Identifying the possibilities and pitfalls of conducting IUCN Red List assessments from remotely sensed habitat information based on insights from poorly known Cuban mammals

Clare Duncan, Monika Böhm, and Samuel T. Turvey

Abstract: The International Union for Conservation of Nature’s Red List of Threatened Species (RLS) is the key global tool for objective, repeatable assessment of species’ extinction risk status, and plays an essential role in tracking biodiversity loss and guiding conservation action. Satellite remote sensing (SRS) data sets on global ecosystem distributions and functioning show exciting potential for informing range-based RLS assessment, but their incorporation has been restricted by low temporal resolution and coverage of data sets, lack of incorporation of degradation-driven habitat loss, and noninclusion of assumptions related to identification of changing habitat distributions for taxa with varying habitat dependency and ecologies. For poorly known mangrove-associated Cuban hutias (Mesocapromys spp.), we tested the impact of possible assumptions regarding these issues on range-based RLS assessment outcomes. Specifically, we used annual (1985–2018) Landsat data and land-cover classification and habitat degradation analyses across different internal time series slices to simulate range-based RLS assessments for our case study taxa to explore potential assessment uncertainty arising from temporal SRS data set coverage, incorporating proxies of (change in) habitat quality, and assumptions on spatial scaling of habitat extent for RLS parameter generation. We found extensive variation in simulated species-specific range-based RLS assessments, and this variation was mostly associated with the time series over which parameters were estimated. However, results of some species-specific assessments differed by up to 3 categories (near threatened to critically endangered) within the same time series, due to the effects of incorporating habitat quality and the spatial scaling used in RLS parameter estimation. Our results showed that a one-size-fits-all approach to incorporating SRS information in RLS assessment is inappropriate, and we urge caution in conducting range-based assessments with SRS for species for which habitat dependence on specific ecosystem types is incompletely understood. We propose novel revisions to parameter spatial scaling guidelines to improve integration of existing time series data on ecosystem change into the RLS assessment process.

Keywords: habitat degradation, hutia, Landsat, mangrove, Mesocapromys, remote sensing

Resumen: La Lista Roja de Especies Amenazadas (LREA) de la Unión Internacional para la Conservación de la Naturaleza es la herramienta mundial más importante para la evaluación objetiva y repetible del estado de riesgo de extinción de una especie y juega un papel esencial en el seguimiento de la pérdida de la biodiversidad y en la orientación de las acciones de conservación. Los conjuntos de datos obtenidos por teledetección satelital (SRS) sobre la distribución y funcionamiento de los ecosistemas globales tienen un potencial emocionante para informar las evaluaciones de la LREA basadas en la extensión de la distribución de la especie, pero su incorporación dentro de...
Introduction

The International Union for Conservation of Nature (IUCN) Red List of Threatened Species (RLS) is the key global tool for objective, repeatable assessment of species’ extinction risk and plays an essential role in tracking biodiversity loss and guiding conservation. The RLS assesses extinction risk across 5 extant categories: least concern (LC), near threatened (NT), vulnerable (VU), endangered (EN), and critically endangered (CR). Species are assessed against 5 quantitative criteria based on extinction risk symptoms: population size reduction (criterion A); restricted geographic range and population fragmentation, decline, or fluctuation (B); small, declining populations (C); very small or restricted populations (D); and probability of extinction (E) (IUCN 2019a). Species are assessed against all criteria by trained assessors, based on multiple information sources, and listed under the highest extinction risk category-triggering criteria (IUCN 2019a). However, misconceptions and data biases drive strong variability in application of categories and criteria (Collen et al. 2016; Santini et al. 2019). Background data and assumptions employed to infer change are influenced by multiple sources of uncertainty that can drastically impact listings (Hall et al. 2009; Joppa et al. 2016; Santini et al. 2019) and should be acknowledged in assessments (IUCN 2019a). The IUCN produces regularly updated guidelines to maximize RLS robustness, consistency, and replicability; however, this guidance is by no means complete, especially when considering how different sources of data and uncertainty influence assessment outcomes for lesser known taxa.

A key predictor of extinction risk is restricted distribution (Hall et al. 2009; Staude et al. 2020), which is assessed under criteria B and D2. Range restriction is estimated based on extent of occurrence (EOO) (i.e., area within shortest continuous boundary around present known or inferred occurrence, which indexes the extent to which risk from threatening processes is spread across species’ distributions) and area of occupancy (AOO) (i.e., area of within-EOO suitable habitat currently occupied, with species occurring in more or larger patches at comparatively lower risk from spatially explicit threats) (IUCN 2019a). These metrics may also inform range-based proxy estimation of population size or trends (criteria A, C, D1) (IUCN 2019a; Santini et al. 2019). For poorly known species, assessment frequently relies on range-based metric estimation (especially EOO) from patchily available locality data and decline or threat inference from often-qualitative habitat knowledge. Such assessments are primarily conducted through labor- and cost-intensive expert-based workshops (Rondinini et al. 2014). Range-based parameter and trend estimation can also be conducted using unbiased, consistently collected satellite remote sensing (SRS) data, which additionally provide opportunities to update the RLS systematically through time (Collen et al. 2016). The SRS-derived...
potential habitat extent (area of habitat [AOH]) has been used to infer surrogate population parameters and habitat distribution change for species dependent on specific habitat types (hereafter habitat-dependent species) (Buchanan et al. 2008; Tracewski et al. 2016), erroneously to infer static EOO (Hall et al. 2009; Ocampo-Peñuela et al. 2016), and to estimate trends in range-based RLS parameters (Tracewski et al. 2016; Santini et al. 2019). Results of these studies show that employing SRS-derived time series habitat information can alter RLS category assignment and improve assessment for poorly known species (Santini et al. 2019). Because habitat maps delineate potential rather than occupied habitat, to aid AOO and EOO estimation they need justification and validation as accurate representations of species’ habitat requirements; to differentiate occupied habitat from potential habitat; and to be scaled to the AOO reference scale (IUCN 2019a). Approaches to relate species’ AOH to EOO (minimum convex polygon [MCP] plotted around EOO) and AOO (AOH scaled to RLS reference scale [2 × 2 km] as an index of species’ maximum AOO) have been explored recently to support consistent application of RLS criteria (Brooks et al. 2019).

