Testing the Benefit of Agroforestry as a Solution for Red Listed Bird Conservation in the Peruvian Amazon

by

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ABSTRACT

Globally, land use change is the primary driver of biodiversity loss (IPBES, 2019). Land use change due to agricultural expansion is driving bird species to the brink of extinction in the Peruvian Amazon rainforest. Agriculture is one of the primary threats to bird species in the region, and agroforestry is being pursued in some communities as a potential solution to reduce agriculture's impacts on species, as agroforestry provides improved habitat for wildlife while also enabling livelihoods for people. Understanding how anthropogenic land use choices affect imperiled species is an important prerequisite for conservation policy and practice in the region. In this thesis, I develop a spatial model for quantifying expected threat abatement from shifting agricultural land use choices towards agroforestry. I used this model explored how agricultural land use impacts imperiled bird species in the Peruvian Amazon. My approach builds on the species threat abatement and restoration (STAR) metric to make the expected consequences of reducing agricultural threats spatially explicit. I then analyzed results of applying the metric to alternative scenarios with and without agroforestry conversion. I found that agroforestry could result in up to 18.68% reduction in mean bird projected population decline. I found that converting all terrestrial agriculture in the Peruvian Amazon to agroforestry could produce a benefit of up to 83% to imperiled birds in the region in terms of improvement in Red List status. This use of the STAR metric to model alternative scenarios presents a novel usage for the STAR metric and a promising approach to understand how to address terrestrial biodiversity challenges efficiently and effectively.

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CHAPTER 1

The world is losing biodiversity at an unprecedented rate as a result of land use choices (McCallum, 2015). One of the key drivers of this loss is habitat destruction (Caro et al., 2022). Megadiverse regions, in particular, are experiencing extreme pressure from a variety of anthropogenic activities (Fajardo et al., 2014). However, agriculture stands out as one of the most negatively impactful industries when it comes to promoting biodiversity loss and habitat destruction and degradation (Dudley & Alexander, 2017). Almost half of Earth's habitable land is covered by agriculture, and this figure is projected to increase (Ritchie, 2013). As the human population grows and per capita resource consumption rises, agriculture is increasingly expanding into wildlife habitat, especially in megadiverse countries (Machovina et al., 2015). These factors present significant challenges to achieving sustainability goals set by governments. Conservation decision makers must therefore find ways to address shifting land use choices and the resultant biodiversity impacts in the most efficient and effective ways possible (Bottrill et al., 2008). Understanding the biodiversity outcomes of current and potential land use choices represents a pressing challenge in identifying effective conservation interventions.

Peru is a megadiverse country where agriculture stands out as a threat to biodiversity. Peru contains 13% of the Amazon rainforest and is home to over 1800 species of birds, making it one of the most biologically diverse countries on Earth (Figure 1; Peru Ministry of Foreign Trade and Tourism, 2020; BirdLife, 2022.). Approximately 19% of Peru's land area is used for agriculture, with 43% of that occurring in Peru's portion of the Amazon basin as of 2018 (USAID, 2018). Current government policies and economic conditions are predicted to exacerbate this issue and allow further agricultural expansion–and thereby deforestation–in the Peruvian Amazon (Sánchez-Cuervo et al., 2020).

Figure 1. Map of Peru with official region boundaries overlaid with the Peruvian Amazon.

Agriculture in the Peruvian Amazon is dominated by pasture and plantations (Ravikumar et al., 2016). Slash and burn practices, coupled with clear-cutting, are efficient at removing large swaths of forest, but such methods destroy habitat that birds depend on for survival (Palm et al., 2005). This region is also experiencing shifts in drivers that are likely to complicate mitigation strategies. Historically, smallholder farming was the dominant driver of deforestation in the Peruvian Amazon, but industrial agriculture is now emerging as the primary threat (Ravikumar et al., 2016). Industrial farming tends to prioritize production of commodity crops and products such as coffee, cacao, palm oil, and beef, which are then exported to wealthier countries in the Global North (Castro-Nunez et al., 2021; Recanati et al., 2015).

These challenges also present opportunities, as alternative land use choices such as agroforestry can help reduce the threat that agriculture poses to biodiversity (as summarized in the theory of change in Figure 2; Pereira & Viola, 2022; Perry et al., 2016; Sanchez-Cuervo et al., 2020; Socolar et al., 2019). Agroforestry has emerged as a potential solution to habitat loss resulting from agricultural activity and presents a middle-ground that can sustain wildlife and humans alike (Tscharntke et al., 2014). Agroforestry is a form of polyculture wherein woody vegetation, such as trees and shrubs, are grown within cropland or pasture. Agroforestry allows cultivated agricultural land to host a higher diversity of vegetation and therefore animal species (Udawatta et al., 2019).Birds, in particular, experience measurable benefits from agroforestry, as this management practice restores lost canopy and mimics secondary forest structure (Bohada-Murillo et al., 2019).

