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3 authors:

Rafael S Ramirez
Manchester Metropolitan University

Franz Mora
Comisión Nacional para el Conocimiento y Uso de la Biodiversidad

Esther Quintero
Comisión Nacional para el Conocimiento y Uso de la Biodiversidad

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Original Research Article

The use of geospatial data and Bayesian Networks to assess the risk status of Mexican amphibians

Rafael S. Ramírez [a], Franz Mora [b], Esther Quintero [a,*]

[a] Subcoordinación de Especies Prioritarias, Comisión Nacional para el Conocimiento y Uso de la Biodiversidad Tlalpan, Ciudad de México, Mexico

[b] Coordinación de Sistema de Información Espacial para el Soporte de Decisiones sobre Impactos a la Biodiversidad, Comisión Nacional para el Conocimiento y Uso de la Biodiversidad (CONABIO), Tlalpan, Ciudad de México, Mexico

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A B S T R A C T

Amphibians are undergoing alarming population declines worldwide, leading to the worst extinction crisis of their history. Here, we use quantitative habitat loss data to assess 144 amphibian species for which we have environmental niche models and environmental remotely sensed information. Moreover, we evaluated previous expert-based assessments replicability using Bayesian Networks (BN) and quantitative habitat loss data as the source of information. BN demonstrated that expert-based assessments are unable to be replicated when using quantitative habitat loss data; the average accuracy for the BN classification by experts was low (42.4% ± 1.5%) with a high percentage of incorrectly classified species (57.6% ± 1.5%). Our assessment offered a high average accuracy (96.1% ± 2%), and a low percentage of incorrectly classified species (3.9% ± 2%). Thus, we propose that qualitative data and expert knowledge should be used together to formalize objective and quantitative evaluation models through BNs to obtain better risk assessments. Only through the use of accurate assessments can we accurately reflect the conservation status of different species groups.

1. Introduction

Populations of many amphibian species are facing the worst extinction crisis of their history (Wake and Vredenburg, 2008; Butchart et al., 2010; Nori et al., 2015). Currently, more than 41% of amphibian species are considered threatened (Pimm et al., 2014), with well-known and documented threats such as emerging diseases, habitat loss and fragmentation as well as climate change (Stuart et al., 2004; Gardner et al., 2007; Garner et al., 2016; Rollins-Smith, 2017). In order to objectively evaluate the current risk status of amphibian species, it is necessary to integrate the best knowledge available, including the extent of their distribution and major threats, with quantitative information sources.

Mexico, as one of the few megadiverse countries in the world (CONABIO, 2014) is the fifth richest in amphibians with between 376 (Parra-Olea et al., 2014) and 394 described species (Frost, 2017) distributed within three orders: Anura (frogs and toads) with 237 species Caudata (salamanders) with 137 and Gymnophiona (caecilians) with two (Parra-Olea et al., 2014). In addition, 67% of all amphibians are endemic to the country, which makes local conservation efforts especially relevant

* Corresponding author.
E-mail address: esther.quintero@conabio.gob.mx (E. Quintero).

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(Parra-Olea et al., 2014). Worldwide, the major recognized threats to amphibians are habitat loss and fragmentation (Badillo-Saldaña et al., 2016), and infectious diseases from the chytrid fungi, *Batrachochytrium dendrobatidis* (Bd) (O'Hanlon et al., 2018). Although there are reports on the presence of Bd among Mexican species (Mendoza-Almeralla et al., 2015), the infection has only been confirmed in 13.30% (50 out of 376) of the species. Therefore, at this moment this disease is not the biggest concern in the country, although there is a clear need of closely monitoring amphibian populations to avoid future and synergistic problems. It thus becomes clear that the most pressing issue right now is to stop habitat loss and transformation for amphibian species in Mexico, to avoid further extinctions.

Species assessments are a first step in determining conservation plans. Mexican species are currently being assessed and listed by two instances with their own methods: a) Mexico's Ministry of Environment (SEMARNAT) through the Mexican National Red List (NOM-059-Semarnat-2010) and its Risk Assessment Method (MER, DOF, 2010), and b) The International Union for Conservation of Nature (IUCN) through the IUCN Red List of Threatened Species (IUCN, 2012). The first global amphibian assessment by the IUCN took place in 2004 (NatureServe, 2004), with a second global assessment in 2014. According to IUCN, 55% of amphibian diversity in Mexico, 211 species, is threatened, which ranks the country second in number of threatened amphibian species worldwide (IUCN SSC Amphibian Specialist Group, 2008). On the other hand, the NOM-059-Semarnat-2010, which is the only officially recognized list within the country, includes 194 amphibians in three risk categories, but out of these 194, only four have been formally assessed using the MER. There are concerns about the accuracy of both IUCN and MER based assessments, specifically regarding the distribution reported, which is one of the key criteria for assessing species worldwide, and especially in tropical countries like Mexico. In the case of IUCN assessments, several recent studies have questioned the way the Extent of Occurrence (EOO) is calculated, as it may be routinely overestimated (see for instance Ocampo-Peñuela et al., 2016; Ramesh et al., 2017). On the other hand, the Risk Assessment Method (DOF, 2010), which is the only officially accepted method in Mexico to assess species, does not have a systematic approach to calculate the EOO for animals and fungi (Ramirez and Quintero, 2016). As an alternative to both, the IUCN and MER approaches in this study, and to avoid the biases detected in each method, we here propose to assess the risk of extinction of amphibians by quantitatively estimating the Remnant Distribution (RD) habitat within the potential distribution of a target species using satellite imagery, as a proxy of species' vulnerability. Moreover, we propose the use of the RD as an assessment criterion formalized as a classification rule based on probabilistic models. The resulting models in turn, can be used when an assessment of a new set of species is needed.