However, SRS-derived product availability and spatial assumptions for RLS parameter calculation may influence extinction risk estimation unevenly across taxa (e.g., according to ecology or habitat dependency). We identified 3 unaddressed issues with time series SRS data in RLS assessment. First, existing SRS-derived ecosystem-change products span relatively short timescales (1–2 decades), but RLS parameter declines are assessed over longer periods, particularly for large-bodied taxa (the longer of 3 generation lengths or 10 years [IUCN 2019a]). Threats and AOH can be highly temporally dynamic, with appropriate threat inference dependent on patterns of temporal change (Collen et al. 2016), such that extended or multiple (or both) timescales are necessary to determine the severity of threats associated with habitat loss. Second, species’ local-scale persistence depends on both habitat quality and extent (Heinrichs et al. 2016). Observed, estimated, inferred, or projected habitat quality declines can contribute to listing under criterion B (IUCN 2019a), so habitat quality proxies may aid determination of occupancy and decline, but these are not included in existing SRS-based RLS assessments. Third, differences in scale and parameter calculation are pervasive in applying range-based RLS criteria and assessment outcomes (Joppa et al. 2016). The SRS-derived AOH at mapped spatial scales has previously been erroneously considered equivalent to EOO (Hall et al. 2009; Ocampo-Peñuela et al. 2016: see IUCN 2019a) or remapped to IUCN-recommended scales to proxy maximum potential AOO (Tracewski et al. 2016; Santini et al. 2019). However, impacts of these approaches on RLS outcomes remain unexamined. Moreover, realized within-EOO occupancy also varies relative to distributions of specific habitat types and is unlikely to approach maximum potential AOO for highly habitat-dependent species (Santini et al. 2019). Instead, exploring spatial scaling flexibility in RLS parameter estimation may be more ecologically appropriate so that uncertainty is incorporated when using SRS-derived habitat data sets to assess taxa with differing or poorly known ecologies, or both. Exploring variation in spatial scaling of SRS-derived RLS parameters may have further implications across taxa because the choice of any species-specific scaling is important in justifying known life history–based inferences of occupied habitat from AOH (IUCN 2019a).

The insular Caribbean has experienced extensive mammal extinctions, and surviving taxa are poorly known and threatened. In Cuba and its offshore cays, dwarf hutias (Capromyidae: Mesocapromys angeli cabreri, Mesocapromys auritus, Mesocapromys nanus, Mesocapromys sanfelipeensis) are among the few mangrove-associated mammals (Turvey et al. 2017). Around 60% of Cuba’s coast is mangrove fringed, and mangroves occur in extensive intertidal areas, notably Zapata Swamp (Claro et al. 2001). All known populations of these Mesocapromys species are restricted to and largely dependent (food or shelter or both) on red mangrove (Rhizophora mangle) (Borrot-Páez & Mancina 2011). Although little recent mangrove loss has been reported from Cuba (Bunting et al. 2018), land reclamation, charcoal production, poor fire management, and infrastructure development may have driven substantial degradation and deforestation in the past (Spalding et al. 2010). Land clearance, conversion, ecological integrity, and threats probably vary across Cuba (Cissell & Steinberg 2019). Mangrove-associated hutias were not assessed under range-based criteria before 2017, and a higher RLS category listing under range-based criteria was assigned to M. angeli cabreri in a recent expert-based reassessment (Turvey et al. 2017) (Table 1). Cuban hutias are therefore a useful group with which to examine how SRS time series data and treatment influence RLS assessments of poorly known taxa because their distribution and status are incompletely understood, they exhibit varying degrees of habitat dependency on specific ecosystems (mangrove forests), and these pertinent ecosystems are readily identifiable from open-access SRS and are experiencing spatiotemporal variation in threats. Furthermore, Turvey et al. (2017) recently provided updated traditional RLS assessments (not based on SRS data) of Cuban hutias, which permits comparison with SRS-derived RLS status assessments.

We conducted a RLS assessment simulation study on Cuban mangrove-associated hutias to dually explore the potential role openly accessible SRS-derived habitat information can play in quantifying range-based extinction risk for poorly known, habitat-dependent species in a real-world example group, and the potential pitfalls associated with applying these data to assess
Table 1. Previous (2008 [IUCN 2018]) and recommended (IUCN 2019b; Turvey et al. 2017) IUCN Red List of Threatened Species (RLS) listings for Cuban mangrove-associated *Mesocapromys* species, and current Cuban mangrove distribution information.a

| Species                  | RLS status 2008 (IUCN 2018) [updated status Turvey et al. 2017] | Population trend 2008 RLS (IUCN 2018) [recent from Turvey et al. 2017 + references therein] | Estimated population size (Turvey et al. 2017) | Number of viable-subpopulations (locations) (Turvey et al. 2017) | Identified threats (IUCN 2018) | Range size (km²) | Percentage and area (km²) mangrove in range (2015) |
|--------------------------|------------------------------------------------------------------|---------------------------------------------------------------------------------------------|-----------------------------------------------|-------------------------------------------------------------------|-----------------------------|------------------|-----------------------------------------------|
| *Mesocapromys angeli cabrerae* | EN C2a(i) [CR B1ab(iii)+2ab(iii)]                                | unknown [unknown]                                                                         | 380−760                                       | 1 (1 additional tiny introduced subpopulation)                     | hunting, competition with introduced *Rattus rattus*              | 9.35             | 82.57 (7.72)                          |
| *Mesocapromys auritus*   | EN C2a(ii) [EN B1ab(iii), C2a(ii)]                               | stable[declining]                                                                         | 400−1320                                      | 1 (possibly 2 additional tiny introduced, possibly extinct- subpopulations) | hunting, competition with introduced *Rattus rattus*              | 85.85            | 70.91 (60.88)                         |
| *Mesocapromys nanus*     | CR (possibly extinct) C2a(i) [CR (possibly extinct) D1]         | unknown[unknown]                                                                         | tens(<50)                                     | 1 (possibly extinct)                                              | competition with introduced *Rattus rattus*, habitat loss from fires | 3,980.49         | 7.23 (287.76)                         |
| *Mesocapromys sanfelipensis* | CR (possibly extinct) D1 [CR (possibly extinct) B1ab(iii,ivv), D1] | unknown[declining]                                                                       | tens(<50)                                     | 1 (possibly extinct)                                              | hunting, competition with introduced *Rattus rattus*, habitat loss from fires | 7.72             | 49.74 (5.84)                          |

a Definitions: IUCN, International Union for Conservation of Nature; EN, endangered (IUCN RLS category); CR, critically endangered; a and b, IUCN RLS subconditions (see IUCN 2019a).

b Calculated from mangrove distributions estimated in this study for 2015.
habitat-dependent species’ range-based extinction risk, so as to identify recommendations for their future use in RLS assessment more broadly. Specifically, we explored potential uncertainty in range-based assessments for our mangrove-associated hutia case study associated with temporal SRS data set coverage, incorporating proxies of (change in) habitat quality, and assumptions on spatial scaling of habitat extent. We used open-access SRS data and classification and trend analyses to evaluate assessments under combinations of time series data sets and spatial inference assumptions. We aimed to provide a first test case with novel quantitative evidence to refine use of SRS in RLS assessment. Based on our results, we devised recommendations for revising RLS guidelines for spatial parameter inference under these tested considerations for semi habitat-dependent and habitat-dependent species.

