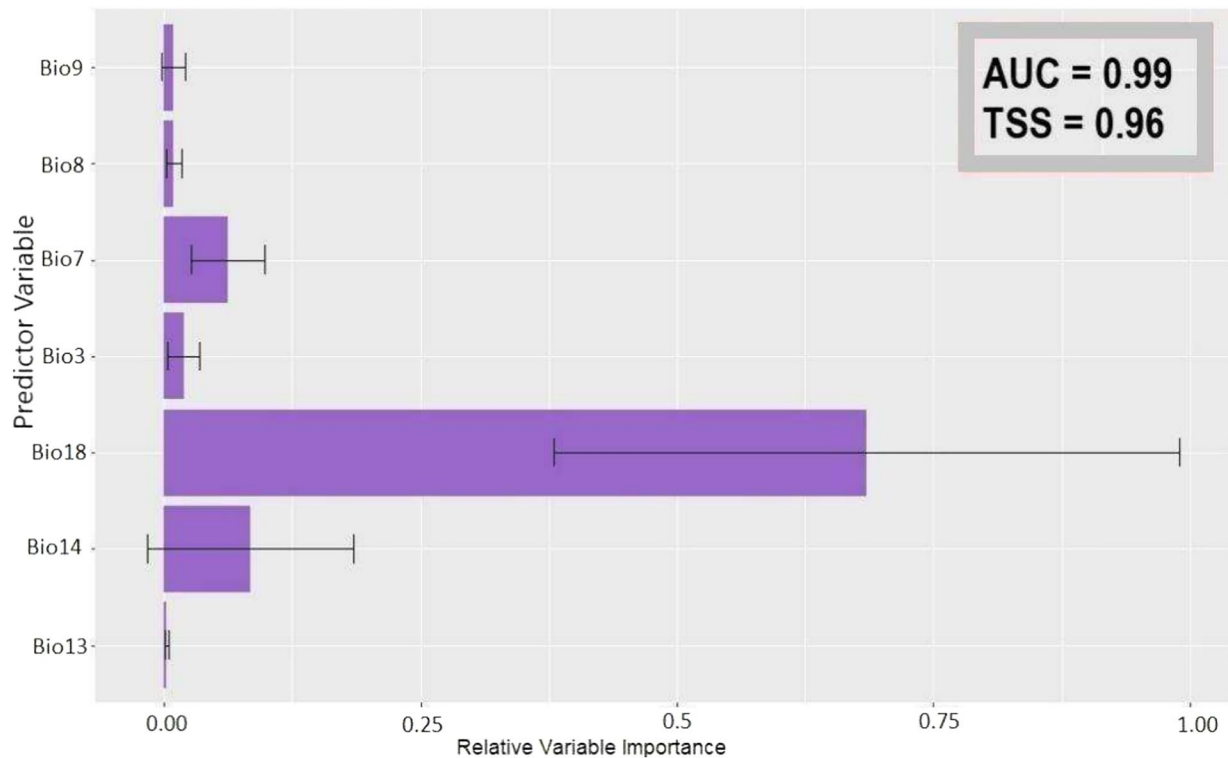


Fig. 1 Relative importance of the bioclimatic predictors explaining the potential distribution of *C. nubiana*. Averages of the true skill statistic (TSS), and area under the curve (AUC) indicate the accuracy

of the ensemble models. The error bars show the 95% confidence intervals. Abbreviations of the bioclimatic variables are described in Table 1

part of Saudi Arabia, particularly the areas near the Red Sea (Fig. 3a, b).

On the other hand, under the high scenarios of climate change (SSP585), the stable areas showed high variation, where the stable area was high under the near future scenario and almost like the stable areas of the low scenarios (Fig. 3c). Whereas the far future of the high scenario showed the very small stable area and restricted mostly to the south and north Sinai (Figs. 3d and 4). The highest loss in suitable habitat was found under the highest scenario of the far future climate change (2081–2100) compared to other scenarios (Fig. 4).