Agroforestry also benefits human wellbeing through crop diversification and improved ecosystem services (Beillouin et al., 2021). Indigenous peoples have practiced agroforestry in the Americas for centuries, employing it across diverse landscapes–

including the rainforests of Amazonia–to meet their needs (Gonzalez & Kroger, 2020). In the Peruvian Amazon, instituting systems that emphasize shade crops, intercropping and alley cropping could partially restore lost canopy, providing birds with critical nesting and feeding resources. A variety of commodity crops grown in the Neotropics, including coffee and cacao, respond positively to shaded systems (Arévalo-Gardini et al., 2021; Hernandez-Aguilera et al., 2019). Emphasizing native vegetation, where possible, may improve the biodiversity benefits accrued and help restore the landscape to its former stable state while building value for farmers (Blare & Donovan, 2016). Consequently, agroforestry presents a viable alternative to current agricultural practices, as it can improve biodiversity outcomes without compromising human wellbeing. Thus, agroforestry is a promising conservation intervention for improving bird outcomes.

Theory of Change: Peruvian bird Conservation Through Agroforestry				
Root Causes	**Causes**	**Problem**	**Mitigation Strategies**	**Outcomes**
Market factors driving commodity crop demand.	Deforestation for agriculture (both smallholder and industrialized).	Decline in bird populations across species in the Peruvian Amazon.	Adoption of sustainable farming practices (e.g. agroforestry) by farmers in the Peruvian Amazon.	Stabilization of bird populations and increase in biodiversity within the Peruvian Amazon.
Lax enforcement of environmental regulations and perverse incentives.	Deforestation for logging and wood harvesting.	Loss of biodiversity in the Peruvian Amazon.	Investment in farming communities by government.	Greater economic empowerment and security for Peruvian farmers.
Economic insecurity and poverty within farming communities, especially for indigenous people and women.	Intentional use of imperiled bird species as a biological resource.		Education of Peruvian farmers on human-wildlife conflict mitigation and sustainable agriculture.	Coexistence between humans and wildlife in tropical landscapes.
Causal Pathway →				

Figure 2. This theory of change lays out agroforestry as a potential pathway for achieving ecological and policy changes that would benefit imperiled birds in the Peruvian Amazon.

The current body of peer-reviewed literature that show favorable results for agroforestry initiatives emphasize stakeholder engagement, education, and government policy as means for achieving desirable conservation outcomes (Dumont et al., 2017; Hemmelgarn & Gold., 2021; Kaonga et al., 2012). However, agroforestry will not feasibly be implemented across the entirety of the Peruvian Amazon, so decision makers must find ways to quantify where its benefits are likely to be most pronounced and therefore which regions are the most appropriate targets for this type of action.

It is difficult to determine where agroforestry interventions should be implemented to maximize efficiency and effectiveness in terms of benefits to biodiversity. Until recently, decision makers lacked a standardized methodology for spatially modeling expected biodiversity responses to threat reduction due to specific land use choices. One novel means by which to achieve this is through use of the species threat abatement and restoration (STAR) metric, that quantifies how mitigating threats can reduce extinction risk for threatened species (Mair et al., 2021). Drawing on IUCN Red List data and area of habitat (AOH) information, the STAR metric is a useful tool that is scalable across species, threats and geographies and can be used in part to assist conservationists in spatially prioritizing biodiversity interventions (Mair et al., 2021). Because the STAR metric can link threats of various resolutions to a species' Red List status, it allows decision makers to trace the direct impacts of specific land use choices to extinction risk and thus can be a useful conservation planning tool.

Currently, terrestrial STAR scores can quantify the expected biodiversity benefits of resolving all the threats facing the species in a region, but to explore the biodiversity implications of agroforestry implementation compared to current agricultural land use trends, STAR must be modified so that it can produce predicted alternative scenarios and disentangle the effects of specific threats. This would entail analyzing single threat categories independently, making threats spatially explicit, and creating a methodology for modeling alternative conditions.

Thus, to explore how current agriculture land use choices are expected to impact bird biodiversity in the Peruvian Amazon and how alternative agricultural practices could potentially improve bird conservation status, I developed a spatial modeling approach to apply these modifications to the STAR metric and then used the new metric to model scenarios that could compare expected outcomes for birds with and without agroforestry interventions. I then compare the scenarios to examine where implementation of agroforestry in the Peruvian Amazon could yield the greatest benefits to imperiled bird biodiversity. This approach allows the STAR metric to be used to model the expected benefits of conservation interventions that act on specific threats but that do not necessarily resolve all threats facing a species in a region and thus provides a useful addition to the conservation planning toolbox. Although this thesis focuses exclusively on birds and agricultural threats, the approach I describe can be applied across threats, taxonomic groups, and landscapes.