Bayesian networks (BN) modelling is a framework that would help in recurrent risk assessments that use RD data by providing a quantitative model and assisting reasoning under uncertainty (McCann et al., 2006; Aguilera et al., 2011). BN also provide a tool for including expert elicitation to build a predictive model, especially when a classification scheme is used recurrently for assessments. Also, BN allows exploring non-evident relationships when the value of different variables for predictive purposes is evaluated. Usually, structure learning algorithms are used for building and exploring new models (Uusitalo, 2007). The use of structure learning in BN generates a plausible model structure when the role of potential explicative variables is tested. In addition, structure learning can help minimize the need for expert elicitation, especially when it becomes a time-consuming process, prone to recurrent errors, and may prove to be too expensive to conduct (Uusitalo, 2007).

By implementing a methodology that integrates BNs and quantitative data, in this paper we assessed the status of 144 Mexican amphibians for which both, potential distribution maps and habitat loss data were available. The species distribution model (SDM) maps that we used were not produced for this study (see methods). Using satellite imagery information, specifically forest cover data derived from the application of remote sensing process, we were able to accurately calculate the amount of habitat loss between 2005 and 2015 within the potential range of the species distributions to obtain the amount of RD. As reference/benchmark, we compared our results with those from the 2014 IUCN global amphibian assessment. Furthermore, using BN as a quantitative classifier derived from data mining, we explored different classification models to understand differences between categories chosen by experts versus by our assessments in terms of 1) relation to habitat loss, 2) replicability, and 3) the discovery and formalization of evaluation models to perform assessments in the future.

2. Methods

2.1. Assessments of Mexican amphibians using geospatial data

Forest cover was the most important variable to evaluate the remnant habitat condition of amphibian species, as amphibians are dependent on tree cover for suitable conditions to thrive, as humidity is essential to them. The Landsat Vegetation Continuous Field (VCF) tree cover layers circa 2005 and 2015 were used as a surrogate for estimating the remnant forest habitat. Tree cover layers containing estimates of the percentage of horizontal ground in each 30-m pixel covered by woody vegetation greater than 5 m in height (Sexton et al., 2013) were overlaid with previously existing geographic Species Distribution Models (SDMs) data (SNIB-CONABIO; http://www.conabio.gob.mx/informacion/gis/). All SDMs were previously modeled using the GARP niche modelling approach using BIOCLIM as predicting variables (Peterson and Vieglais, 2001). These SDMs were part of a set of projects commissioned by Mexico's National Commission for the Knowledge and Use of the Biodiversity (CONABIO) with the aim and scope to identify gaps in conservation in the country. All SDMs in CONABIO's geolibrary have been expert-validated.

Forest cover is used here as the most important habitat variable due to "habitat split" (occurrence of habitat dry fragments) as a result of forest cover loss. Usually, habitat split is also associated with leaf-litter conditions, since small-scale connections between habitat explains amphibian biodiversity (Becker et al., 2007). Since nearly 82% of amphibian species are forest-dependent (Stuart et al., 2004), clearcutting and land conversion can reduce amphibian richness and abundance by reducing species survival in inhospitable habitats (clearcuts or dry fragments). Landscape studies have also shown that salamander presence is highly correlated with forest cover, more often than for frogs (Semlitsch et al., 2009). Previous studies have demonstrated that usually forest cover reductions up to 30% results in highly fragmented forests (Riitters et al. 2002). However, an exploratory data analysis of VCF and data from the national forest inventory (NFI) showed that significant tree distribution was occurring even below a VCF value less than 30%. For that reason, we assumed that significant remnants can be occurring in areas approaching 20% of forest cover, since the remotely sensed VCF may be sub-estimating the amount of remnant forest.

Therefore, for each species, the RD was calculated as the area containing suitable habitat, which we defined as that with at least 20% of tree cover, within the SDMs calculated for each of the 144 amphibian species. A 20% threshold was selected as a general tipping point for all species in lack of specific information for all individual species. We believed that below it, the occurrence of dry fragments as a result of forest cover loss would prevent the survival of most of amphibians, as such, is an optimistic threshold. Moreover, this amount of continuous area is associated with the availability of leaf-litter conditions, which in small-scale conditions can create connections between habitat patches that can in turn explain amphibian biodiversity (Becker et al., 2007).