Methods

Habitat Distribution Change

We assessed long-term change in Cuban mangrove cover (Fig. 1) via land-cover classification on moderate-resolution multispectral imagery for 1985, 1995 (Landsat 5 TM), 2005 (7 ETM+), and 2015 (8 OLI/TIRS). For each year, we searched Landsat Surface Reflectance (SR) Tier 1 archives in Google Earth Engine (GEE) (Gorelick et al. 2017) and obtained all dry-season (November–April) tiles over preceding and subsequent dry seasons (Appendix S1). We masked cloud and cloud-shadow pixels via the quality assessment band, and median-mosaicked and cropped year-specific tiles (n = 260, 554, 521, 840, for 1985, 1995, 2005 and 2015, respectively) for Cuba’s coastal region (maximum buffer 70 km) in GEE to produce single dry-season composites. The mosaic procedure removed missing data in year 2005 from Scan Line Corrector failure in ETM+ imagery. To reduce computational requirements, we split GEE-outputted composite imagery into 27 approximately equal-sized slices (7,834–15,669 km²). Further analyses were conducted in R 3.5.1 (R Development Core Team 2018). We masked pixels >35 m elevation in Shuttle Radar Topography Mission 30-m DEM data (USGS 2014) because mangroves cannot persist beyond this limit, and removed year-specific permanent waterbodies by thresholding at >0 on the automated water extraction index (AWE E L0) (Duncan et al. 2018).

We calculated vegetation (n = 2), soil (n = 1), and water indices (n = 3) on masked period-specific Landsat SR composites (Appendix S2). We conducted unsupervised classifications for each slice for 1985, 1995, 2005, and 2015 based on selected cross-sensor complementary bands (red, near-infrared, shortwave infrared 1 and 2) and calculated indices. To produce conservative mangrove change estimates, we applied classification only to pixels with normalized difference vegetation index (NDVI) ≥0.4 (Yo et al. 2013). We used k means clustering (Hartington-Wong) to group slices into spectrally similar classes (Wegmann et al. 2016) based on random sampling of 10,000 pixels and 100 model iterations over 25 random starts (Leutener & Horning 2016). We visually identified 6 land-cover classes (NDVI ≥ 0.4) from 1985 red-green-blue composite imagery: mangrove, marsh, terrestrial forest, scrub or grassland, productive agriculture, and unproductive agriculture. Presence of classes varied across slices (4–6 classes/slice). Low- and high-productivity mangroves were identified as distinct classes in some slices (n = 3). We conducted postclassification filtering with 3 × 3 pixel moving-window modal filters (Wegmann et al. 2016) and visually identified mangrove-specific classes in each slice for extraction (QGIS Development Team 2018). We conducted visual accuracy assessment of unsupervised mangrove classifications from high-resolution optical imagery, where available (2005 and 2015 [Appendix S3]). Due to introduction of classification error at 2 time periods, we conducted pixel-specific mangrove change assessment (Duncan et al. 2018). Gain or loss pixels in later classifications (1995, 2005, 2015) were conservatively retained only if NDVI change was ≥25% from the previous time step. We then created a mosaic of period-specific classified slices to produce Cuba-wide mangrove distributions for each year. We assessed temporal mangrove distribution changes within geographic ranges for all hutia species (Fig. 1) via raster overlay functions.

Habitat Quality Change

We created an index of change in primary productivity (habitat quality proxy) in identified constant mangrove distributions based on all Cuba-specific dry-season Landsat SR imagery. We assumed that hutia species inhabiting constant mangrove pixels experienced degradation or enhancement of habitat (available food or shelter or both [mangrove tree biomass]) where primary productivity significantly decreased or increased over time, respectively. For each dry season from 1985 to 2018 (November 1984–April 1985 to November 2017–April 2018), we extracted, cloud masked, and created a median mosaic of all available tiles and calculated sensor-specific (TM, ETM+, or OLI/TIRS) yearly composite NDVI rasters in GEE (Appendix S4). Owing to Landsat 7 Scan Line Corrector errors, we preferentially employed Landsat 5 and 8 data. Pixel-specific missing data were filled with corresponding Landsat 7 composite data to first-pass NA (not available)-fill NDVI time series. We cropped required time series composite rasters to period-specific constant mangrove distributions, and interpolated missing pixel-specific time series observations by attributing missing observations at the
beginning of time series to the first available non-NA observation, filling internal missing observations with the most recent available observations. To identify significant primary productivity changes (Duncan et al. 2018), we conducted nonlinear prewhitened Mann Kendall trend analyses for 1985–2015 and 1995–2015 constant mangrove distributions’ median dry-season NDVI composite time series (zyp.trend.vector) (Bronaugh 2013).

To explore temporal variation in habitat quality change, we also conducted trend analyses for 1985–1995, 1995–2005, and 2005–2018, and masked pixels with fewer than 5 data points from NDVI trend analyses (<0.01% pixels [cloud cover]). We calculated proportions of pixels with significant NDVI change from period-specific trend analysis raster outputs (tau $p < 0.05$) (Duncan et al. 2018).

Figure 1. Cuban archipelago (upper panel) and Mesocapromys species distributions: (a) distribution of Mesocapromys sanfelipensis on Cayos Juan Garcia and Real, (b) distribution of M. nanus in Zapata Swamp, (c) distribution of M. auritus on Cayo Fragoso, and (d) distribution of M. angelcabraei in Cayos Salinas. Satellite imagery from Google Earth, and species distribution data from IUCN (2018).
Range-Based RLS Assessments

We conducted range-based RLS assessments under criteria B1 (restricted EOO) and B2 and D2 (restricted AOO). For listing under criterion B, 2 of 3 subconditions (a–c) must be met alongside restricted EOO or AOO: subcriterion a, occurrence in few locations or severe population fragmentation; b, “continuing decline observed, estimated, inferred or projected in any of (i) EOO, (ii) AOO, (iii) area, extent and/or quality of habitat, (iv) number of locations or subpopulations, and (v) number of mature individuals”; c, “extreme fluctuations in any of (i) EOO, (ii) AOO, (iii) number of locations or subpopulations, and (iv) number of mature individuals” (IUCN 2019a). Subcondition b(iii) (continuing decline in habitat) requires caution to ensure habitat (i.e., “the area, characterized by its biotic and abiotic properties, that is habitable” by a species) is assessed appropriately (IUCN 2019a). Habitat delimitation and quantification of declines from SRS can thus guide b(iii) decision making.