METHODS

I developed a spatially-explicit model to quantifying the expected biodiversity benefits of implementing agroforestry land use in the Peruvian Amazon in place of existing agricultural use. I focused on determining how threats to birds listed as threatened or near threatened on the IUCN Red List can be expected to be reduced, as a case study. I calculated both the expected population decline and the current opportunity to reduce the study species' extinction risk using the STAR metric and then compared these measures to the expected outcome if agroforestry were implemented everywhere that terrestrial agriculture occurs in the Peruvian Amazon. I did the latter through a modified usage of the STAR metric that allows it to be used to estimate the potential benefits of conservation interventions that act on specific threats but that do not necessarily resolve all threats facing a species in a region. This process is summarized in the workflow shown in Figure 3; each step is explained in the methods below.

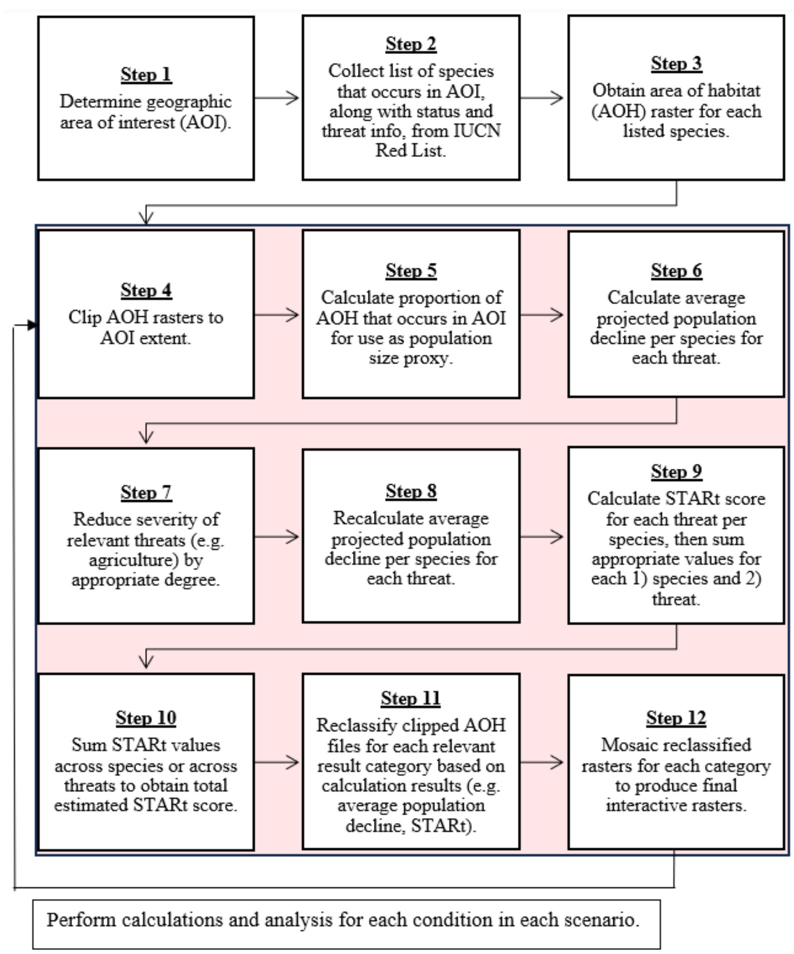

Figure 3. Methods workflow of the process for calculating and mapping 1) mean projected population decline and 2) STARt values for the relevant species.

Study Site and Species Selection (Steps 1-2). I focus on the Amazon rainforest in Peru, an inland region in western Peru dominated by moist broadleaf tropical rainforest. This area is one of the most biologically diverse regions on earth, making it a critical area of concern for conservationists (IUCN, 2023). The region contains a human population of approximately 1.5 million, or 5% of the national population, and this number is projected to increase over the coming decade (ARCA, 2019; Peru National Institute of Statistics and Informatics, 2017). The most recent data collected by the Peruvian government indicates that agriculture covers approximately 50,890 square kilometers of the Peruvian Amazon (Figure 4; MINAM, 2018). In some regions, such as Ucayali, up to 40% of the population's annual income is derived from forest and environmental products, demonstrating the importance of intact forests and rich biodiversity to the livelihoods of people living in the Peruvian Amazon. Yet agriculture and livestock production are also significant sources of income at 25% and 11% in Ucayali, respectively (Porro et al., 2015). Similar trends can be seen across the other regions that occur within Peru's Amazon rainforest. This reliance on both intact and manipulated land creates some conflict and raises questions about alternative land uses that may be able to meet all of these needs (e.g. agroforestry). Although the extent of agriculture varies between regions, it is generally a significant land use in the study area, particularly in regions that occur in the western Peruvian Amazon (Table 1).