Through spatial analysis techniques, RD, was calculated for both 2005 and 2015. With this information, we calculated several variables describing the change of habitat:

(1) Species distribution area extent (SDE_0) (km^2): extent of potential SDMs.
(2) Distribution Remnant 2005 (RD_{2005}). Extent of remnant habitat based on tree cover satellite imagery 2005, expressed in km^2
(3) Distribution Remnant 2015 (RD_{2015}). Extent of remnant habitat based on tree cover satellite imagery 2015, expressed in km^2
(4) Habitat loss (HL) (2005–2015):$HL = 1 - \frac{RD_{2015}}{RD_{2005}}$
(5) Percentage of Remnant Habitat 2005) (RH%):$RH_{2005} = 1 - \frac{RD_{2005}}{SDE_0}$
(6) Percentage of Remnant Habitat 2015) (RH%):$RH_{2015} = 1 - \frac{RD_{2015}}{SDE_0}$
(7) Annual Rate of Habitat Loss (ARHL) (km^2/yr):$ARHL_{2005-2015} = \frac{HL_{(2005-2015)}}{15yrs}$
(8) Extent of Habitat Loss (EHL) (km^2):$EHL = SDE*ARHL$
(9) Time to Forest Cover Loss (TFCL) (2015) (yrs):$TFCL_{2015} = \frac{RD_{(2015)}}{EHL}$
(10) Time to Forest Cover Loss (T_0) (yrs):$TFCL_0 = \frac{SDE_{(0)}}{EHL}$

After obtaining the habitat change variables described in section *2.1*, we proceeded to assess the 144 species of amphibians. We considered variables 2 and 3 as the current distribution extension remnant for each species for 2005 and 2015 respectively. As IUCN's Red List Categories and Criteria v. 3.1 are widely used and accepted, we used the thresholds for criterion B to assign comparable categories to our assessment. Using these results, we conducted a quantitative comparison between the 2015 expert-based and our assessment. The results are presented in the form of a confusion matrix, and the percentage of agreement between the two approaches using khat statistics (a kappa approximation, Congalton, 1991). Both, confusion matrixes and the percentage of agreement are used for testing significant differences between paired classes.

2.2. Mining IUCN Red List categories: Bayesian Networks

A Bayesian Network (BN) is a probabilistic model, represented in an acyclic graphical form, using a set of variables (nodes) and directed arcs that describe the sets of conditional dependencies between these variables (Pearl and Russell, 2000). BN have been widely used for classification purposes (Hruschka et al., 2007; Madden, 2009; Taheri and Mammadov, 2015) and for inferring causality to support decision-making (Zheng and Pavlou, 2010). Here, BN are used (a) to evaluate the experts' replicability in IUCN Red List assessments; and (b) to explore the discovery and formalization of evaluation models for performing recurrent assessments.

In order to test the replicability of the expert assessment, and explore the BN structure due to habitat loss information, we mined a set containing all variables described in section *2.1* and the results of the 2014 Global Amphibian Assessment for structural learning. First, we established a *priori* model according to the categories assigned by the experts, and afterwards, we used a new classification using the data obtained in section *2.1*.. The methods used for structural learning are based on the search-and-score concept, reflecting the goodness of fit and model parsimony. Here we used the following two methods:

(a) Hill-Climber and LAGD Hill-Climber (Tsamardinos et al., 2006);
(b) Tabu search (Bouckaert, 2008)

All algorithms were available using the WEKA software, which is a data mining system developed by the University of Waikato in New Zealand (Witten et al., 2016). Scoring functions used for evaluation of BN relied on the Minimum Description Length (MDL) (Heckerman et al., 1995). The test options included a 10-fold cross-validation scheme for accuracy assessment.We evaluated learning methods in terms of their predictive accuracy and their ability to reconstruct the true underlying network. Statistical evaluation of BNs consisted in the assessment of model performance by using the following measures: (a) Accuracy (overall number of correctly classified cases); kappa statistic; (c) Mean Absolute Error (MAE); (d) Root Mean Square Error (RMSE); (e) Relative Absolute Error (RAE) and (f) Root Relative Squared Error (RRSE).

3. Results

3.1. 2005 and 2015 assessments using geospatial data

The assessments for 2005 and 2015 using geospatial data led to significant changes in the risk categories compared to those made through expert-based evaluation (Fig. 1). The categories with most changes were Endangered (EN) and Least Concern (LC). For the 2015 assessment, EN went from 37 species assessed by experts to 59 via geospatial assessment (Fig. 1), whereas LC went from 28 to 13 (Fig. 1). For 2005, EN went from 37 species by expert assessment to 57 via geospatial reassessment, whereas LC had 28 species and was reduced to 14 species for the same year (Fig. 2).