We calculated EOOs and AOOs with the redlist R package (Lee et al. 2019). For RLS criterion B1, we calculated EOOs from expert-derived RLS range maps (100% MCP) (Joppa et al. 2016) for evaluation against EOO thresholds (IUCN 2019a). Continuing declines in EOO—subcondition b(i)—were not assessed. Case study hutia species’ degree of mangrove habitat dependence is unknown. Therefore, in the absence of an RLS threshold for AOH (outside of treatment as maximum potential AOO and using respective AOO thresholds [Ocampo-Peñuela et al. 2016; Brooks et al. 2019]), we assumed that species-specific AOH mapped at 30-m (Landsat) resolution is proportional to AOO. The RLS guidelines recommend up-scaling fine-resolution maps for AOO calculation to the reference scale (2 × 2 km) by increasing grid dimensions (e.g., here approximately 67 × 67 30-m pixel resolution reduction) or by application of a scale correction factor (C) calculated from an area–area curve slope (Appendix S5) (IUCN 2019a). Using C to estimate AOO can also be refined by qualitative life history information (dispersal ability, habitat specificity) regarding species’ likelihood to fully occupy 2 × 2 km resolution cells (e.g., in adjacent habitat types), where decreasing C reflects more saturated distributions (resultantly greater AOO estimates) more appropriate for wider ranging, habitat-generalist species (IUCN 2019a). For criterion B2 and subcondition b(ii) (continuing decline in AOO), we scaled period-specific classified mangrove extent at 30 m to 2 km resolution (AOOR) (IUCN 2019a) by applying C for evaluation against AOO thresholds:

$$\text{AOOR} = \text{AOOO} \times 10^{\left(\frac{\text{Ag} - \text{AgO}}{\text{AgO}}\right)}$$

where AOOO is the estimated AOO (mangrove extent) at available mapping resolution (square kilometers) and Ag and AgO are grid cell areas (square kilometers) at 2 × 2 km reference and original mapping resolutions (30 × 30 m), respectively. Subcondition (a) is from Turvey et al. (2017): inferred population or subpopulation numbers and viability, where known threats affect all population or subpopulation locations (Table 1). For condition b(iii), we calculated change in habitat area from period-specific classified mangrove distributions and habitat quality change from range-wide proportional significant mangrove NDVI change. We took conditions b(iv) and b(v) (continuing declines in numbers of mature individuals and subpopulations or locations, respectively) from Turvey et al. (2017). Conditions c(i–v) were excluded based on current knowledge from Turvey et al. (2017). For VU D2 assessment (the only threatened category applicable to criterion D2), restricted AOO or location numbers must occur alongside plausible future threats that could lead to a CR or EX listing within circa 1–2 generations (IUCN 2019a). Plausible threats were based on Turvey et al. (2017).

We simulated range-based RLS assessments to account for 4 assumptions (i.e., sources of variability). We varied time series data sets for EOO, AOO, and habitat change calculation from 1995–2015, 1985–2015 (approximately 3 Mesocapromys generation lengths [Turvey et al. 2017]), and 2005–2015 (recent change) (assumption 1). We assumed mangrove pixels with significantly declining NDVI became unusable at Kendall’s tau of −0.4, −0.6, −0.8, and −1.0 (habitat never unusable); pixels below these thresholds were removed from 2015 distributions (assumption 2). We considered the difference between pixels significantly increasing and decreasing in NDVI as significant (not statistically significant) (i.e., net change) at 0%, 5%, and 10% thresholds (assumption 3). We adjusted C from 0.25 (mean C of 0.03 to 3.00 km area–area curve slope, 0.179; range: 0.141–0.247 [Appendix S5; IUCN 2019a]) to 0.90 (intervals: 0.25, 0.50, 0.75, 0.90) to examine the impact of scale assumptions (level of assumed distribution saturation across adjacent ecosystems) on AOO-based assessment (assumption 4). We deemed fully unsaturated distributions impossible due to partial mangrove-dependence across species (Turvey et al. 2017), with C = 0.90 the highest level. We simulated assessments under all assumption combinations (144 simulations/species) and combinations of assumptions 1–3 with AOO as AOH at 30-m resolution (assumption 4) (e.g., Ocampo-Peñuela et al. 2016) (36 simulations/species).

Results

Mangrove Distribution Change

Visual accuracy assessment showed no substantial variation in unsupervised classification model accuracies across years; mean true positive and negative rates were 84.00% (SD 1.41) and 83.00% (SD 9.76) and 92.00% and

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Figure 2. Mangrove (a–e and k–o) distribution-change detection (yellow, constant mangrove distribution; green, gained mangrove distribution; red, lost mangrove distribution between periods) and (f–j and p–t) primary productivity (NDVI [normalized difference vegetation index], habitat quality proxy) trend analysis (to 2018) (orange, pixels with significantly decreasing NDVI [from dark orange −1 to light orange 0 for Kendall’s tau]; green, pixels with significantly increasing NDVI [from light green 0 to dark green Kendall’s tau]) over time series for M. angelcabrerai and M. auritus.

72.50% (SD 17.52) in 2005 and 2015, respectively. Across Cuba and all hutia ranges, we observed mangrove distribution change in the periods 1995–2015 and 1985–2015, and variation in distribution change in the 3 internal periods (Figs. 2 and 3; Appendix S6). We identified 3915.31 km² of mangroves across Cuba in 1985. This amount increased by 3.34% to 4045.99 km² in 2015. This increase fluctuated, with some loss (−3.25%) over 1995–2005. Total distribution-change detection did not vary substantially between 1995 and 2015 (2.93% increase) and 1985 and 2015 (3.34% increase). However, proportions of mangrove distribution changes within different species ranges varied between time series. A fluctuating increase, mirroring Cuba-wide mangrove change, was seen for M. nanus, where mangrove area increased by 3.00% over 1995–2015 and 4.65% from 1985 to 2015 (Fig. 3a–e). Mangrove area decreased in the periods 1995–2015 and 1985–2015 for M. auritus (−3.65% and −5.92% loss, no substantial loss from 2005 to 2015) (Fig. 2k–o) and M. sanfelipensis (fluctuating decrease: −7.68% and −7.26%) (Fig. 3k–o). Mangrove area increased substantially for M. angelcabrerai (13.37% 1995–2015, 47.59% 1985–2015), owing to cumulative gains in the periods 1985–1995 and 1995–2005 (Fig. 2a–c). Mesocapromys angelcabrerai was the only species with recent (2005–2015) area decline (−6.30%) (Fig. 2c).

Mangrove Habitat Quality Change

Cuba-wide and within most hutia ranges (except M. sanfelipensis), primary productivity of constant mangroves predominantly increased (>5% more significantly increasing than decreasing pixels) over 1995–2018 and 1985–2018 (Appendix S7). Pixels exhibiting significant increases in NDVI were substantially more numerous than those exhibiting significant decreases (predominant significant increases) over 1985–2018 than over 1995–2018. For internal periods, Cuba-wide NDVI substantially increased only across 2005–2018 (8.55%). In 1985–1995, predominant significant increases were
observed for *M. angelcabrerai* (48.66%) and *M. auritus* (14.37%) (Figs. 2f and 2p). In 1995–2005, predominant significant decreases were observed for *M. auritus* (13.90%) and *M. sanfelipensis* (30.30%) (Figs. 2g and 3q) and predominant significant increases for *M. angelcabrerai* (38.60%) (Fig. 2g). In 2005–2018, predominant significant increases were observed for *M. auritus* (7.82%) (Fig. 2r) and predominant significant decreases for *M. angelcabrerai* (20.63%) (Fig. 2h). *Mesocapromys angelcabrerai* had no substantial change over 1995–2018, although predominant significant increases were observed over 1985–2018 (51.16%) (Figs. 2i and 2j).