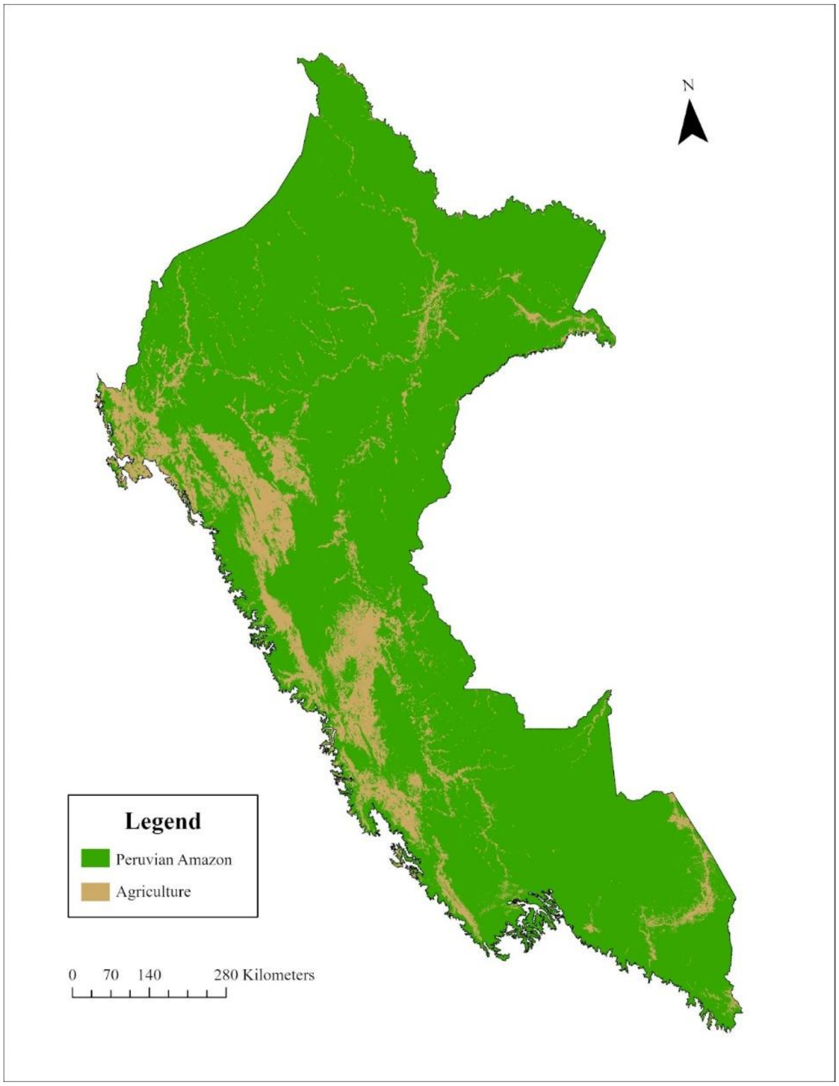

Figure 4. Extent of recorded agricultural areas in the Peruvian Amazon as of 2018, according to The Ministry of Environment of Peru (MINAM, 2018).

Bird biodiversity is particularly rich in the Peruvian Amazon. Over 800 bird species reside in this region, a number of which are endemic (ARCA, 2019). Of those more than 800 bird species, over 130 are listed as imperiled on the IUCN Red List of Threatened Species, the vast majority of which are experiencing global population decline (Figure 5; IUCN, 2022). Some of these species have extremely patchy or geographically limited distributions, making them vulnerable to population fragmentation as a result of habitat loss (Carrete et al., 2009). Birds can also reliably be treated as indicators of overall ecosystem health, making them a logical conservation focus (Roth & Weber, 2008). Moreover, birds and their threats are generally better documented in the Red List than other species groups, giving conservationists a clearer understanding of their threats, as well as potential solutions (Bachman et al., 2019).

Table 1

Regional Statistics for the Peruvian Amazon

Region	Human Population (as of 2017)	Total Region Area (km^2)	Aricultural Area (km^2)	Proportion of Region Covered by Agriculture (%)
San Martin	829,520	51,005	11,002	21.57%
Huanuco	854,234	37,529	4,437	11.82%
Amazonas	421,122	39,274	3,875	9.87%
Pasco	301,988	23,895	1,839	7.70%
Cajamarca	2,100,090	32,834	2,514	7.66%
Junin	1,512,111	44,150	3,001	6.80%
Ucayali	489,664	105,123	5,664	5.39%
Madre De Dios	134,105	84,617	1,634	1.93%
Loreto	1,028,968	374,939	5,668	1.51%
Ayacucho	681,149	43,598	563	1.29%
Piura	2,753,890	35,554	238	0.67%
Cusco	1,488,112	72,005	414	0.57%
Huancavelica	491,278	22,079	84	0.38%
Lambayeque	1,250,349	14,499	52	0.36%
Puno	1,690,783	67,609	206	0.31%
La Libertad	2,201,112	25,226	7	0.03%

*Note***.** This table shows Peruvian regions that occur in the Peruvian Amazon and each of their respective 1) human population size, 2) total land area, 3) total land area covered by agriculture, and 4) proportion of total land area covered by agriculture.

