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Research article

# Present and future habitat suitability for fishing cat (*Prionailurus viverrinus*) in Thailand

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## Abstract

**Importance of the work**: The fishing cat (*Prionailurus viverrinus* Bennett, 1833) is a poorly studied wildcat that inhabits floodplains and wetlands. It is threatened throughout its entire range and has even been extirpated in some locales due to human-driven habitat loss.
**Objectives**: To use the maximum entropy algorithm to assess the environmental factors and the present and future habitat suitability for fishing cats in Thailand.
**Materials and Methods**: Occurrence data (2007–2022) were used from 28 areas in the published literature and unpublished data to develop habitat suitability models.
**Results**: Key variables influencing fishing cat habitat suitability were identified: mean diurnal range of temperature, annual precipitation, topographic wetness index and elevation. The analysis identified areas of highly suitable habitat totaling 1,237 km$^2$ outside and 64 km$^2$ (approximately 5%) within six protected areas. These findings emphasized the importance of conserving both protected and nonprotected land to support fishing cat populations, especially in the provinces of Phetchaburi, Prachuap Khiri Khan, Samut Sakhon, Samut Prakan and Samut Songkhram. Projections indicated that the area of suitable habitat would rebound in the 2050s and 2070s, but with large decreases within protected areas to even less area than at present (approximately 40%), due to climate change.
**Main finding**: These results underscored the need for proactive conservation measures in the face of ongoing environmental changes and for conservation outside protected areas. Urgent actions are required to implement effective management strategies and policies that address habitat loss and secure the long-term survival of this vulnerable species.

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## Introduction

The fishing cat (*Prionailurus viverrinus* Bennett, 1833) is a mesocarnivore that primarily inhabits wetlands and lowland areas near water resources (Kolipaka et al., 2019), where it plays a crucial role in regulating prey species populations (Patumrattanathan et al., 2014). Its distribution stretches across South Asia, including Bangladesh, India, Nepal, Pakistan and Sri Lanka, to Southeast Asia, including Cambodia, Myanmar, Vietnam, Malaysia, Indonesia and Thailand (Lekagul and Mcneely, 1977; Sunquist and Sunquist, 2002; Mukherjee et al., 2016). However, fishing cat populations have been greatly impacted by human activities, such as land-use changes, human population growth and economic development, resulting in habitat loss and declining populations (Mukherjee et al., 2016; Thaung et al., 2018; Phosri et al., 2021).

A better understanding of wildlife-habitat relationships can contribute to the development of management guidelines (Johnson et al., 2012). Species distribution modeling (SDM) is a valuable tool that enables potential habitat identification and future range shifts (Prayoon et al., 2021; Phommexay et al., 2024). SDM uses presence data of the target species to create regional distribution maps and by incorporating various biological, physical and environmental variables, this tool can identify the critical habitat requirements necessary for species survival.

Fishing cats were historically abundant in natural forests; however, their numbers have dwindled due to wetland removal, reductions in prey populations and various anthropogenic factors (Mishra et al., 2018). Human activities, including land change policies, forest encroachment, overexploitation, illegal grazing, foraging of nontimber forest products (Grassman et al., 2005; Taylor et al., 2016) and wetland conversion into aquaculture, agriculture and brick factories, have led to habitat destruction (Melisch et al., 1996; Mukherjee et al., 2012). Additionally, local communities have experienced human-fishing cat conflicts, leading to the killing of fishing cats, further exacerbating the potential for rapid declines in their populations (Chowdhury et al., 2015; Mukherjee et al., 2016; Thaung et al., 2018). These threats have led to the classification of the fishing cat as vulnerable in the International Union for Conservation of Nature Red List (Mukherjee et al., 2016). However, there has been no previous report on the distribution of fishing cats across the entire country.

Therefore, with the aim of supporting effective conservation planning and surveys of fishing cat populations in Thailand, species distribution modeling was applied using MaxEnt models to clarify the habitat suitability of the species and to elucidate the environmental variables that influence their range. By understanding the habitat suitability and environmental preferences of fishing cats, conservation efforts can be directed toward key habitats, ensuring the survival of this vulnerable species in Thailand.

## Materials and Methods

### *Study area*

The study was conducted in Thailand within two major geographical regions: Mainland Southeast Asia (or Indochina) spanning northward and Sundaland spanning southward. As a result, Thailand has high biodiversity and diverse ecosystems and is home to approximately 7% of the world's flora and fauna, containing 352 mammalian species, 1,083 bird species, at least 141 amphibian species, over 350 reptilian species and at least 10,250 flora species (Luangjame et al., 1997; Parnell, 2000; Chan-ard, 2003; Middleton, 2003; Sullivan et al., 2014; Chan-ard et al., 2015; International Union for Conservation of Nature, 2024). The study incorporated data from various areas throughout the country, including islands. The geographical coordinates of the study area ranged from 5° 36' 46.9"N and 97° 20' 36"E to 20° 27' 54"N and 105° 38' 13"E, covering a total area of 515,415 km² (Fig. 1).