Potential changes in conservation status under climate change scenarios and adjustment to EOO

The projected status of extinction risk uplisted to a higher category than its current status category, “Vulnerable”, based on the loss in AOO according to IUCN Red List criterion A3(C) under both climate and dispersal scenarios (Table 2). The loss % in AOO showed a higher value in the case of the adjusted, suitable area or map to the EOO with a value of 96.19, while the value of loss % AOO for the not adjusted to EOO was 93.91, and this indicates the

importance of adjustment in the context of conservation assessment where the extinction risk increased with uplisted IUCN Red List category CR “Critically Endangered.” Under the other lower scenarios of climate change, the conservation status of *C. nubiana* was uplisted to EN “Endangered” (Table 2). There was a dissimilarity between the AOO loss %, which was calculated based on the adjustment to EOO, and the AOO loss % that was calculated not adjusted to EOO; meanwhile, dispersal scenarios showed similarity in the AOO loss % (Table 2), and this indicates the importance of using EOO to adjust or clip the suitability (grid cells) along with dispersal scenarios.

Discussion

Climate change has a significant effect on ecosystem services, species biodiversity, and distributions worldwide status (Agudelo-Hz et al. 2019; Díaz et al. 2019). Recently, climate modelling provided a better understanding of the climate change effects on biodiversity and ecosystems (Harris et al. 2014). The results of the bioclimatic variables analysis indicated that the most important variables explaining the potential distribution of *C. nubiana* were the annual temperature range (Bio7), precipitation of the