My study area provided the basis for the area of interest (AOI) extent that informs all calculations related to the STAR metric. The study site and the area of interest can be the same, but do not necessarily need to be (Mair et al., 2021). The effects of changing the AOI extent are explored further below. In this thesis, the AOI will always refer to either the Peruvian Amazon or a subset of the Peruvian Amazon.

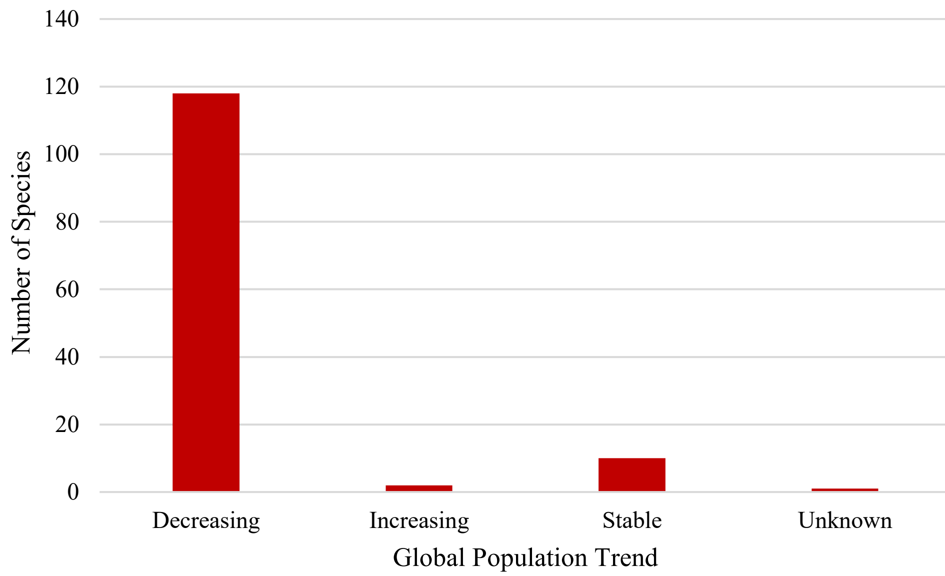

Figure 5. Global population trends for imperiled bird species occurring in the Peruvian Amazon, according to the IUCN Red List of Threatened Species (2022).

Data Collection (Steps 2-5). First, I compiled a study dataset of imperiled birds that reside in the Peruvian Amazon (see Appendix). Using the International Union for Conservation of Nature's (IUCN) Red List of Threatened Species website, I downloaded a list of bird species whose ranges overlapped with the Peruvian Amazon and that were listed as near threatened, vulnerable, endangered, or critically endangered, which I collectively refer to as "imperiled" in this thesis (IUCN, 2022). My final dataset contained 131 bird species ranging from near threatened to critically endangered. I then gathered detailed information from the IUCN Red List for each species on this list, including Red List status, threat details, population trends, habitat and elevation associations, and taxonomy information. Red List threat information for each species included each threat's name, code, timing, scope and severity. There are 12 overarching threat categories maintained by the Red List by which species' threats are categorized (see Appendix; IUCN Threats Classification Scheme Version 3.3, 2022). For a specific threat affecting a species, scope refers to the "proportion of the total population affected," while severity refers to the "overall declines caused by the threat" (IUCN Red List Classification Scheme Version 3.3, 2022).

I then collected area of habitat (AOH) raster data for each species for use as a proxy for population size and to later build my raster mosaics. Area of habitat refers to "the habitat available to a species, that is, habitat within its range," meaning it excludes unsuitable habitat and elevations within a species' range where that species would not occur; it is thus a more accurate measure of species occurrence than range alone (Lumbierres et al., 2022a). Practically, area of habitat is spatial data, typically stored and manipulated as a raster. I first downloaded publicly available AOH rasters generated by Lumbierres et al. (2022a), which are hosted on the data publishing platform Dryad (Lumbierres et al., 2022b). AOH rasters were available for all the study species except for *Hemitriccus cohnhafti*, whose AOH raster file was not generated by Lumbierres et al. (2022b). To compensate for the missing *H. cohnhafti* AOH data file, I created an AOH raster file with a 100 meter resolution–to match the Lumbierres et al. (2022a) rasters–using the species' range shapefile, habitat association information, and elevation limit data, all recorded by BirdLife International and downloaded from the IUCN Red List website (BirdLife, 2017). Ecosystem types for the habitat association component were determined using European Space Agency land cover data (ESA, 2017). Using ArcGIS Pro (ESRI, Version 3.1), I then validated each species' AOH occurrence in my AOI by overlaying the AOH rasters with a shapefile of the Peruvian Amazon and confirming that each species' AOH overlapped with that shapefile by at least one 100 meter pixel.