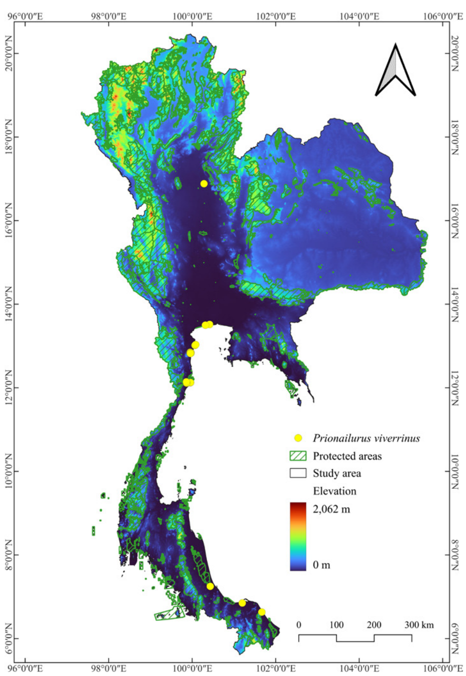


**Fig. 1** Study area and occurrence points of fishing cats in Thailand based on records from 2007 to 2022

The elevation in Thailand is mostly (64.1%) below 250 m above sea level, while approximately 9% of the land lies between 750 to 2,700 m above sea level (in highland areas). Most protected areas (PAs) have been established in highland areas, with 66% of the land above 1,000 m being protected, in contrast to only 6% of the land below 250 m (Singh et al., 2021) (Fig. 1).

Based on an inventory in 1999, Thailand had approximately 36,600 km² of wetlands (7.5% of the country), including 61 wetlands of international importance, 108 sites of national importance and over 40,000 sites of local importance distributed across the country, especially in the central and southern parts (Office of Environmental Policy and Planning, 1999). Additionally, 15 wetland sites have been designated as Ramsar Sites, including Khao Sam Roi Yot National Park in Prachuap Khiri Khan province (Department of Water Resource, 2023). However, large areas of wetlands were converted into agricultural land and shrimp farms during the 19th and 20th centuries, and now few wetlands remain in their natural state (Trisurat, 2006).

### *Species occurrence data*

Occurrence data for fishing cats were collected from various publications and unpublished data, consisting of eight occurrence points from Chutipong et al. (2019) (obtained from personal communications, newspaper articles, social media pages and publications), seven points from Jamjuree Thotong (2021, personal communication; obtained from occupancy surveys), nine points from Akarapon Bunyarat and Jedsada Noowong (2022, personal communication; obtained from occupancy surveys) and four points from Pornlapat Pakamas (2022, personal communication; obtained from occupancy surveys). These 28 occurrence points were compiled to generate present and future fishing cat habitat suitability models (Table 1). By incorporating information from different locations and time periods, the models could capture the ecological requirements and preferences of fishing cats in Thailand. Most of the occurrence points (82%) were located in agricultural land and wetland outside PAs (Fig. 1).

**Table 1** Environmental variables for each scenario

| Environmental variables | Scenario | | Source |
|---|---|---|---|
| | Present | Future | |
| Land cover variable | | | |
| Percent tree cover | 2000–2022 (downloaded from Google Earth Engine) | 2000–2022 (downloaded from Google Earth Engine) | The Terra Moderate Resolution Imaging Spectrora Diometer, Vegetation Continuous Fields (MODIS VCF) (Dimiceli, 2017) |
| Forest type* | 2018 | 2018 | Royal Forest Department, Ministry of Natural Resources and Environment (RFD) (RFD, 2018) |
| Topographic variables | | | |
| Elevation | Downloaded from Google Earth Engine | Downloaded from Google Earth Engine | The National Aeronautics and Space Administration Shuttle Radar Topography Mission (NASA SRTM) (Farr et al., 2007; Gorelick et al., 2017) |
| Topographic wetness index (TWI) | Extracted from digital elevation model (DEM) | Extracted from DEM | Extracted from DEM (Beven and Kirkby, 1979) |
| Anthropogenic variables | | | |
| Nighttime light | 2011–2021 (downloaded from Google Earth Engine) | 2011–2021 (downloaded from Google Earth Engine) | National Oceanic and Atmospheric Administration (NOAA) (Elvidge et al., 2021) |
| Bioclimatic variables (BIO1–7, BIO10–17) | 1970–2000 | 2050s (average for 2041–2060) and 2070s (average for 2061–2080) (MPI-ESM-LR and RCP45) | https://www.worldclim.org (WorldClim version 2.1) (Fick and Hijmans, 2017) |

BIO1 = annual mean temperature; BIO2 = mean diurnal range; BIO3 = isothermality; BIO4 = temperature seasonality; BIO5 = maximum temperature of warmest month; BIO6 = minimum temperature of coldest month; BIO7 = temperature annual range; BIO10 = mean temperature of warmest quarter; BIO 11 = mean temperature of coldest quarter; BIO12 = annual precipitation; BIO13 = precipitation of wettest month; BIO 14 = precipitation of driest month; BIO15 = precipitation seasonality; BIO16 = precipitation of wettest quarter and BIO17 = precipitation of driest quarter; MPI-ESM-LR = earth system model; RCP45 = temperature change emissions scenario.

* There were 18 different forest types, including forests/grasslands and non-forest area.