**Range-Based RLS Assessments**

Simulated range-based assessments were variable across spatial habitat-change assumptions; assessments for 2 species ranged over multiple RLS categories (Table 2; Appendix S8). For all species, variation in time series habitat distribution and quality change data sets affected simulated assessments most severely. *Mesocapromys angelcabrerai* was assessed as VU D2 or NT in all 1985–2015 and 75% of 1995–2015 assessments, but CR in all 2005–2015 and 25% of 1995–2015 assessments. *Mesocapromys auritus* was assessed as EN B1ab(iii)+2ab(iii) in all 1995–2015 and 1985–2015 assessments, but NT in 75% of 2005–2015 assessments owing to recent mangrove recovery (Tables 2 and 3 & Fig. 2). *Mesocapromys sanfelipensis* was consistently assessed as CR, although recent mangrove recovery meant that condition b(iii) was not met in 2005–2015. *Mesocapromys nanus* was consistently assessed as NT based on habitat change.

Variation in unusable habitat within time series affected some assessments. Simulated change in habitat area based on the highest unusable habitat degradation threshold (tau ≤ −0.4) resulted in CR status for *M. angelcabrerai* (25% assessments) in 1995–2015 and EN status for *M. auritus* (25% assessments) in 2005–2015. Scale correction factor C generated variable AOO estimates, with C > 0.25 driving VU D2 assessments for

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**Figure 3.** Mangrove (a–e and k–o) distribution-change detection (yellow, constant mangrove distribution; green, gained mangrove distribution; red, lost mangrove distribution between periods) and (f–j and p–t) primary productivity (NDVI [normalized difference vegetation index, habitat quality proxy] trend analysis (to 2018) (orange, pixels with significantly decreasing NDVI [from dark orange −1 to light orange 0 for Kendall’s tau]; green, pixels with significantly increasing NDVI [from light green 0 to dark green Kendall’s tau]) over time series for *M. nanus* and *M. sanfelipensis*. 
Table 2. Proposed IUCN Red List of Threatened Species (RLS) extinction risk status and rationale used in extinction risk assessment for *Mesocapromys* species from range-based criteria (this study) and population-based criteria (Turvey et al. 2017) under all simulated assumption combinations.

| Period and spatial scaling assumption | Mesocapromys angelcabrerai | Mesocapromys auritus | Mesocapromys nanus | Mesocapromys sanfelipensis |
|--------------------------------------|---------------------------|---------------------|--------------------|---------------------------|
| 1995–2015                            |                           |                     |                    |                           |
| AOO on AOH scaled to 2-km resolution  |                           |                     |                    |                           |
| AOO on AOH mapped at 30-m resolution  |                           |                     |                    |                           |
| || NT[18.75%; tau < 0.4; C = 0.25]   | ENB1ab(iii)+2ab(iii)     | NT(EOO: 6,819.55; AOO: 578.39–1,946.84) | CR B1ab(iii,iv,v) [75.00%; C < 0.9] |
|                                        | (EOO: 405.10; AOO: 73.77–248.29) |                     |                    |                           |
| VU D2 to CR                            |                           |                     |                    |                           |
| B1ab(ii,iii)+2ab(ii,iii) [25%; tau: 0.4; AOO: 8.38–28.21] | (EOO: 16.60; AOO: 8.38–28.21) |                     |                    |                           |
| VU D2 to CR                            |                           |                     |                    |                           |
| B1ab(ii,iii)+2ab(ii,iii) [25%; tau: 0.4; AOO: 8.38–28.21] | (EOO: 16.60; AOO: 8.38–28.21) |                     |                    |                           |

1985–2015                            |                           |                     |                    |                           |
| AOO on AOH scaled to 2-km resolution  |                           |                     |                    |                           |
| AOO on AOH mapped at 30-m resolution  |                           |                     |                    |                           |
| || NT[25.00%; C = 0.25]               | ENB1ab(ii,iii)+2ab(ii,iii); (AOO: 63.24–66.42) | NT(EOO: 310.36–312.55) | CR B1ab(ii,iii,iv,v) [75.00%; C < 0.9] |
|                                        | (EOO: 405.10; AOO: 73.77–248.29) |                     |                    |                           |
| VU D2[75.00%; C > 0.25]               |                           |                     |                    |                           |
| (EOO: 15.56; AOO: 8.38–28.21)        | (EOO: 16.60; AOO: 8.38–28.21) |                     |                    |                           |
| VU D2(AOO: 8.27–8.36)                |                           |                     |                    |                           |
| ENB1ab(ii,iii)+2ab(ii,iii) (AOO: 62.84–66.42) | NT(EOO: 310.31–312.55) |                     |                    |                           |
| CR B1ab(ii,iii,iv,v) [75.00%; C < 0.9] | (EOO: 16.60; AOO: 8.38–28.21) |                     |                    |                           |
| CR B1ab(ii,iii,iv,v) [75.00%; C < 0.9] | (EOO: 16.60; AOO: 8.38–28.21) |                     |                    |                           |
| CR B1ab(ii,iii,iv,v) [75.00%; C < 0.9] | (EOO: 16.60; AOO: 8.38–28.21) |                     |                    |                           |

Continued
Table 2. (Continued).