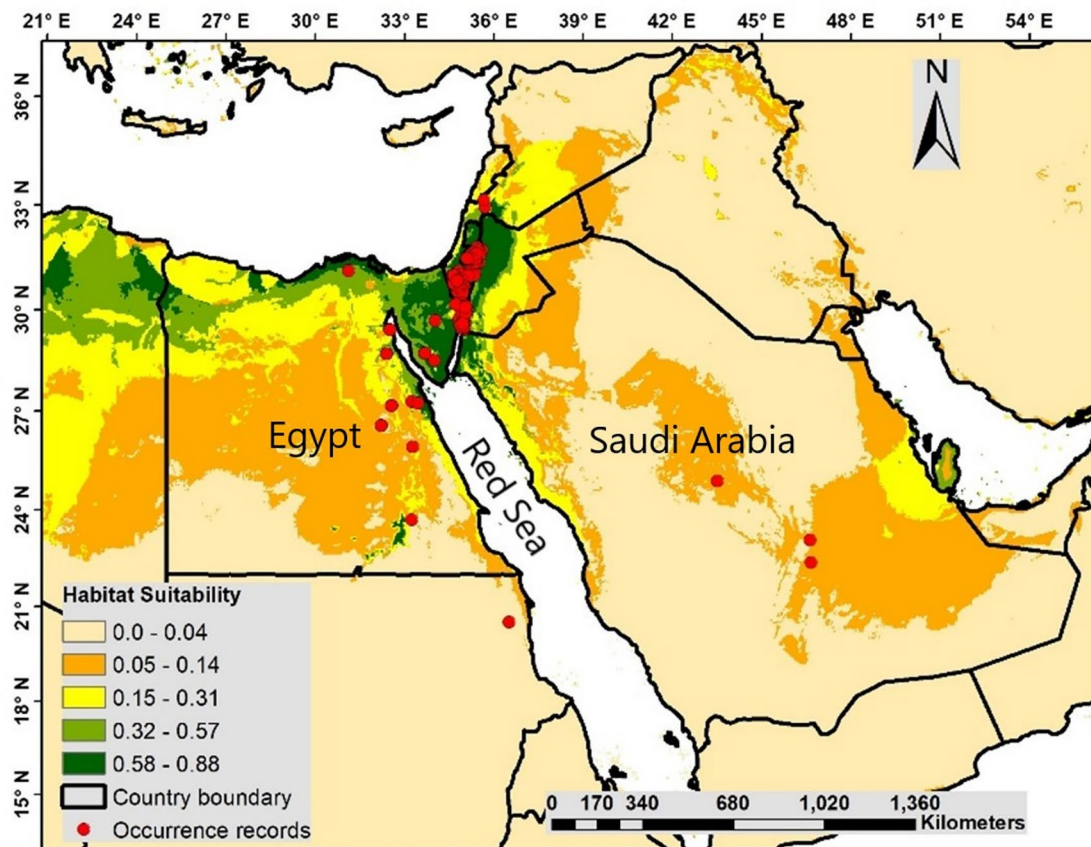


Fig. 2 Global distribution of *C. nubiana* and potential habitat suitability under present climate. *C. nubiana*

Table 2 Loss % in the area of occupancy (AOO) and conservation status of *C. nubiana* under the four scenarios of climate change, adjustment assumptions to EOO, and the two dispersal scenarios

Climate change scenario	AOO loss % adjusted to EOO		AOO loss % not adjusted to EOO		Proposed IUCN status	Status potential change
	Full dispersal	Limited dispersal	Full dispersal	Limited dispersal		
SSP126_2021-2040	60.95%	60.96%	68.62%	68.80%	EN	Uplisted
SSP126_2081-2100	63.98%	63.99%	70.99%	71.05%	EN	Uplisted
SSP585_2021-2040	60.92%	60.93%	67.36%	67.47%	EN	Uplisted
SSP585_2081-2100	96.19%	96.19%	93.85%	93.91%	CR	Uplisted

EN endangered, *CR* critically endangered

warmest quarter (Bio18), and precipitation of the driest month (Bio14). Particularly, precipitation of the warmest quarter (bio18) is considered a crucial factor in *C. nubiana* distribution, as per Salas et al. (2020). This variable, along with temperature, controls *C. nubiana* models in several studies, including Salas et al. (2020) and Gebremedhin et al. (2021). The outcomes of the study reveal that a decline in precipitation, particularly in the lower elevations, could be associated with a loss of suitable habitat for *Capra sibirica* (Asiatic *C. nubiana*) (Salas et al. 2020).

Moreover, this *C. nubiana* has a comparatively low sensitivity to precipitation variability (Wang et al. 2017). However, the probability of the presence of *C. nubiana* will increase with the increase of the precipitation in the driest month (Bio14). Thus, the water availability-related variables, particularly the precipitation in the driest month, contributed considerably to the increase of *C. nubiana* presence. It was found that precipitation can affect the distribution of herbivores in dried environments (Bartzke et al. 2018), as the precipitation will affect the forage quality and