### Environmental variables

The habitat suitability models were developed using 20 environmental variables that were divided into four subgroups: two land cover variables, two topographic variablesone anthropogenic variable, and fifteen bioclimatic variables. All 20 environmental variables are provided in Table 1.

The selection of bioclimatic variables (BIO1–7, BIO10–17) followed the method proposed by Chaiyes et al. (2022), considering their relevance to the habitat suitability of fishing cats. Notably, Mishra et al. (2022) highlighted that the precipitation variables BIO12–17 are important predictors of habitat suitability for fishing cats. The bioclimatic variables describe temperature and precipitation conditions.

The two topographic variables were selected by considering that fishing cat survive in wetlands (using the topographic wetness index (TWI), which describes the probability of an area accumulating water) and lowlands (Mukherjee et al., 2016; Mattivi et al., 2019) and implemented the approach by Petersen et al. (2022), with elevation being described as the most important variable for predicting fishing cat habitat suitability (Silva et al., 2020; Mishra et al., 2022)

The two land cover variables were selected to describe land covers and habitat conditions suitable for the fishing cat. Variable selection improves model effectiveness by eliminating multicollinearity among variables and reducing the number of necessary variables (Dormann et al., 2013; Yi et al., 2016). The variance inflation factors (VIFs) of the 20 environmental variables were tested using the 'vifstep' function from the 'usdm' package (Naimi et al., 2014), within the R studio and R software packages (R Core Team, 2018). VIFs were based on correlation coefficients. Variables with VIFs >5 were eliminated and the procedure was repeated until no variables with a VIF > 5 remained (Chatterjee and Hadi, 2006). Ultimately, 10 variables were selected for inclusion in the model: percent tree cover, forest type, elevation, TWI, nighttime light, BIO2, BIO4, BIO12, BIO14 and BIO15. These variables were used for modeling both the present and future scenarios (Abdelaal et al., 2019).

The present model used bioclimatic data for 1970–2000. The future models incorporated bioclimatic variables based on the MPI-ESM-LR model, which is suitable for Southeast Asia (McSweeney et al., 2015) and the representative concentration pathway 4.5 scenario (medium-low carbon emissions by humans), according to Wang et al. (2017). All environmental variables used in the developed models were resampled using the bilinear re-sampling technique, except for forest types (categorical data) that were resampled using the nearest neighbor re-sampling technique (Ren et al., 2016) and clipped to the same dimensions at a 30-arcsecond resolution (providing approximately 1 km spatial resolution) in ASCII format using R studio and the R software packages (R Core Team, 2018). The models were reprojected on a Universal Transverse Mercator basis at 1 km spatial resolution to calculate areas. By incorporating a range of topographic and bioclimatic variables, the habitat suitability models provided a comprehensive understanding of the environmental factors influencing the presence of fishing cats in Thailand, which can be applied to inform assessments of current and future habitat suitability to assist conservation and management efforts.

### Maximum entropy algorithm (MaxEnt)

Maximum entropy estimation is used widely in ecological SDM for wildlife research (Yackulic et al., 2013), because such a machine-learning method offers efficient performance compared to other methods. When applying the MaxEnt algorithm, the suitability of an area is evaluated based on the highest entropy value by deriving the probability of the MaxEnt distribution from the correlation function and comparing the probability of the entropy value of that image point with all image points in the study area that allows the probability that the target species is present in the study area to be determined (Phillip et al., 2006). Advantages of MaxEnt estimation include: it uses presence-only population data and environmental data; it can be used with low sample sizes; it can incorporate both continuous and categorical data for environmental variables; it outputs continuous data, which can be interpreted more easily than binary (presence and absence) data; it can calculate relative percentage contributions, sample averages and responses of each environmental variable; and it can be applied to future projections based on climate change (Elith et al., 2006; Phillips et al., 2006; Phillips and Dudik, 2008; Kumar and Stohlgren, 2009; Elith et al., 2011; Arnold et al., 2014; Halvorsen et al., 2014; Abdelaal et al., 2019; Jha and Jha, 2021).

### Habitat suitability model

The habitat suitability models for both the present and future scenarios were constructed using the MaxEnt algorithm implemented in MaxEnt ver. 3.4.4 (Phillips et al., 2017). The models were built and tested on 10 replicates and a maximum of 500 iterations, utilizing the default 10,000 background units with a bootstrap replicated run type. For model evaluation, 75% of the data was allocated for training and the remaining 25% for testing. Only linear features, quadratic features and product features were used in this study due to the small sample sizes and to simplify the model's overall complexity and prevent model overfitting (Elith et al., 2011; Radosavljevic and Anderson, 2014). The outputs were presented using log-log (clog-log) format (Trisurat et al., 2014; Bai et al., 2018; Cobos et al., 2019; McGarvey et al., 2021) (Fig. 2). In this study, duplicated presences within the same cell were not removed because duplicate occurrences within a single cell were interpreted as increased sampling effort, resulting in a higher probability of detection (Merow et al., 2016). The models were calibrated to assign suitability values on a scale from 0 to 1, where 0 indicates the least suitable and 1 indicates the most suitable, classified into four levels: unsuitable, 0.00–0.25; poorly suited, >0.25–0.50; moderately suited, >0.50–0.75; and well suited, >0.75–1.00.