| Period and spatial scaling assumption | Mesocapromys angelcabreraei | Mesocapromys auritus | Mesocapromys nanus | Mesocapromys sanfelipensis |
|--------------------------------------|-----------------------------|----------------------|-------------------|---------------------------|
| 2005−2015                            | CR B1ab(iii)[75.00%: C < 0.9] | NT[75.00%: tau −0.4] | NT(EOO: 6,819.55; AOO: 578.59−1,946.84) | CR B1ab(iv,v)[75.00%: C < 0.9] |
| AOO on AOH scaled to 2-km resolution | CR B1ab(iii)+2ab(iii)[25.00%: tau <−0.4] | EN B1ab(iii)+2ab(iii)[25.00%: tau <−0.4] (EOO: 405.10; AOO: 75.77−248.29) | NT(EOO: 310.65−312.55) | CR B1ab(iv,v)+2ab(iv,v) (AOO: 4.08−4.16) |
| mapped at 30-m resolution             | CR B1ab(ii,iii)+2ab(ii,iii)(AOO: 6.79−8.36) | NT to EN B1ab(ii,iii)+2ab(ii,iii)[25%; tau: −0.4] (AOO: 65.32−66.42) | NT(AOO: 73.77−28.21) |
| Proposed RLS status                   | CR B1ab(iii) | EN B1ab(iii)+2ab(iii); C2a(ii) | CR (possibly extinct) D1 | CR (possibly extinct) B1ab(iv,v); D1 |
| Assessment rationale                 | Does not meet higher extinction risk category under other RLS criteria (Turvey et al. 2017). Meets CR status (criterion B) in 41.67% of assessments. Meets CR status in 100% of assessments over 2005−2015 (B1, B2) due to declining habitat area and quality (biii). The period 2005−2015 is deemed representative of threat from current habitat loss following post-2005 causeway construction into Cayos Salinas (Turvey et al. 2017). | Does not meet higher extinction risk category under other RLS criteria due to a large EOO and simulated AOO. Does not meet threatened status based on AOO (B2) in any assessment. Very slight declines in AOO observed over 2005−2015 (<0.5%), and no declines observed in habitat area, extent, or quality (biiii). Therefore, assessed as NT under criterion B, but qualifies as CR under criterion D1 (Turvey et al. 2017). | Does not meet any RLS threat category on range-based criteria due to restricted EOO and known subpopulation (biv) and mature individual declines (bv) (Turvey et al. 2017). No habitat area declines (biiii) observed over 2005−2015, but observed over all other time series. Subcriterion B2 is cautiously not included in proposed status due to uncertainty in AOO, nor is condition biiii included because recent habitat recovery may be sufficient to counteract historical losses (see Appendix S6). | Does not meet any RLS threat category on range-based criteria due to a large EOO and simulated AOO. Does not meet threatened status based on AOO (B2) in any assessment. Very slight declines in AOO observed over 2005−2015 (<0.5%), and no declines observed in habitat area, extent, or quality (biiii). Therefore, assessed as NT under criterion B, but qualifies as CR under criterion D1 (Turvey et al. 2017). |

Abbreviations: IUCN, International Union for Conservation of Nature; NT, near threatened (IUCN RLS category); VU, vulnerable; EN, endangered; CR, critically endangered; a and b, IUCN RLS subconditions (see IUCN 2019a and Methods); EOO, extent of occurrence (RLS range-based parameter); AOO, area of occupancy; NDVI, normalized difference vegetation index; tau, threshold of Kendall's tau for pixels significantly decreasing in NDVI assumed to represent unusable habitat; C, mangrove AOO scale-correction parameter assumption; AOH, area of (potential) habitat.

Within time series−specific simulation results (n = 48 per species) show percentage of assessment simulations identifying different RLS categories. Simulated spatial assumptions are in brackets.

a For AOO on AOH scaled to 2-km resolution: C = 0.25, 0.50, 0.75, and 0.90.
Table 3. Recommendations for implementation and updating of International Union for Conservation of Nature (IUCN) Red List of Threatened Species (RLS) (IUCN 2019a) guidelines based on findings from poorly known habitat-dependent Cuban hutia (Mesocapromys) species.*.

| Consideration | Parameter employed | Possible (species-specific) parameters | Ecological relevance | Areas of occupancy (AOO)-based RLS assessment impact | RLS (2019) guidelines | Recommendation |
|---------------|--------------------|----------------------------------------|----------------------|-----------------------------------------------------|----------------------|----------------|
| Temporal coverage for habitat (AOH/AOO) change quantification | Time series | long-term (here 1985–2015, 1995–2015) | N/A | Varies (subcondition b(iii)): habitat change over 3 (hutia) generation lengths (IUCN 2019a); change assumed linear (internal variation missed) | ✓(the longer of 1 or 2) | Examine interdecadal periods to explore relative severity of recent habitat availability change. Assessors should follow IUCN (2019a) guidelines on validation of (interdecadal) habitat availability (AOH/AOO) maps. |
| | recent (here 2005–2015) | N/A | habitat change over 10 years (IUCN 2019a) | no historical context | ✓ | |
| | inter-decadal (here 1985–1995, 1995–2015, 2005–2015) | subdecadal | relative (recent) severity of habitat change | inference from (nonlinear) historical context | ✗ | |
| Habitat quality or degradation | Removal of significantly degraded habitat (here loss of primary productivity) from AOH: here temporal trend in NDVI (unusable at Kendall’s tau = −0.4, −0.6, −0.8, and −1.0) | elevation or topography inundation regime vegetation structure species composition sedimentation etc. | restricted occupied habitat area (AOH/AOO) where degraded habitat is unusable by a species | smaller AOO and enhanced extinction risk categorization (subcondition b(iii)); | ✗ | Refine occupied habitat distribution (AOH/AOO) with spatially explicit measures of temporal habitat degradation (and improvement). Employ indices or proxies of temporal change in habitat quality with ecological relevance to the ecosystem and species in question. |
| | 2. cross-distribution habitat loss (here significant net change only at 0%, 5%, and 10% greater NDVI loss than gain of pixels) | spatial differences in occupied habitat quality change across distribution ranges (i.e., relative proportions of recovering vs. degraded habitat) | | none; theoretically reduced AOO where lower significant new change thresholds are employed | |

* Continued
| Consideration | Parameter employed | Possible (species-specific) parameters | Ecological relevance | Areas of occupancy (AOO-based RLS assessment impact) | RLS (2019) guidelines | Recommendation |
|---------------|--------------------|----------------------------------------|----------------------|-----------------------------------------------|-----------------------|----------------|
| Scaling available habitat (AOH) to IUCN reference AOO scale (2 × 2 km) | treating occupied AOO as proportional to AOH (e.g., not as maximum AOO bounds): varied scale correction factor, here C = 0.25, 0.50, 0.75, and 0.90 | N/A | restricting scaled occupied AOO by life-history influences on spatial saturation across habitat type mosaics (hutias: small body size and dispersal distance; semihabitat dependence) | smaller AOO and enhanced extinction risk at lower spatial distribution saturation assumptions (i.e., higher C) √ / X (reference scale correction required, but no quantitative life history-based guidelines) | √ | Assessors follow IUCN (2019a) guidelines and scale AOH (/AOO) to the IUCN reference AOO scale (2 × 2 km). IUCN should develop explicit quantitative guidelines for varying scale correction factor (C) according to relevant life history information, and to encourage flexible C simulation to incorporate uncertainty in assessments of poorly known species. |
| 2. AOH not scaled, C = 0 | True AOH at mapped scales (e.g., 50 × 30 m)—not a true measure of AOO per IUCN (2019a) guidelines | N/A | AOO (for semihabitat-dependent species) underestimated and extinction risk overestimated | | X | |

*Abbreviations: AOH, area of habitat; AOO, area of occupancy; NDVI, normalized difference vegetation index.*
M. angelcabrerai in 1995–2015 (75% non-CR assessments) and 1985–2015 (75% assessments) and \( C = 0.9 \) driving addition of subcriterion B2 for M. angelcabrerai (25% CR assessments, 1995–2015; 25% assessments, 2005–2015) and M. sanfelipensis (25% assessments, all time series) (Table 2). The threshold of significant change in habitat quality (assumption 3) had no impact on simulated assessment outcomes. Conversely, AOO estimation from AOH at 30-m resolution affected assessments for all species. No NT assessments were simulated for M. angelcabrerai; subcriterion B2 was met for M. auritus (all EN assessments, all time series) and M. sanfelipensis (100% assessments, all time series); and condition b(ii) was met for M. angelcabrerai (all CR assessments [25%], 1995–2015: 100% assessments, 2005–2015), M. auritus (all EN assessments, all time series), and M. sanfelipensis (100% assessments, 1995–2015 and 1985–2015).