A comparison between the expert-based and our own assessment for 2015 based on geospatial data is presented in a confusion matrix (Table 1). This method helps to predict results on a classification problem, giving a percentage of accuracy from the algorithm we employed for each class, in our case, the class is each risk category. Thus we can notice which species were correctly classified by the experts and us according to their distribution remnant using IUCN Criteria B1 thresholds.

The overall rate of agreement between these two approaches was only 22% (khat = 0.223 ± 0.007). On a class-by-class comparison, Near Threatened (NT) and Vulnerable (VU) were the categories with more disagreement (NT = 89.1%; VU = 75.5%); Critical Endangered (CR) (54.8%) and EN (61.4%) showed a disagreement greater than 50% (Table 2); while LC showed the highest agreement value (76%, Table 2). As observed, the expert-based classification tends to underestimate the number of species for the CR and EN categories, while overestimating the VU category, compared to our own assessment.

3.2. Mining IUCN Red List categories: Bayesian Networks

The results obtained with the structural learning methods for the BNs to test the reliability and consistency of the expert-based assessment for 2004 and 2014 are presented in Tables 3 and 4 respectively. Here, the IUCN assessments were tested based on quantitative estimates of the RD data. Overall, the results showed low precision and accuracy when trying to replicate the expert-based categorization based on SDMs and habitat loss data.

For the 2004 expert-based assessment (Table 3), the average accuracy for the classification of IUCN's categories were very low (average accuracy = 43.5% ± 0.8%), with a high percentage of incorrectly classified species (56.5% ± 0.8%), and a very low probability that the classification would be better than chance (average kappa = 0.245 ± 0.013). The error contained in all models was high (e.g., RMSE = 0.338 ± 0.002; MAE = 0.222 ± 0.008) which was observed consistently in all error metrics (RAE = 84% ± 3.1%; RRSE = 93% ± 0.5%).

The results of the assessment for 2014 were not significantly different than those for 2004 (Table 4). The average accuracy for the classification of IUCN's categories by experts was also very low (average accuracy = 42.4% ± 1.5%), with a high percentage of incorrectly classified species (57.6% ± 1.5%), and a very low probability that the classification could be better than chance (average kappa = 0.223 ± 0.022). The error contained in all models was also very high (e.g., RMSE = 0.329 ± 0.003; MAE = 0.215 ± 0.004) and supported by the remaining error metrics (RAE = 82.9% ± 1.5%; RRSE = 91.4% ± 0.7%).

The results obtained with the structural learning methods that define several BN structures based upon our 2015 assessment using geospatial data are presented in Table 5. Our assessment produced a new risk categorization applying

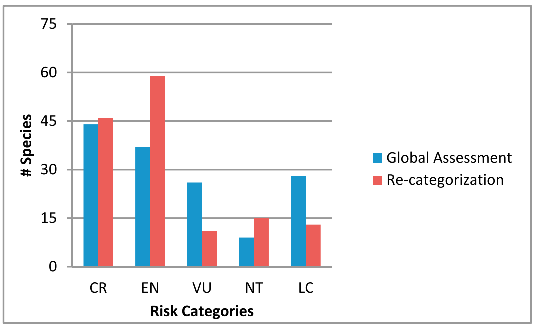

Fig. 1. Comparison between risk categories for the 144 amphibian species obtained during the 2014 global amphibian assessment (blue), and the assessment done using geospatial data (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

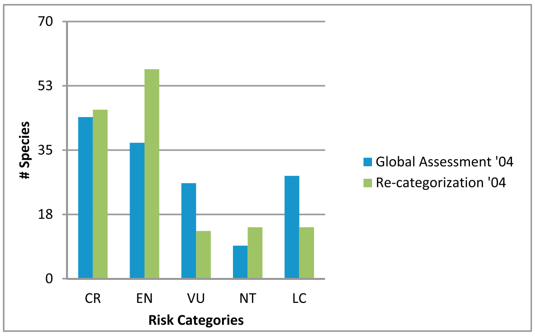

Fig. 2. Comparison between risk categories for the 144 amphibian species obtained during the 2014 global amphibian assessment (blue), and the assessment done using geospatial data (green). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Confusion matrix showing risk categories assigned by expert-based assessment and our geospatial assessment of the 144 species used to compare and test compare our geospatial method. Diagonal Highlighted numbers are the species classified equal by both methods.

Expert-based assessment Geospatial assessment		IUCN Risk Category					TOTAL
		CR	EN	VU	NT	LC	
IUCN Risk category	CR	**21**	18	6		1	46
	EN	15	**23**	12	5	4	59
	VU		1	**3**	3	4	11
	NT				**2**	13	15
	LC				3	**10**	13
TOTAL		36	42	21	13	32	144

Table 2
Class disagreement of IUCN risk categories from expert-based and our geospatial assessment. Higher percentage higher de disagreement between methods or vice versa, Both methods seem to agree more when species are Critical Endangered (CR) and Least Concern (LC).