Model performance was assessed using the area under the curve (AUC). The AUC value indicates the model efficiency in identifying species presence versus absence in a given area. The model performance was rated as: excellent = AUC >0.9; good = >0.80–0.90; fair = >0.70–0.80; poor = >0.60–0.70; and unacceptable, >0.50–0.60 (Swets, 1988; Venne and Currie, 2021). The median output results were reclassified as suitable habitat and visualized using the QGIS ver. 3.30 software (QGIS.org, 2024). The analysis was performed using R Studio to identify suitable habitat areas within and outside PAs in Thailand.

Changes in bioclimatic variables over time were considered for the future habitat suitability models. This enabled the assessment of how the habitat suitability of fishing cats might evolve under different climatic scenarios. The models were applied to identify suitable habitat areas within and outside PAs in Thailand, considering potential shifts in suitable habitat due to changing environmental conditions.

## Results and Discussion

### *Habitat suitability and key variables influencing fishing cat habitat suitability*

All habitat suitability models had excellent performance based on mean AUC ± SD (present model = 0.989 ± 0.004; 2050s future model = 0.993 ± 0.003; 2070s future model = 0.988 ± 0.006). Among the environmental variables, mean diurnal range (BIO2) and annual precipitation (BIO12) had the highest contributions in all models, which were followed by percent tree cover and TWI, as the most influential topographic variables (Table 2 and Figs. 3–4).