Proposed RLS assessments derived from our simulated assessments for range-based criteria and available information on other threats and population parameters are presented and compared with Turvey et al. (2017) and latest RLS status in Table 2. Recommendations for implementation and revision of RLS guidelines are in Table 3.

### Discussion

Our findings reveal extensive variation in simulated range-based RLS assessments from SRS information for a group of poorly known threatened mammals, owing to variation in assumptions around temporal and spatial scales and habitat-quality proxies. Differing parameter estimates resulted in simulated assessments varying by up to 3 categories within the same time series. Our findings indicate caution should be taken when conducting range-based RLS assessment based on SRS without accounting for species’ ecology, especially where habitat dependence is incompletely understood. In the absence of explicit IUCN guidelines for AOO scaling across species with varying levels of habitat dependency or saturation across landscapes (i.e., amending scale parameter \( C \) according to species-specific life histories), we advise combining simulated spatial assumptions with expert-derived contextual information in RLS assessment of poorly known species (Table 3).

The temporal span of parameter estimation was the largest source of variation in simulated assessments, owing to fluctuations in estimated habitat change across time series. Although minimal change was observed across time series for M. nanus and M. sanfelipensis, use of 2005–2015 data suggested a higher (CR) outcome for M. angelcabrerai and lower (NT) outcome for M. auritus than over longer time series. Interdecadal analysis of habitat change enabled determination of long-term trends, relative severity of recent change, and identification of appropriate species-specific time series (Table 3). This contrasts with previous large-scale studies in which range-based assessment has been conducted with SRS information. These studies have explored long-term habitat change at discrete classification time steps (Buchanan et al. 2008; Hall et al. 2009) or land-cover maps (Santini et al. 2019) or explored globally available time series data sets over short periods (Ocampo-Peña et al. 2016; Tracewski et al. 2016). However, these approaches cannot be used to explore relative impacts of temporal fluctuations in habitat change (e.g., from novel threats or conservation interventions). Indeed, some ecosystems (e.g., mangroves) are highly dynamic and can recover quickly from disturbance, meaning fine-scale changes can be missed without isolating high temporal-resolution slices within longer term time series. For example, Santini et al. (2019) suggested M. angelcabrerai experienced no change in AOH from 1992 to 2015 because recent extensive habitat declines were obscured in longer term (and coarser) data sets (ESA 2019), resulting in proposed LC/NT assessment. Overestimation or misidentification of continuing declines is also possible for species whose habitats are undergoing recovery (e.g., Song et al. 2018). Conversely, globally available ecosystem change data sets with high spatiotemporal resolution presently cover limited time frames, often insufficient to determine complex dynamic change (Hansen et al. 2013; Bunting et al. 2018). Although globally available data sets provide standardized data for some habitat-dependent species, specific data sets do not exist for many ecosystems, and fluctuating change in habitat area and quality across long-term, recent, and interdecadal time series suggests their coverage is currently insufficient for broad application across taxa. Rather than incorporating recent data sets in blanket RLS assessments (e.g., Santini et al. 2019), careful consideration of SRS-derived data sets is necessary to estimate continuing declines for given taxa and account for confidence in RLS assessments (Table 3). Although we promote consistency in change estimation between multitemporal unsupervised land-cover classifications, and limited accuracy assessment showed no substantial variation between years (Appendix S3), the absence of more extensive ground-truthed data made it impossible to validate our time series data or our identified AOO and habitat availability changes over the longer term, contrary to shorter term standardized globally available data sets with temporally consistent mapping errors (e.g., Hansen et al. 2013). Future researchers using SRS-derived data must seek to validate long-term habitat mapping data via available ground-truthed data or expert information prior to their inclusion in AOO and habitat availability quantification (as per IUCN 2019a).

We also identified the impact of incorporating change in ecosystem condition, instead of binary habitat presence or absence, on RLS assessment. Habitat degradation reduces local-scale persistence and increases extinction risk (Heinrichs et al. 2016), and its explicit
inclusion in defining occupancy-based parameters should refine assessments and improve objectivity in applying subcriterion b(iii). Cuba-wide, limited mangrove degradation occurred over 1985–2015, and only the minimum degradation threshold affected some assessments. However, habitat degradation may be extensive and substantially influence assessments for other taxa, but it cannot be estimated from ecosystem distribution or land-cover conversion data sets alone. We propose incorporating measures of ecosystem condition in quantification of species’ distribution change to indicate change in both habitat quality and extent (Table 3). Furthermore, differences exist in estimated trends in Cuban mangrove coverage (Spalding et al. 2010; Cissell & Steinberg 2019), which cannot be resolved without widespread ground-truthed data across multiple time series, but this highlights the importance of standardizing SRS incorporating ecosystem distribution and condition change for consistency in trend identification. The advent of cloud-based analytical platforms now permits combining long-term SRS-derived ecosystem-specific (Bunting et al. 2018) or change in land cover data sets (ecosystem classifications) (ESA 2019) with selected ecosystem indicators (here primary productivity, but additional constraints to species-specific occupancy can also be indexed from SRS-derived data) (Table 3) to achieve standardized AOO estimation approaches. However, defining degradation thresholds beyond which species-specific persistence becomes impossible remains challenging, especially without detailed knowledge on species’ ecology. Lacking quantitative thresholds, we employed a multithreshold approach.