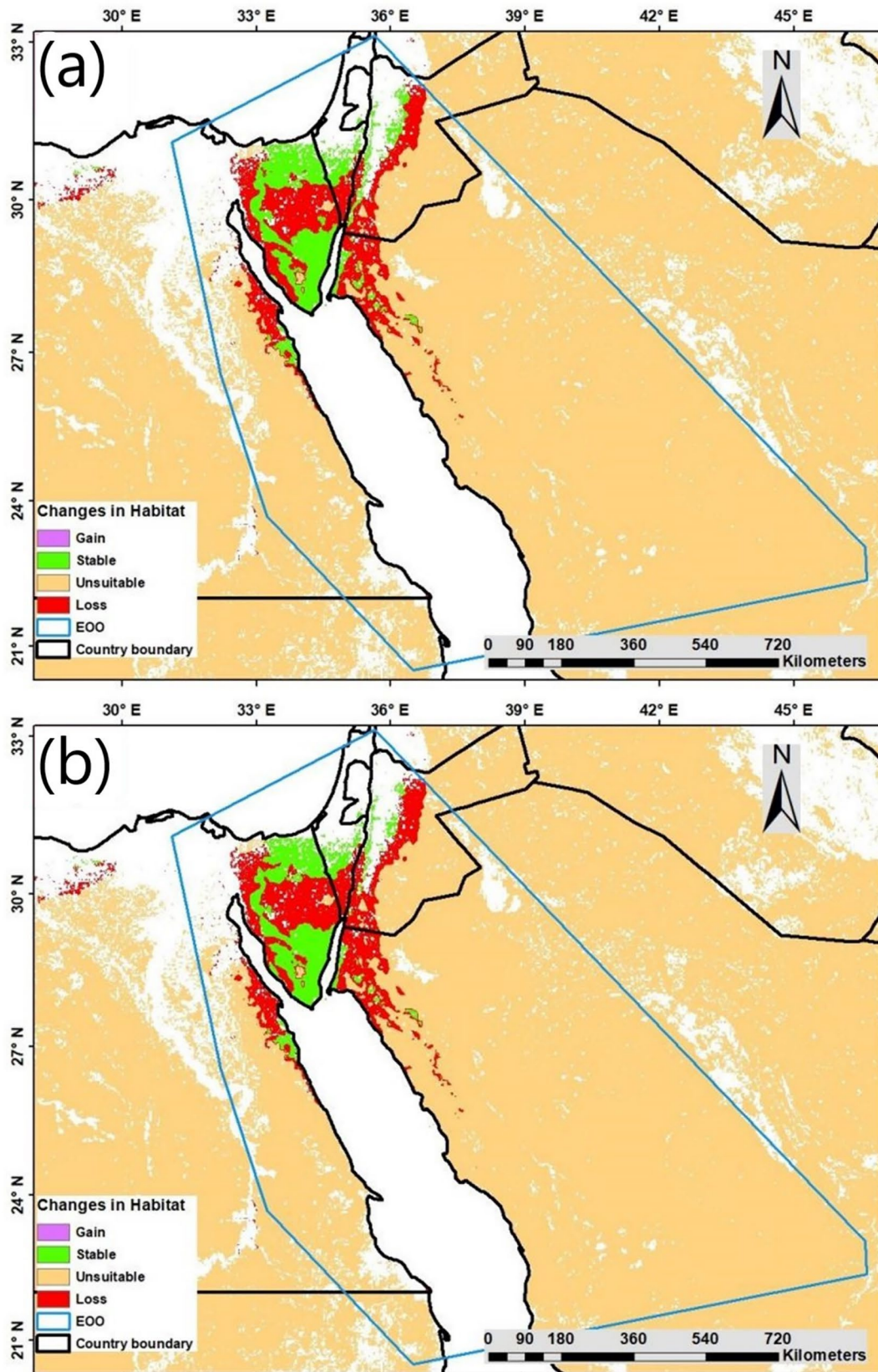


Fig. 3 Potential changes in habitat using the threshold $MTSS=0.32$ ‘Maximum training sensitivity plus specificity’ under the future climate scenarios: **a** SSP126_2021-2040; **b** SSP126_2081-2100; **c**

SSP585_2021-2040; **d** SSP585_2081-2100. This figure was zoomed to the relevant area of the extent of occurrence (EOO)