I then calculated the proportion of the global population of each species that occurred within the AOI for each scenario. In order to determine the proportion of each species' global population occurring within each AOI, I clipped each species' AOH raster to the AOI extent. For each species, I then divided the clipped AOH area by the area of that species' global AOH and used these proportions as proxies for population size when calculating STARt (see detailed methods below). Other spatial data collected includes the extent of the Peruvian Amazon, Peruvian administrative boundaries, deforestation data, and agricultural data, all of which I obtained from the Ministry of Environment of Peru (MINAM) open data portal (MINAM, 2018), with the exception of the Peruvian Amazon boundaries, which I obtained from the Amazon Network of Georeferenced Socio-Environmental Information (RAISG, 2022). I performed all spatial data manipulations in ArcGIS Pro (ESRI, Version 3.1).

Scenario Details and Basis for STAR Modification. To estimate the expected response of birds in the Peruvian Amazon to different agricultural land use scenarios, I calculated the 1) mean projected population decline and 2) STARt scores for three scenarios, each with two conditions. The former is an intermediary used to produce the latter, but mean projected population decline can stand as its own measure. The primary differences between the three scenarios are the extent of the area of interest (AOI) and the Red List threat information included in the calculations for mean projected population decline and STARt scores. In this thesis, "area of interest" (AOI) refers to the geographic area that bounds the spatial analysis and related calculations. It is critical to calculating the proportion of a species' AOH that occurs within the AOI, as changing the AOI extent will cause this proportion to adjust accordingly. The AOI and the study area are the same for Scenarios 1 and 2 (e.g. the Peruvian Amazon), but the AOI in Scenario 3 is restricted to agricultural areas in the Peruvian Amazon (Table 2). The AOI in Scenario 3 is thus a subset of the AOI used in Scenarios 1 and 2. This restriction of the AOI in Scenario 3 is critical for making the STAR metric reflect the "real world" better, as unlike the traditional STAR metric, it does not assume that threats are happening everywhere equally, but rather restricts calculation of STARt scores such that they are only spread across areas where the relevant threats occur.

The second major difference is the number and type of major IUCN threat categories considered in the calculations. For Scenario 1, my calculations incorporated all recorded threat data for my study species, irrespective of the category each threat fell into. In other words, Scenario 1 looked at all threat impacts, rather than agriculture alone. Conversely, Scenarios 2 and 3 exclusively incorporate agricultural threat data and exclude all other threat impacts from the calculations (Table 2). For each scenario's calculations, I kept the severity of all non-agricultural threats the same between the "Actual" and "Agroforestry" conditions for Scenario 1; Scenarios 2 and 3 exclusively used Red List data from agricultural threat categories, meaning all threat severity scores were by default reduced by 1 in their "Agroforestry" scenarios. The species list remained the same across all three scenarios. By calculating and mapping three separate scenarios, I was able to distinguish how the traditional STAR metric versus my modified usage of the STAR metric might yield different prioritization results (see Discussion).

For each scenario, I explored the difference in outcomes between two conditions. The “Actual” condition represented the world “as is;” in other words, it used the most up to date Red List data to capture an approximation of threat scope and severity, as well as species population trends, for my study species within the AOI. I then constructed the “Agroforestry” condition to represent a potential situation in which all current terrestrial agricultural areas in the Peruvian Amazon were converted to agroforestry; in other words, if the severity of all agricultural threats was partially abated and reduced as a result of widespread agroforestry adoption, what might happen? The “Agroforestry” condition in each scenario used a modified methodology to calculate mean projected population decline and STARt scores, which is described in detail below. I kept the severity of all other non-agricultural threats the same between the “Actual” and “Agroforestry” conditions for Scenario 1; Scenarios 2 and 3 exclusively considered agricultural threats, meaning all threat severity scores were reduced by 1 in their “Agroforestry” scenarios. Finally, I calculated the difference between the “Actual” and “Agroforestry” conditions to produce “Achieved” STARt values, which represent the biodiversity benefit gained by converting agriculture to agroforestry in the AOI.