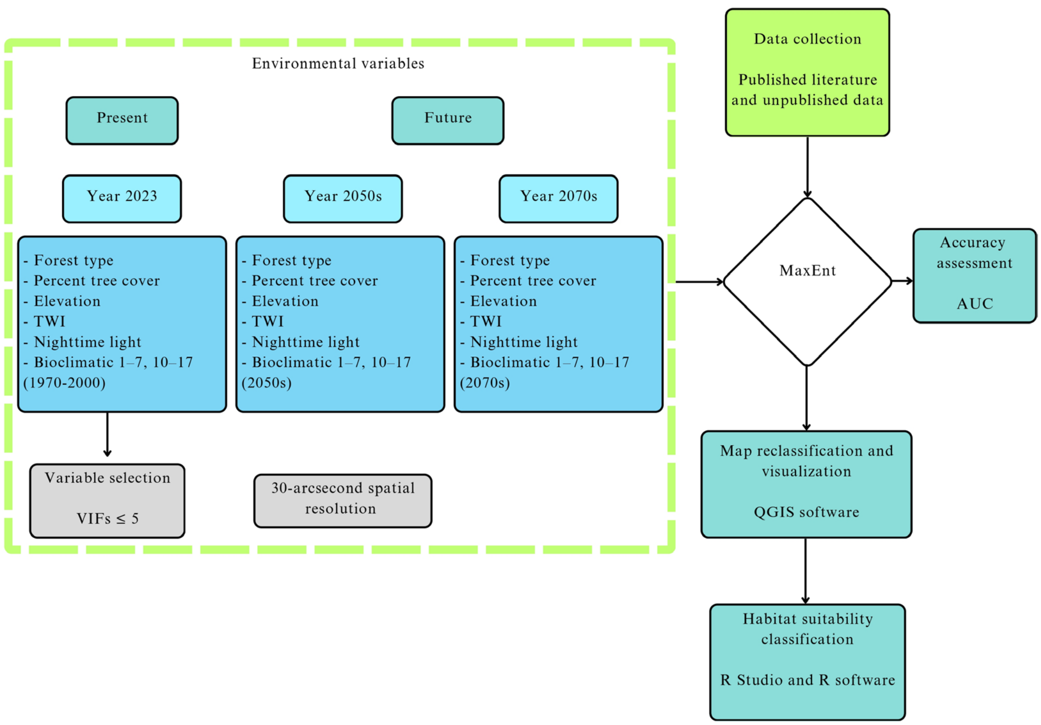


**Fig. 2** Schematic diagram of species distribution modeling workflow

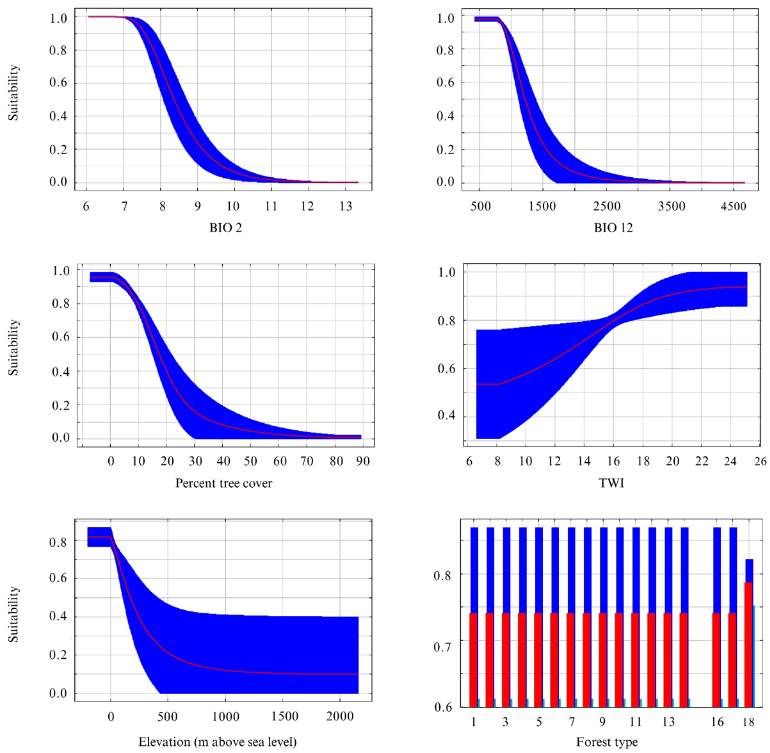


**Fig. 3** Key variable response curves (clog-log output) of fishing cat to current environmental conditions

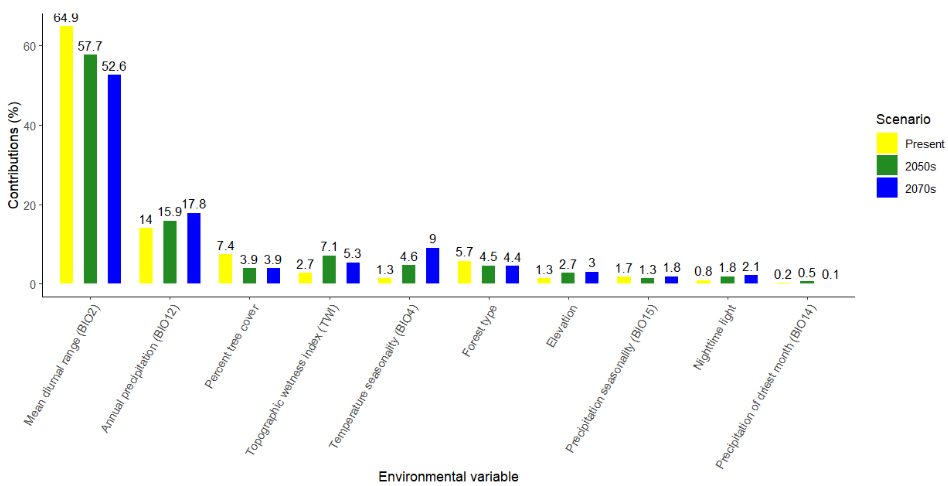


**Fig. 4** Key variables influencing fishing cat habitat suitability in each scenario in Thailand

In the present scenario, approximately 1,301 km$^2$ (0.250% of the area of Thailand) was identified as well-suited habitat for fishing cats, with 64 km$^2$ (0.012% of the area of Thailand) located within the six PAs. The most important contributors to the present model were BIO2 (64.9%), BIO12 (14%) and percent tree cover (7.4%), as shown in Tables 2 and 3.

For the 2050s future scenario, 1,715 km$^2$ (0.330% of the area of Thailand) was identified as well-suited habitat, with 38 km$^2$ (0.007% of the area of Thailand) located within five PAs. The most influential variables for this model were BIO2 (57.7%), BIO12 (15.9%) and TWI (7.1%), as shown in Tables 2 and 3. Similarly, in the 2070s future scenario, 1,955 km2 (0.376% of the area of Thailand) was identified as well-suited habitat, with 39 km$^2$ (0.008% of the area of Thailand) located within five PAs, consistent with the present and 2050s models. The most influential variables for this model were BIO2 (52.6%), BIO12 (17.8%) and BIO4 (9%), as shown in Tables 2 and 3.

**Table 2** Relative percentage contribution (RC) and sample average of environmental variables in models of fishing cat habitat suitability in Thailand

| Environmental variable | Present (AUC = 0.989) | | 2050s (AUC = 0.993) | | 2070s (AUC = 0.988) | |
|---|---|---|---|---|---|---|
| | RC (%) | Sample average (± SD) | RC (%) | Sample average (± SD) | RC (%) | Sample average (± SD) |
| Land cover variable | | | | | | |
| Percent tree cover | 7.4 | 10.68 ± 1.46% | 3.9 | 10.64 ± 1.23 % | 3.9 | 10.81 ± 1.44 % |
| Forest types | 5.7 | Non-forest area | 4.5 | Non-forest area | 4.4 | Non-forest area |
| Topographic variable | | | | | | |
| Elevation | 1.3 | 20.27 ± 6.14 m | 2.7 | 19.03 ± 6.02 m | 3 | 20.75 ± 8.16 m |
| Topographic wetness index (TWI) | 2.7 | 15.36 ± 0.54 | 7.1 | 15.47 ± 0.49 | 5.3 | 15.3 ± 0.42 |
| Anthropogenic variable | | | | | | |
| Nighttime light | 0.8 | 1.53 ± 0.22 nW/sr/cm$^2$ | 1.8 | 1.69 ± 0.22 nW/sr/cm$^2$ | 2.1 | 1.64 ± 0.22 nW/sr/cm$^2$ |
| Bioclimatic variables | | | | | | |
| Mean diurnal range (BIO2) (Mean of monthly (max temp - min temp)) | 64.9 | 7.88 ± 0.17°C | 57.7 | 8.05 ± 0.14°C | 52.6 | 8.09 ± 0.1°C |
| Temperature seasonality (BIO4) (standard deviation ×100) | 1.3 | 124.71 ± 5.21°C | 4.6 | 115 ± 4.85°C | 9 | 115.92 ± 3.23°C |
| Annual precipitation (BIO12) | 14 | 1,032.75 ± 69.5 mm | 15.9 | 1,318.29 ± 60.1 mm | 17.8 | 1,306.52 ± 59.06 mm |
| Precipitation of driest month (BIO14) | 0.2 | 11 ± 2.08 mm | 0.5 | 20.12 ± 2.66 mm | 0.1 | 19.12 ± 3.1 mm |
| Precipitation seasonality (BIO15) | 1.7 | 78.4 ± 1.54 mm | 1.3 | 67.71 ± 1.11 mm | 1.8 | 68.55 ± 0.93 mm |