IUCN Risk Category	Conditional Kappa	Disagreement
CR	0.452	54.80%
EN	0.386	61.40%
VU	0.245	75.50%
NT	0.109	89.10%
LC	0.762	23.80%

Table 3
Accuracy in assigning IUCN Red List Categories using Criterion B1 during the 2004 Expert-based assessment.

Search method	Accuracy	Incorr. Classified	Kappa statistic	MAE	RMSE	RAE	RRSE
HillClimber	42.9%	57.1%	0.235	0.227	0.338	85.8%	93.2%
LAGDHillClimber	42.9%	57.1%	0.235	0.227	0.338	85.8%	93.2%
RepeatedHillClimber	42.9%	57.1%	0.235	0.227	0.338	85.8%	93.2%
Tabu search	42.9%	57.1%	0.235	0.227	0.338	85.8%	93.2%
Mean	43.5%	56.5%	0.245	0.222	0.338	84.0%	93.0%
Std. Dev.	0.8%	0.8%	0.013	0.008	0.002	3.1%	0.5%

Table 4
Accuracy in assigning IUCN Red List Categories using Criterion B1 during the 2004 Expert-based assessment.

Search method	Accuracy	Incorr. Classified	Kappa statistic	MAE	RMSE	RAE	RRSE
HillClimber	42.9%	57.1%	0.230	0.216	0.327	83.2%	90.8%
LAGDHillClimber	42.9%	57.1%	0.230	0.216	0.327	83.2%	90.8%
RepeatedHillClimber	42.9%	57.1%	0.230	0.216	0.327	83.2%	90.8%
Tabu search	42.9%	57.1%	0.230	0.216	0.327	83.2%	90.8%
Mean	42.4%	57.6%	0.223	0.215	0.329	82.9%	91.4%
Std. Dev.	1.5%	1.5%	0.022	0.004	0.003	1.5%	0.7%

Table 5
Accuracy in assigning IUCN Red List Categories using Criterion B1 for the 2015 assessment using geospatial data.

Search method	Accuracy	Incorr. Classified	Kappa statistic	MAE	RMSE	RAE	RRSE
HillClimber	96.8%	3.2%	0.954	0.039	0.120	14.0%	32.0%
LAGDHillClimber	96.8%	3.2%	0.954	0.039	0.120	14.0%	32.0%
RepeatedHillClimber	96.8%	3.2%	0.954	0.039	0.140	14.0%	32.0%
Tabu search	96.8%	3.2%	0.954	0.039	0.120	14.0%	32.0%
Mean	96.1%	3.9%	0.945	0.035	0.123	18.5%	32.1%
Std. Dev.	2.0%	2.0%	0.029	0.014	0.017	13.2%	3.9%

qualitative reasoning and quantitative geographic data. In contrast to the expert-based classification, these results showed high accuracy in determining IUCN categories (average accuracy = 96.1% ± 2%), with a very low percentage of incorrectly classified species (3.9% ± 2%); and a very high probability that the classification obtained was better than chance (average kappa = 0.945 ± 0.029), taking into consideration that the assessments were done based on the species' distribution range and their distribution remnant over time. The error contained in the models was very low (e.g., RMSE = 0.123 ± 0.017; MAE = 0.035 ± 0.014), supported by the values obtained for the remaining error metrics (RAE = 18.5% ± 13.2%; RRSE = 32.1 ± 3.9%).

4. Discussion

Our aim in this study was to propose an approach to improve species risk assessments. We found that the results of the global amphibian assessments (2004 and 2014) are not reflecting the real conservation status and trends for amphibian species inhabiting Mexico. Furthermore, as in the case of Mexico, we are lacking behind in terms of official assessments in the country, as only four amphibian species have been assessed using the MER (DOF, 2010),. it is critical to use all available resources to produce quick and sound evaluations to inform conservation actions. As traditional assessment methods do not reflect the rate of habitat loss, which is one of the main threats to the biodiversity in tropical countries, the approach presented here can reduce the time it takes to produce species' assessments. Using the proposed method, the interval between assessments can be reduced to 4–5 years, as, Mexico's VCF is updated every 3–4 years. Reducing the time between assessments improve the chances to prevent or identify species near to extinction faster.

Moreover, our results rank very low in precision and accuracy the 2004 and 2014 global amphibian assessments in comparison to those based on SDMs and habitat loss data. This is especially the case for the Endangered (EN) category where we obtained a difference in 22 species (Fig. 2). This difference shows that assessing amphibians through criterion B using EOO, can be better achieved through the use of SDMs and Geographic Information Systems, rather expert knowledge, especially in those cases when data about species' distributions is scant. The use of SDMs in such cases can be seen in studies such as the one of Bicknell et al. (2017), that assessed mammals in Guinea, where data collection is scant. The same is true for mammal assessments in plant-oil plantations, where habitat loss is used as the only variable to define risk status (Budiharta et al., 2018). On the other hand, Critically Endangered (CR) and Least Concern (LC) categories were almost always correctly categorized by the experts (Table 2). Thus, we can conclude that experts have good knowledge on species that are either CR or LC, but the same cannot be said for those species categorized as EN, VU and NT. The low accuracy and replicability found in the expert-based assessments on most categories contradicts one of the requirements when for assessing extinction risk, i.e., to provide a system that can be applied consistently by different experts (IUCN, 2012; Ramirez and Quintero, 2016).For this reason, we encourage the use of this type the presented approach on assessments for species with scant information, especially when species distribution is the only information that can be used to perform a quantitative and replicable assessment.