Table 2

Scenario Descriptions

Scenario	**Area of Interest (AOI)**	**Threats Considered**
1	Peruvian Amazon	IUCN Categories 1-12 (all possible threats)

2	Peruvian Amazon	IUCN Threat Category 2 (agricultural threats)
3	Agricultural areas in Peruvian Amazon	IUCN Threat Category 2 (agricultural threats)

Note. This table details the three scenarios calculated, with key differences between scenarios highlighted (with green indicating similarities between scenarios within a column, and red indicating differences). The study species and conditions analyzed remained consistent across scenarios.

Traditional and Modified Approaches to Calculating Population Decline (Steps 6-8). I calculated the mean projected population decline for each species to represent the "Actual" condition. Using the IUCN Threat Impact Scoring System (see Appendix) in combination with Red List threat scope and severity scores for the study species, I calculated a threat impact score for each individual threat impacting each species using the IUCN Threat Impact Scoring System Version 1.0 (IUCN, 2022). This matrix translates raw, qualitative threat scope and severity information into standardized, numeric scores. I then translated these scores to mean projected population decline for each individual threat per species using a matrix developed by Hawkins et al. (2018) (see Appendix). This projection represents estimated average decline over 10 years or 3 generations, whichever is longer for that species, per the Red List's evaluation criteria.

I modified the mean projected population decline calculation for the "Agroforestry" condition to represent conversion of current agriculture to agroforestry. To do so, I used the same calculation process as above, but I altered agricultural threat severity scores to represent an expected decrease in threat from agriculture. I elected not to alter the scope scores to retain the ratio between threat scopes for each species and to demonstrate that the extent of agricultural threats would not be changed under the "Agroforestry" conditions. The scientific literature has consistently demonstrated that agroforestry reduces population decline of species (De Benhouwer et al., 2013; Torralba et al., 2016), so decreasing the severity scores was most appropriate. However, because the bird biodiversity benefits of agroforestry are not equivalent to those of primary forest, I did not reduce agricultural threat severity scores to zero in the "Agroforestry" conditions. Instead, each species' agricultural threat severity score obtained from the IUCN Threat Impact Scoring System was reduced by 1 (e.g. a "Very rapid" severity score of 3 would reduce to a "Rapid" score of 2).

These calculations resulted in two mean projected population decline percentages for each species in each scenario: one value for the "Actual" condition and one value for the "Agroforestry" condition. I also calculated the difference in mean projected population decline across species between the "Agroforestry" and "Actual" conditions for each scenario, representing reduction in mean projected population decline due to the intervention. Calculating mean projected population decline is a critical intermediary step needed to use the STAR metric. However, mean percent population decline is also frequently used by scientists as a measure to discuss biodiversity trends. It may therefore be useful as a standalone metric in some instances (see Discussion for further details).

Calculating "Actual" STARt Scores (Steps 9-10). To explore how threat abatement would result in expected species benefits, I calculated STARt scores for each species in my study using the following equation:

$$T_{t,i} = \sum_{s}^{N_s} P_{s,i} W_i C_{s,t}$$

Here, STARt scores (T) were calculated for each threat (t) within the AOI (i). This was done by multiplying the proportion of each species'(s) population that occurs in the AOI (P) by its Red List category weight (W) and the relative pressure (C) of each threat impacting it. The proportion of a species' global AOH that overlapped with the AOI (P) acted as a population size proxy. The Red List category weight was based on an equal steps approach–thus, near threatened equaled 100, vulnerable equaled 200, endangered equaled 300, and critically endangered equaled 400. Relative threat pressures were obtained by summing the mean projected population declines across all threats for each species (as calculated above), then dividing the projected population decline for the individual threat by that total. All relative threat pressures for each species sum to 1; within the equation, this means that C for each individual threat affecting a species will always be less than or equal to 1. Scores are summed across species to achieve a final STARt score for that threat (Table 3). Scores can then be summed across threats to achieve a total estimated STARt score for all threats within the AOI (Table 4) (Mair et al., 2021).

Table 3

Example Calculations

Species (s) Scientific Name	Population Proportion in AOI (P)	RL Status Weight (W)	Threat Code	Threat Scope	Threat Scope Score	Threat Severity (Actual)	Threat Severity Score (Actual)	Average Projected Population Decline (Actual)	Relative Threat Pressure (C)	STARt Score (T) per Threat (t) (Actual)
Aburria aburri	0.44	100	5.3.3	Majority (50-90%)	2	Slow, Significant Declines	1	9	0.33	14.58
Aburria aburri	0.44	100	5.1.1	Majority (50-90%)	2	Slow, Significant Declines	1	9	0.33	14.58
Aburria aburri	0.44	100	2.1.3	Majority (50-90%)	2	Slow, Significant Declines	1	9	0.33	14.58