AUC = area under curve; CV = coefficient of variation.

**Table 3** Suitable habitat for fishing cats in Thailand in present and future

| Habitat suitability | | | Present | 2050s | 2070s |
|---|---|---|---|---|---|
| Unsuited | All of Thailand | Area (km$^2$) | 514,925 | 512,580 | 511,273 |
| | | % (of Thailand) | 98.997 | 98.614 | 98.362 |
| | Within protected area | Area (km$^2$) | 112,327 | 112,139 | 111,943 |
| | | % (of Thailand) | 21.595 | 21.574 | 21.536 |
| | Outside protected area | Area (km$^2$) | 402,598 | 400,441 | 399,330 |
| | | % (of Thailand) | 77.401 | 77.040 | 76.826 |
| Poorly suited | All of Thailand | Area (km$^2$) | 2,263 | 3,869 | 4,731 |
| | | % (of Thailand) | 0.435 | 0.744 | 0.910 |
| | Within protected area | Area (km$^2$) | 127 | 165 | 333 |
| | | % (of Thailand) | 0.024 | 0.032 | 0.064 |
| | Outside protected area | Area (km$^2$) | 2,136 | 3,704 | 4,398 |
| | | % (of Thailand) | 0.411 | 0.713 | 0.846 |
| Moderately suited | All of Thailand | Area (km$^2$) | 1,655 | 1,621 | 1,826 |
| | | % (of Thailand) | 0.318 | 0.312 | 0.351 |
| | Within protected area | Area (km$^2$) | 41 | 66 | 93 |
| | | % (of Thailand) | 0.008 | 0.013 | 0.018 |
| | Outside protected area | Area (km$^2$) | 1,614 | 1,555 | 1,733 |
| | | % (of Thailand) | 0.310 | 0.299 | 0.333 |
| Well suited | All of Thailand | Area (km$^2$) | 1,301 | 1,715 | 1,955 |
| | | % (of Thailand) | 0.250 | 0.330 | 0.376 |
| | Within protected area | Area (km$^2$) | 64 | 38 | 39 |
| | | % (of Thailand) | 0.012 | 0.007 | 0.008 |
| | Outside protected area | Area (km$^2$) | 1,237 | 1,677 | 1,916 |
| | | % (of Thailand) | 0.238 | 0.323 | 0.369 |
| Summary area of Thailand (km$^2$) | | | 520,144 | 519,785 | 519,785 |

Overall, the habitat suitability model encompassed approximately 519,785 km$^2$ of Thailand (based on the raster MaxEnt model and a grid size of 1 km ×1 km). Within this area, approximately 1,600 km$^2$ was categorized as well-suited, 1,700 km$^2$ as moderately suited and 3,600 km$^2$ as poorly suited habitat for fishing cats. The majority of Thailand (512,900 km$^2$) was deemed unsuitable habitat. Most of the well-suited habitat was located outside PAs (Table 3), in areas with intensive human activities and settlements; this trend highlighted the importance of TWI as a variable, which represents the lowland areas used by humans. Similarly, Palei et al. (2018) in India, Patumrattanathan et al. (2014), Cutter (2014), Chutipong et al. (2019) and Phosri et al. (2021) in Thailand, Timilsina et al. (2021) in Nepal and Petersen et al. (2022) in tropical Asia reported that fishing cats lived near human habitations, while avoiding humans. However, Mishra et al. (2021) reported that fishing cats entered fishponds more frequently than natural wetlands in PAs and that human activities did not impact fishing cat distributions. In contrast, Suksavate et al. (2022) reported that human activities impacted wildlife distributions.

Based on the results from the current study (Table 3 and Fig. 6), there was a large decrease in the area of suitable habitat within and outside PAs in the 2050s and 2070s compared to the present scenario (approximately 40%). The primary environmental variables influencing the present scenario were BIO2, BIO12 and percent tree cover. In the future models, BIO2 alone was the most influential variable. In all modeled periods, fishing cats displayed a preference for areas with high topographic wetness, indicating wetland areas (Grabs et al., 2009) with low diurnal temperature ranges and open forest in non-forest areas (low percent tree cover). They also exhibited a preference for tropical sub-humid climates characterized by moderate annual precipitation and moderate temperature variations (Petersen et al., 2022). Fishing cats avoided habitats with high elevation, arid conditions and high climatic variations (Table 2).