Our BN identified the remnant habitat area for all species at the time of the evaluation (in this case, RD-2015) as the main variable to conduct an accurate assessment, as it was the direct node determining threat categories in all models (Fig. 3). Studies like those by Pettorelli et al. (2014) supports the idea that remote sensing data can indirectly infer habitat loss. Using land cover loss, as we do here, is gaining more acceptance and is being used worldwide. Moreover, Tracewski et al. (2016) consider that objective estimates of habitat loss can be produced through remote sensing, making it easier and feasible to compare rates of habitat loss from local to global scales and then perform species risk assessments.

Knowledge gaps are extensive, especially for amphibians, where 88% of species have no available information. For instance, Conde et al. (2019), have found that age- or stage-specific birth and death rates are available for only 1.3% of tetrapods, which means that only 0.2% of the 1714 threatened amphibians worldwide, might have this sort of information; this issue makes demographic-based assessments too complicated.

By using accurate information of habitat loss, we found that there was a negative trend in the conservation status of Mexican amphibians. Our findings suggest that Mexico's conservation actions are not good enough to protect these species, especially when it has been demonstrated that land cover change has a direct impact in the viability of populations (Santini et al., 2019), which can generate further demographic problems (Frankham, 2005; Frankham et al., 2010). Moreover, It is important to mention that out of the 144 assessed species, 103 were endemic to Mexico, which means that the vast majority