We showed that not adhering to IUCN AOO spatial scaling guidelines (using unscaled AOH) substantially affected range-based assessment for subcriterion B2. This approach artificially decreased estimated AOO, increased extinction risk estimation and AOO change rates, and ignores requirements for standardizing spatial inference in across-taxa assessment (IUCN 2019a). The scale-correction parameter C altered effective AOO estimates and caused wide variation in within time series assessments. Available starting data set resolution will also affect scaling to IUCN-recommended scales. For example, Santini et al. (2019) determined AOO for *M. anaculbreraei* at almost twice that determined here (with $C = 0.25$) when scaling from 300-m resolution land-cover data, whereas 2 other species fell within our simulated ranges. We recommend that explicit IUCN guidelines be developed for C implementation based on known or inferred levels of habitat dependence (likely saturation of within-EOO distribution), or encourage flexible C simulation to incorporate uncertainty for poorly known species, to enable more effective incorporation of SRS for systematic assessments and reassessments (Table 3). Addressing this issue now as incorporation of SRS into RLS assessments is taking off (and with explicit incorporation of uncertainty) will allow uniform application of techniques and realign AOO estimation with its theoretical basis before discrepancies become widely established (e.g., Joppa et al. 2016). Where uncertainty surrounds species’ habitat dependence, this should be explicitly incorporated into assessments, as for any RLS parameter, by specifying a best estimate and range of plausible AOO values based on AOH-estimated occupied habitat (Table 3) (IUCN 2019a). Quantified AOH could equate to a species’ AOO upper bound (Brooks et al. 2019), with lower bounds derived from known locality records overlaid with a 2 × 2 km grid. Additional knowledge of ecology and threats should inform a precautionary but realistic assessment approach for species with uncertain metrics, and justifications for the final category assignment should be documented in assessments (IUCN 2019a).

Our proposed species assessments vary from those in the 2008 Global Mammal Assessment (Schipper et al. 2008), where none were assessed under range-based criteria. We broadly agree with recent updates that were not informed by long-term time series habitat data (Turvey et al. 2017). We confirm the recent uplisting of *M. anaculbreraei* from EN to CR due to restricted EOO and observed recent extensive declines in habitat extent and quality. However, we recommend listing only under CR B1ab(iii), excluding B2ab(iii) due to AOO scaling uncertainty. We support assessment of *M. auritus* as EN B1ab(iii) + 2ab(iii) due to restricted EOO and confirm restricted AOO (regardless of scaling approach) alongside long-term habitat extent and quality decline. We also support assessment of *M. sanfelipensis* as CR B1ab(iv,v), and the inapplicability of range-based criteria to assess *M. nanus* owing to wide and uncertain EOO and simulated AOO. We have provided the first empirical spatial evidence for range-based criteria to assess these taxa. Our results also reflect known regional environmental changes: *M. anaculbreraei*, the only species occurring outside the region affected by Hurricane Michelle in 2001 (Cissell & Steinberg 2019), is the only species in our analyses that did not experience habitat declines over 1995–2005.

Our conclusions highlight the qualitatively well-acknowledged importance of including expert-derived information in RLS assessment. First, where species span ≥2 categories due to data uncertainty, expert-derived information can enable a precautionary but realistic approach to final category assignment. Second, other important below-canopy threats (e.g., hunting, invasive competition or predation) cannot be understood from SRS imagery alone and can drive populations below levels predictable from these data sets (Green et al. 2020). Indeed, recent macroecological modeling of population sizes and trends based on habitat change by Santini et al. (2019) estimated population sizes for 3 *Mesoscapromys* species 1–3 orders of magnitude greater than field surveys (Turvey et al. 2017). In reality, both *M. nanus* and
M. sanfelipensis may already be extinct due to threats additional to habitat change (Turvey et al. 2017). We therefore stress that SRS-derived habitat change-based inference of demographic RLS metrics should not be attempted for species known to have major threats not explicitly related to habitat loss or degradation. We also note that fossil data for M. nanus and M. sanfelipensis suggest wider past distributions and habitat associations (Silva Taboada et al. 2007) and their restriction to mangroves as refugia. Indeed, Zapata Swamp represents a refugium for relict populations of other taxa (Garrido 1980). Our analyses remain valid because these species have occurred in mangroves only during recent history. Such insights further highlight the importance of understanding species’ habitat dependency in range-based RLS assessment based on SRS data.

With the RLS now containing >100,000 assessments, expediting reassessments is vital to maintain an up-to-date RLS and drive timely and appropriate conservation actions. This is particularly important given the RLS’ role as a major biodiversity indicator via the IUCN Red List Index (RLI) and its sampled approach (Baillie et al. 2008) and in measuring progress toward the 2050 vision to bend the curve of biodiversity loss (Mace et al. 2018). It is clear that SRS can play a major role in producing information on changing habitat extent and quality for the RLI (Rondinini et al. 2014) and in automating range-based RLS assessments, especially for those species affected primarily by habitat loss. However, its limitations must first be understood. Data from SRS also form only part of the picture of extinction risk-related data for RLS assessments. The RLS process assesses species against all 5 assessment criteria, and validation of SRS data against other sources and expert opinion is still required to finalize assessments (cf. AOO quantification [Appendix S4]) (IUCN 2019a). This is particularly important because our study provides empirical evidence that a one-size-fits-all approach to incorporating SRS into RLS assessment is inappropriate and a more comprehensive approach incorporating expert-derived information and species-specific ecologies should instead be applied, particularly for poorly known species. The RLS exists to provide an objective, repeatable extinction risk assessment framework appropriate to all taxa, but it cannot do so if applied SRS approaches are inaccurate for certain taxa. We propose explicit assessment of the relative severity of recent versus long-term habitat change in range-based RLS parameter assessment from SRS time series; identification of species-specific thresholds of habitat degradation preventing local-scale persistence and their incorporation within assessment of degradation-driven habitat loss and range-based RLS parameters; and revision of RLS guidelines to facilitate ecologically meaningful AOO scaling across taxa and incorporation of uncertainty for poorly known semi habitat-dependent or habitat-dependent species. These issues may have profoundly affected previous global assessments. An informative future endeavor lies in exploring the impacts of using our approaches across representative RLS-assessed taxa for which SRS can accurately delineate habitat, particularly those contributing to large-scale assessments in biodiversity indicators.

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Supporting Information

APPENDIX S1: Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI/TIRS Surface Reflectance (SR) Tier 1 satellite imagery tiles employed for landcover classification and change analysis.

APPENDIX S2: Vegetation, sediment and water indices.

APPENDIX S3: Accuracy assessment of Landsat-based unsupervised landcover classification.

APPENDIX S4: Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI/TIRS Surface Reflectance (SR) Tier 1 satellite imagery tiles employed for NDVI trend analysis 1985-2018.

APPENDIX S5: Red List of Ecosystems (RLS) Guidelines for Using the IUCN Red List Categories and Criteria Version 14 (August 2019): Section 4.10 Area of occupancy (criteria A, B and D) (IUCN 2019, p. 51-60).

APPENDIX S6: Results of landcover classification and change analysis from Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI/TIRS Surface Reflectance (SR) Tier 1 satellite imagery.

APPENDIX S7: Results of NDVI trend analysis from Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI/TIRS Surface Reflectance (SR) Tier 1 satellite imagery.

APPENDIX S8: Results of IUCN RLS assessments for Cuban hutia species under all combinations of assumptions (1-4).

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