The highest regularized training gain (2.15) for the current scenario model was achieved when BIO 2 was used in isolation to run the model, followed by elevation (1.4), with a regularized training gain greater than 1. These were key environmental factors for the training gain in the current scenario model (Fig. 5). The lowest regularized training gain occurred when BIO 2 was removed from the model, followed by BIO12 and percent tree cover, respectively. Therefore, BIO 2 was the most important contributor to classified habitat suitability for the fishing cat (Fig. 5).

In all modeled periods, mean diurnal range of temperature, annual precipitation, topographic wetness and elevation played crucial roles in determining the presence of fishing cats in Thailand. Specifically, temperatures with a mean diurnal range of 6–8°C, annual precipitation of 400–1,000 mm, topographic wetness of 15–25 and elevations in the range 0–100 m above sea level were most suitable for fishing cats (Fig. 3). In all modeled periods, fishing cats preferred habitats characterized by wetlands, lowlands, a low mean diurnal range of temperature and occupied by humans. Highly suitable areas were predominantly located only in the wetland and lowland regions of central coastal Thailand, with most of these areas being occupied by humans, particularly in agricultural regions, encompassing 12 provinces, including Bangkok, with only five provinces being currently considered core areas: Phetchaburi, Prachuap Khiri Khan, Samut Sakhon, Samut Prakan and Samut Songkhram. However, in the future,

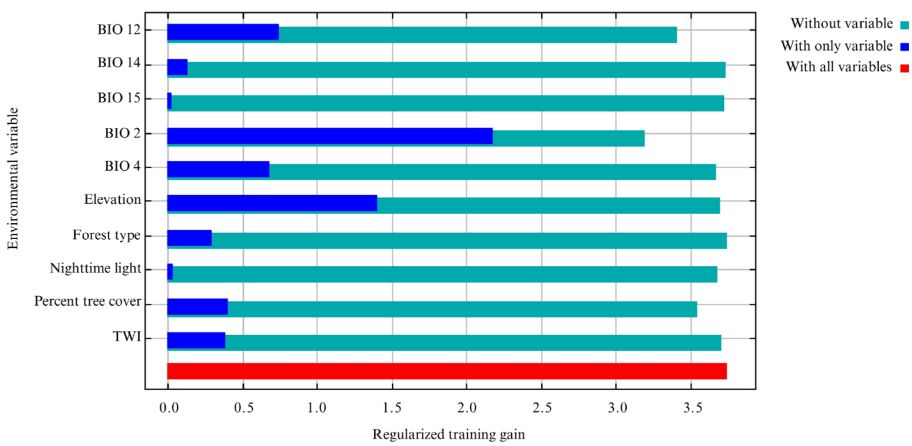


**Fig. 5** Results of jackknife test of variable importance of fishing cat to current environmental conditions

only two provinces will remain as core areas: Phetchaburi and Prachuap Khiri Khan. Very suitable areas were confined within nine PAs in all modeled periods: Khao Sam Roi Yot National Park (the only large single area among these PAs), Khao Nang Phanthurat Forest Park, Cha-am Forest Park, Pran Buri Forest Park, Thao Ko Sa Forest Park, Khao Ta Mong Lai Forest Park, Bang Pra Non-hunting Area, Phanthai Norasing Non-hunting Area and Thao Ko Sa Forest Park (Fig. 6). Similarly, Tantipisanuh et al. (2014), Cutter (2014) and Phosri et al. (2021) reported the presence of fishing cats within Khao Sam Roi Yot National Park, but not within the PAs. In contrast, Cutter and Cutter (2009) reported evidence of fishing cats in the Thale Noi Non-Hunting Area, without identifying any very suitable areas in their study. In West Java (Indonesia), fishing cats inhabited coastal areas (Melisch et al., 1996) and in Nepal, they lived near wetland streams and riparian habitats (Taylor et al., 2016). In tropical Asia, fishing cats have been observed to prefer wetland habitats, low elevations and moderate temperature variations (Petersen et al., 2022). Mishra et al. (2018, 2022) emphasized elevation and precipitation in the warmest quarter as the most important variables for predicting habitat suitability for fishing cats. In Nepal, fishing cat habitats were predominantly in lowland and wetland areas (<300 m above sea level); in Thailand, fishing cats are restricted to lowland wetlands (<300 m above sea level) (Cutter, 2009); and in Sri Lanka, they have been detected in wetlands within hilly regions (Thudugala, 2016). Mukherjee et al. (2016) recorded fishing cats at elevations of up to 1,800 m above sea level. In Thailand, >90% of the well-suited areas exist outside PAs; however, in Nepal, two-thirds of the well-suited areas are located within PAs due to strong conservation measures (Mishra et al., 2022). Notably, Taylor et al. (2016) reported that denser fishing cat populations may be possible in highly modified reserves compared to natural habitats.