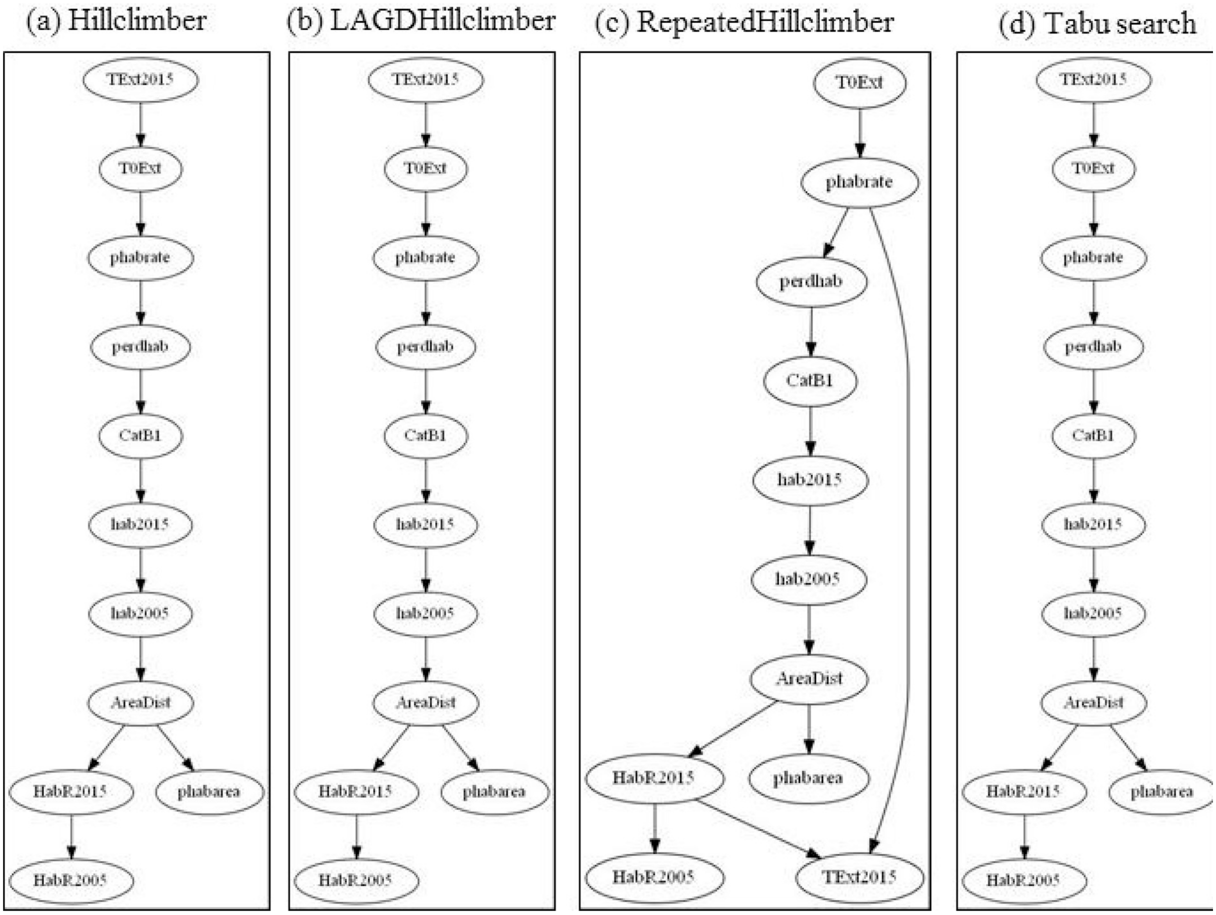

Fig. 3. Model structure in Bayesian Network models for describing the IUCN Red List Categories obtained with our own 2015 geospatial assessment. Habitat loss (perdhab) in a, b, c and d resulted as the main node to perform the assessments.

of the included species in this analysis are a reflection of the threats and current conditions that amphibians endure in the country.

We are well aware of the caveat of relying on SDMs for this assessment approach (see for instance Galante et al., 2018), A lack of occurrences happens in the majority of species (Soberón et al., 2000; streiburg también) making the production of SDMs difficult due to a lack of distribution data. However, SDMs with good records (or at least with confirmation that the species is known to occur in site) and biotic and abiotic properties of the sites can yield proper estimates of suitability for the species (Elith et al., 2006; Galante et al., 2018). Besides, SDMs are important for data-poor species like the ones assessed in this study; in a scenario with a complete lack of demographic data, we propose that performing risk assessments using habitat, expressed as SDMs as a proxy, is a valid approach. SDMs have become a widely used tool in ecology and conservation. There is no doubt that SDMs can help in conservation assessments (Anderson and Martínez-Meyer, 2004), and in predicting where a species may occur, giving the opportunity to infer if any threats overlap with its possible distribution using remote sensing layers (Pettorelli et al., 2014; He et al., 2015; Tracewski et al., 2016), just like in the case of the VCF we used as surrogate of remnant habitat here. Finally, it is important to highlight the SDMs we used in this study are the only ones available for these species. Producing new SDMs was beyond the scope of our study, so instead we are using the best available science to our disposal to perform assessments in a more accurate, quantitative and replicable manner.

The results of this study does not imply that expert knowledge is not required or should be let aside when performing species assessments. On the contrary, we suggest that decisions made by experts when conducting assessments are difficult, if not impossible, to replicate when other, probably better, sources of data are used. Thus, we propose that supporting information should be a key component of any successful and sound evaluation, and therefore the availability of digital sources, both contextual and geographical during assessment workshops should be a must. Digital sources can foment real time discussions and feedback among experts, leading to expertise being formalized in an evaluation model. The idea to incorporate SDMs as support information to take decisions is not new; Blair et al. (2012) suggest incorporating climate change SDMs into expert workshops to define better priority conservation areas across species' ranges. Furthermore, studies which use similar methods to assess species, like we present here, are in good agreement that this type of assessment is helpful for species classified as Data Deficient (DD) or to validate if Least Concern species are really not-threatened or maybe they are due to high rates of habitat loss (Tracewski et al., 2016; Santini et al., 2019). For example, Fig. 1 showed a decrease of 53.57% from species classified as LC by our geospatial assessment, comparing to the expert assessment. In these cases, the species would have to be reclassified, according to the remaining suitable habitat on their distributions and the achieved thresholds stablished for criterion B1 by the IUCN Red List. Furthermore, species such as *Smilisca dentata* (Fig. 4a), was categorized as endangered by the experts, even though our data show that it has lost 97% of its potential habitat and is only 21 years away from habitat depletion assuming habitat loss rates remain constant. It should be noted that by IUCN standards, under criterion B1, species with >20,000 km^2 of EOO are automatically placed in a non-risk category due to their large distribution range, considering there is not any other source of data to use. However, for some species data show that despite their large distribution, habitat loss rate is high and thus the time to habitat depletion is short; such is the case for *Tlalocohyla godmani* (Fig. 4b), classified as NT by experts, and *Dendropsophus ebraccatus* (Fig. 4c), classified as EN. Our assessment places *T. godmani* as EN, even though is clear that its habitat is been quickly lost, and its threat status should be much higher. Moreover, there are other aspects that should be considered apart from rate of habitat loss, as can be seen in *Thorius pulmonaris* (Fig. 4d) and *Plectrohyla pachyderma* (Fig. 4e), both of which have very narrow distributions with a low rate of habitat loss (habitat depletion of 2328 and 405.6 years respectively); however, in both cases their habitat is highly fragmented, which poses an entirely different threat, that should be dealt with at some point. Finally, we have identified cases, such as with *Thorius grandis* (Fig. 4f), where species with small distribution (<100 km^2) but with a very low rate of habitat loss are placed in a very high risk category. The question remains as to which species is more threatened, a widely distributed species with a high rate of habitat loss or a species with a very small distribution but with a low rate of habitat loss? Just as Fahrig (2001) suggests, how much habitat is enough for a species survival? It becomes clear that our findings beg for a more thorough discussion on how quantitative criteria should be incorporated into assessment systems.