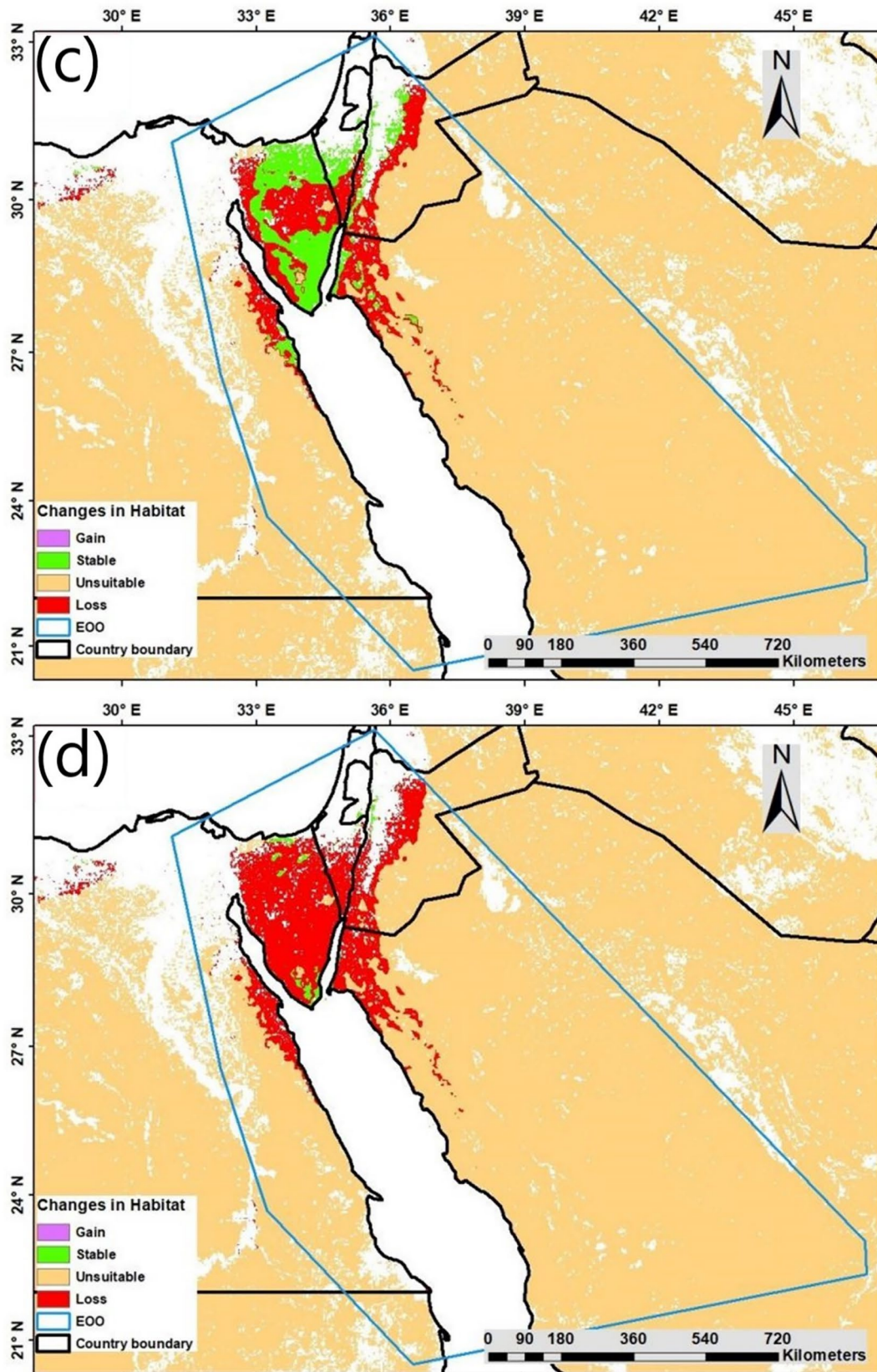


Fig. 3 (continued)