## *Conservation implications*

The current study, conducted using the MaxEnt algorithm, has provided valuable insights into the habitat suitability for fishing cats in Thailand. The prediction results indicated that well-suited habitat for fishing cats was limited in wetland and lowland area in central Thailand and was primarily occupied by humans. Such regions face major threats due to land-use changes, population growth and economic development. Furthermore, these regions are seriously underrepresented by the current PA conservation program, as well as being inadequately covered (Singh et al., 2021). Additionally, human-fishing cat conflicts occur in many areas across the distribution of the cats where human and agricultural pressures are high.

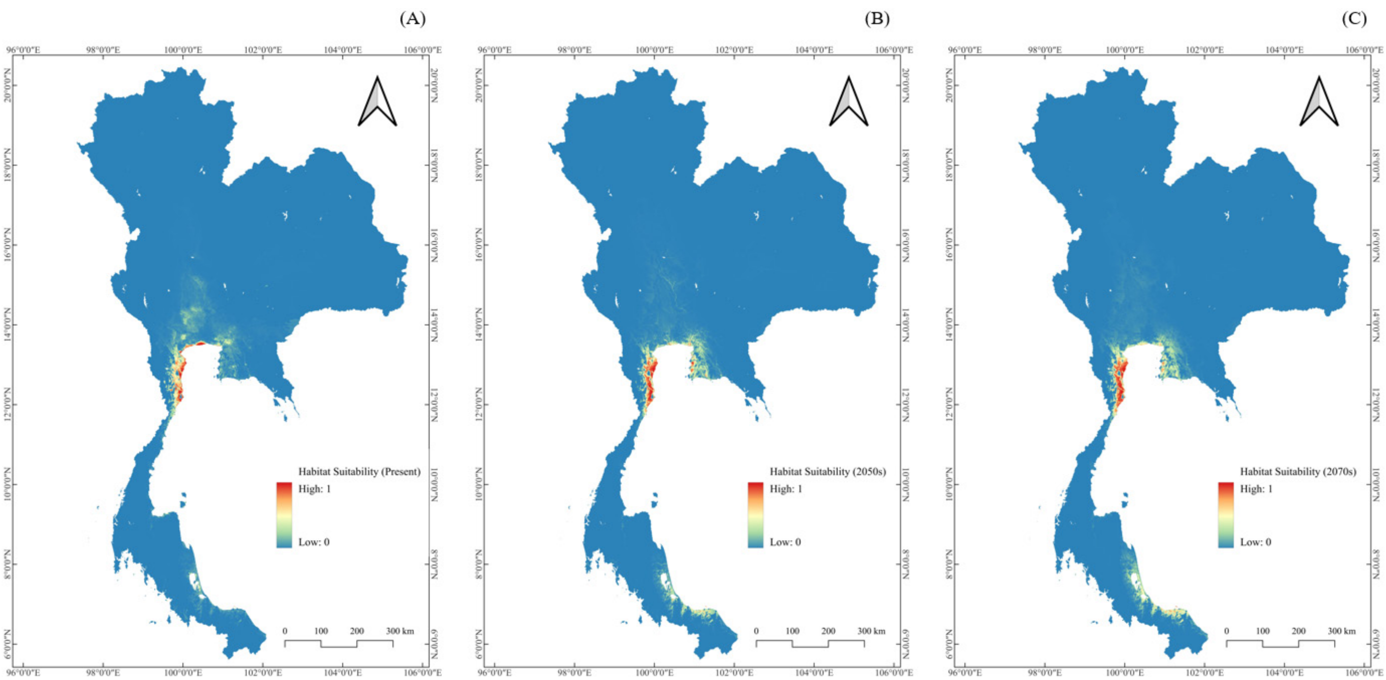


**Fig. 6** Habitat suitability for fishing cats in Thailand: (A) present; (B) 2050s; (C) 2070s

Crucially, community management and the implementation of effective conservation strategies must be prioritized to protect these habitats, relieve human-fishing cat conflicts and mitigate the impacts of land-use changes across Thailand, especially because most of the well-suited habitat exists outside PAs. Among the key recommendations for conservation planning, special attention should be given to the wetland and lowland areas in Phetchaburi, Prachuap Khiri Khan, Samut Sakhon, Samut Prakan and Samut Songkhram provinces. These areas have demonstrated stability regarding long-term suitability for fishing cat populations and can support gene flow among PAs (Kolipaka et al., 2019).

Khao Sam Roi Yot National Park in Prachuap Khiri Khan province should be the top priority for habitat protection because it has the highest density of fishing cat populations in Thailand (Phosri et al., 2021).

Further surveys should be encouraged to identify new populations in moderate-to-well-suited areas and to study the population status and carrying capacity of areas where fishing cats are currently present in Thailand. Such information should be instrumental in developing effective conservation measures and in ensuring the long-term viability of fishing cat populations.

In conclusion, the current findings should provide valuable insights to support conservation efforts outside PAs and emphasize the need for effective strategies. These strategies should aim at fostering a positive attitude and awareness towards the fishing cat, as well as encouraging community participation, which will help prioritize the protection and management of suitable habitats to ensure the long-term survival of fishing cat populations in Thailand.

## Conflict of Interest

The authors declare that there are no conflicts of interest.

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