5. Conclusions

Our study show that expert-based classifications obtained during the global assessments of 2004 and 2014 do not accurately reflect the condition of Mexican amphibians. Although we are aware of the differences on how RD and EOO are

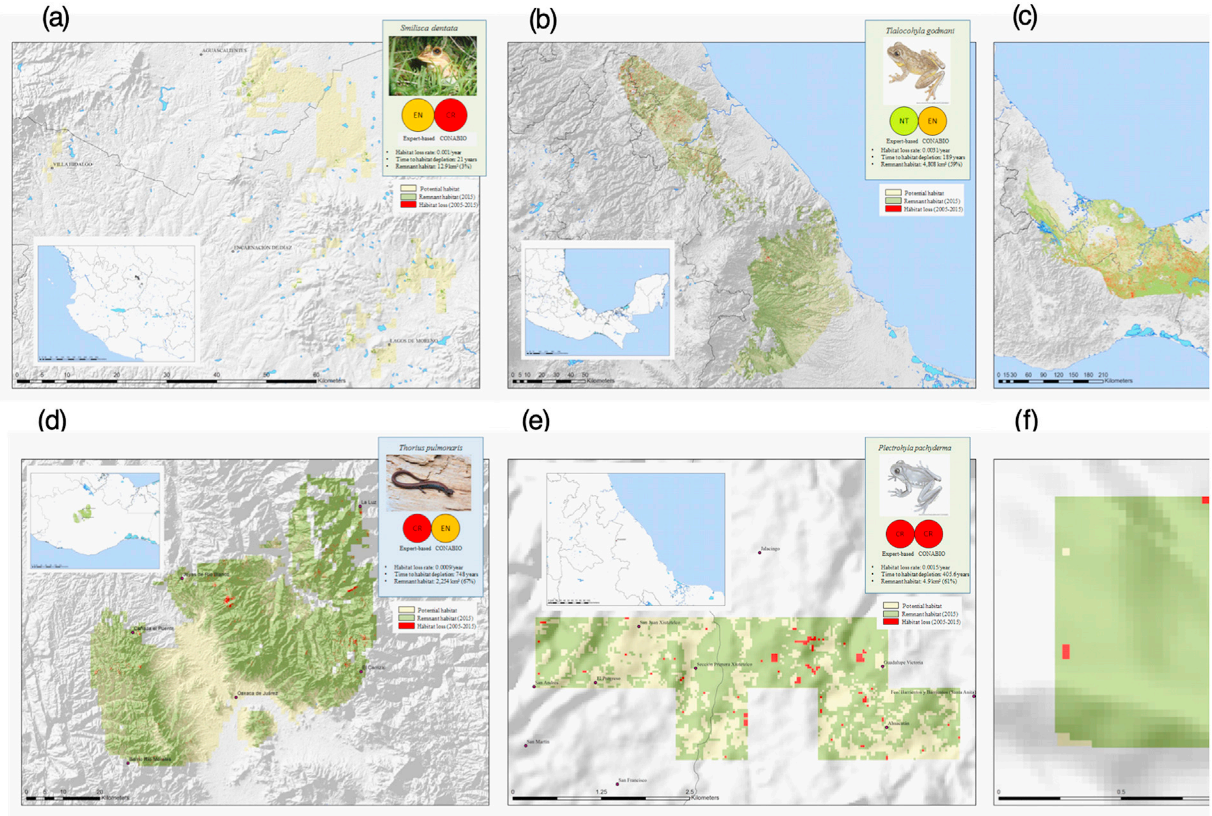

Fig. 4. A comparison between maps drawn by experts (upper left corner), and those produced during our geospatial assessment, showing potential habitat, remnant habitat in 2015, habitat loss between 2005 and 2015, time to habitat depletion and IUCN Risk Category assigned by experts and through our analysis (see text).

calculated, the inconsistency between assessments is still too big when a quantitate value like geographic range is used for assessment purposes. Our study suggests that an accurate quantitative measure of habitat loss can give additional support to the risk assessment of poorly known species as well of those with very restricted distributions. Despite the biases that we found during expert-based assessments, we still believe that if qualitative data and expert knowledge are used to formalize objective and quantitative evaluation models with BNs, risk assessment methods can be enhanced, performed faster and reflect reliable trends in the status of species groups. These results are the ones we should aspire to in a megadiverse country in order to implement effective actions to halt the impending loss of biodiversity. Lastly one of the ideas of this study is to generate a wider discussion among academics and decision makers regarding conservation policies, not only for amphibians; the proposed risk assessment method can also be used for non-volant mammals and reptiles, in order to generate conservation plans either for groups which share or overlap distributions or to specific species where habitat loss is pushing them to extinction.

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