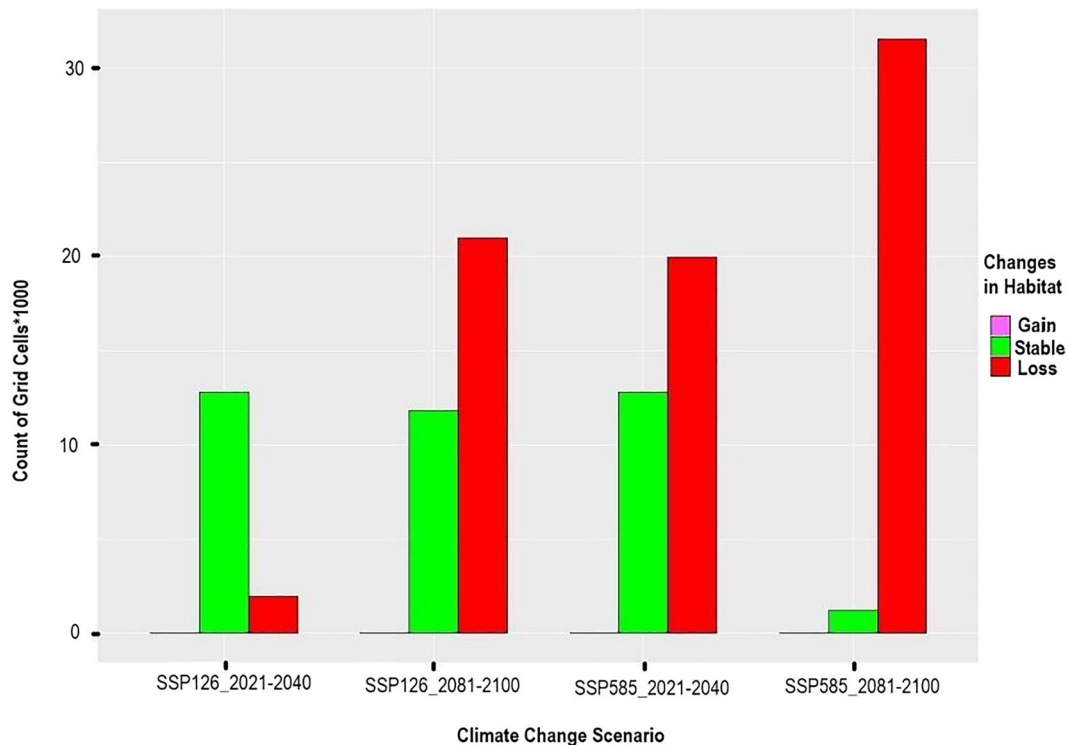


Fig. 4 Changes in potential habitat (gain, stable and loss) based on the number of grid cells (size of 2 km × 2 km * 1000) within the EOO of under the four future climate scenarios. Note that across all scenarios, there was no discernible gain in habitat

consequently that will affect the population structure of large herbivores (Marshall et al. 2008; Bartzke et al. 2018). However, a recent study presents a negative relationship between the number of water site visits by *C. nubiana* and landscape greenness, as *C. nubiana* reduced the number of visits to permanent water sites during the greater greenness appeared in the landscape (Attum et al. 2022). This indicates that *C. nubiana* can obtain water needs from forage, besides the other temporary water resources that arise during the precipitation (Attum et al. 2022). This could explain the increased probability of the presence of *C. nubiana* under the precipitation of the driest month.

In terms of the annual temperature range, *C. nubiana* is well adapted to the situation of the hot desert environment, which is characterized by extremely high temperatures, and intense solar radiation (Habibi 1994; Chebii et al. 2021), which provides an explanation of the possible distribution *C. nubiana* under this variable. Moreover, a study investigated the genome scan for variable genes for *C. nubiana* revealed a variation from the sequence data, those genes involved hair follicle development and skin barrier, which indicated that *C. nubiana* has adapted techniques to face the extrema temperature and solar radiation in the desert environment (Chebii et al. 2021).

Species dispersal has a crucial role in estimating the effect of climate change on the species in the future, as the actual

distribution of habitat is essential for species to survive during climate change (Årevall et al. 2018). This recommends immediate actions such as reintroduction planning of the *C. nubiana* and taking the findings of the suitable habitat or climatically stable areas as a decision support tool.

The current IUCN conservation status for *C. nubiana* has been declared vulnerable (VU) (Ross et al. 2020). The prediction of this study exposed a tendency of decline in the suitable habitat of the current AOOs of *C. nubiana*. Thus, the status of *C. nubiana* should be up-listed to the “Critically Endangered” category at the ssp585_2090 scenario, and the “Endangered” category in the other scenarios, under all combinations of climate and dispersal scenarios. Even though there is a possibility of adaptation to climate change by genetic adaptation (Al-Ghafri et al. 2021; Chebii et al. 2021), migration to high habitat-suitability areas, and shifting toward higher elevations and latitudes (Nanaei et al. 2022), the prediction from this study of the future loss of AOO of *C. nubiana*, should be considered regarding future loss of habitat and risk of extinction.

Conservation efforts targeting *C. nubiana* have a major difficulty and deficiency in the current information about its population trends, status, and distribution range (El Alqamy et al. 2010). Thus, conservation efforts should be given to this species, and any future conservation actions should consider the north-western area of Saudi Arabia, Jordan, and

Sinai, as the range occupied by *C. nubiana* in the mountains of Sinai represents an important corridor between its distribution in Asia and Africa (El Alqamy et al. 2010). In Saudi Arabia, it occurred in rugged and mountainous terrain; however, recently, it was found in Hawtat Bani Tamim *C. nubiana* Reserve in Central Saudi Arabia (Barichiev et al. 2018). Hence there is a well-developed conservation strategy in Saudi Arabia (Barichiev et al. 2018). Moreover, the *C. nubiana* population in Jordan is influenced by several factors, such as the distribution of waterholes, increasing the number of tourists in the area, and overhunting that is not allowed (Eid and Mallon 2021). However, the *C. nubiana* populations are protected in Jordan found in the Dana and Mujib Biosphere Reserves, as well as the Wadi Rum Protected Area, under the law, the species is subjected to hunting that is the major cause of the sharp decline in the Arabian Peninsula and in Jordan and the Nubian Ibex is listed as Endangered in Jordan (Habibi 1994; Eid et al. 2020; Eid and Mallon 2021). The future loss of *C. nubiana* habitat will affect the ecosystem services as it has a role in influencing the vegetation community by feeding on vegetation. Also, it has a potential effect on the availability of predator populations (Sipl 2003). One of the conservation strategies to cope with climatic change is to identify and protect the climate change refugia, which is an area relatively protected from human-induced change that causes habitat loss, degradation, and fragmentation, which will enable the sustainability of the natural resource (Balantic et al. 2021; Rojas et al. 2022). This perspective will provide a new approach to ecosystem management in the face of climate change.

In order to fully understand the effect of climate change and land use changes on suitable habitats for *C. nubiana*, it is crucial to take into account the limitations of future land use scenarios. Integrative modeling methods should incorporate these limitations to assess the combined impact of climate and land use changes on the species' habitats.

Limitations

This study, while comprehensive, acknowledges certain limitations. Firstly, the predictive modeling did not consider all topographic factors and habitat types, which could potentially enhance the robustness of species distribution modeling. The inclusion of these factors in future studies could provide a more nuanced understanding of species distribution. Secondly, inherent uncertainties associated with such studies must be acknowledged. These uncertainties stem from the modeling techniques employed, including the selection of Shared Socioeconomic Pathways (SSPs) and General Circulation Models (GCMs). These choices may significantly influence the outcomes and interpretations of the study. Lastly, the assessment of species extinction risk

based on the relative loss percentage in projected Areas of Occupancy (AOOs) has its limitations. While this approach provides a useful metric, it may oversimplify the complex dynamics of species extinction risk. Future studies could benefit from incorporating additional metrics to provide a more holistic view of extinction risk. In conclusion, while this study provides valuable insights, these limitations should be considered when interpreting the results and planning future research.

Conclusions

Significant change in *C. nubiana* distribution predicted herein highlights the importance of establishing a global action plan to mitigate the impact of climate change on one of the remaining apex mountain ungulate species. We suggest the conservation action give more focus on the sites that were identified as stable in our study because they would be a refuge site for this species, and conserving these sites that they are the most suitable area in the future. This information is valuable for informing conservation efforts by addressing issues such as habitat fragmentation, connectivity, and the species' ability to disperse across different areas. This can lead to more effective conservation strategies being developed. Finally, the findings of the current study could be assumed as decision support tools for in-situ conservation planning (based on the model's output maps (Fig. 3) of stable and suitable areas) as well as ex-situ conservation or reintroduction planning (based on the model's output maps (Fig. 3) of loss and gain areas).

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s42991-024-00445-z>.

Author contributions Rana O. Khayat and Mohammed A. Dakhil performed the data analysis, and visualization, and wrote the manuscript. All authors reviewed the manuscript.

Data availability The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare no competing interests.

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