Species (s) Scientific Name	Population Proportion in AOI (P)	RL Status Weight (W)	Threat Code	Threat Scope	Threat Scope Score	Threat Severity (Agroforestry)	Threat Severity Score (Agroforestry)	Average Projected Population Decline (Agroforestry)	Relative Threat Pressure (C)	STARt Score (T) per Threat (t) (Agroforestry)
Aburria aburri	0.44	100	5.3.3	Majority (50-90%)	2	Slow, Significant Declines	1	9	0.33	14.58
Aburria aburri	0.44	100	5.1.1	Majority (50-90%)	2	Slow, Significant Declines	1	9	0.33	14.58
Aburria aburri	0.44	100	2.1.3	Majority (50-90%)	2	Negligible Declines	0	0	0.00	0

Species (s) Scientific Name	Population Proportion in AOI (P)	RL Status Weight (W)	Threat Code		Threat Scope Score		Reduction in Threat Severity Score (Actual to Agroforestry)	Reduction in Average Projected Population Decline (Actual to Agroforestry)	Relative Threat Pressure (C) (Abated)	STARt Score (T) per Threat (t) (Achieved)
Aburria aburri	0.44	100	5.3.3		2		0	0	0.00	0.00
Aburria aburri	0.44	100	5.1.1		2		0	0	0.00	0.00
Aburria aburri	0.44	100	2.1.3		2		1	9	0.33	14.58

Note. This table shows example calculations for threat severity impact score modification, mean projected population decline, and STARt scores (Actual, Agroforestry, and Achieved) for *Aburria aburri*. Red highlighted cells show modified values for the Agroforestry condition and subsequent values for reduction in mean projected population decline and Achieved STARt scores.

Table 4

Example of Calculated Values Per Threat Category

Scenario 1							
Threat Code	Threat Category (t)	Average Projected Population Decline (%)		Total STARt Score (T)	Achieved STARt Score	Remaining STARt Score
		"Actual"	"Agroforestry"			
2.1.1	Shifting Agriculture	0.00	0.00	0	0	0
2.1.2	Small-holder farming	14.67	12.00	765	607	158
2.1.3	Agro-industry farming	9.00	3.00	1510	1032	478
2.1.4	Scale Unkown/Unrecorded	5.00	54.00	566	566	0
2.2.1	Small-holder Plantations	9.00	110.00	73	73	0
2.2.2	Agro-Industry Plantations	5.00	122.00	121	121	0
2.2.3	Scale Unknown/Unrecorded	14.67	14.00	233	185	47
2.3.1	Nomadic grazing	0.00	0.00	0	0	0
2.3.2	Small-holder grazing, ranching or farming	14.67	13.00	894	720	174
2.3.3	Agro-industry grazing, ranching or farming	7.00	5.00	1586	1176	410
2.3.4	Scale Unknown/Unrecorded	0.00	50.00	0	0	0
2.4.1	Subsistence/Artisinal Aquaculture	0.00	0.00	0	0	0
2.4.2	Industrial Aquaculture	0.00	0.00	0	0	0
2.4.3	Scale Unknown/Unrecorded	0.00	0.00	0	0	0

Note. This table shows example mean projected population decline and STARt calculations for agricultural threats (t) in Scenario 1, summed across all study species (s).

Calculating "Agroforestry" STARt Scores Using the Modified STAR Metric (Steps 9-10). To construct the alternative "Agroforestry" land use models for each scenario, I used the modified mean projected population decline values based on the altered severity scores as described above. Additionally, I used the same STARt equation shown above but altered the relative threat pressure (C) component of the STARt calculation as follows. I divided the average population decline values for the "Agroforestry" conditions by the summed values from the "Actual" conditions for each species rather than summing the average population decline values across threats for each species, then dividing the individual scores by that sum to obtain relative threat pressures (see Appendix for example calculation). Subsequently, the relative threat pressures did not necessarily sum to 1, but often summed to less than 1. This modification alters the total estimated STARt score summed across species and threats to reflect the expected effect of converting agriculture to agroforestry by reducing relevant threat severity scores. If this step were not taken, the final summed STARt score would be the same for the "Actual" and "Agroforestry" conditions because of the way threats are scaled in the equation. This modification allows the STAR metric to be used to model the potential benefits of conservation interventions that act on specific threats but that do not necessarily resolve all threats facing a species in a region.

Calculating "Achieved" STARt Scores With a Modified STAR Metric (Steps 9-10). To construct the expectations of how species benefit from agroforestry land use, I calculated "Achieved" STARt scores across threats, which represents the theoretical benefit gained by agroforestry implementation in the study system. To do this, I subtracted the "Agroforestry" STARt score for each individual species from that species' "Actual" STARt score, in each scenario. This "Achieved" STARt measure should be understood as a theoretical ideal "Realised" STARt measure. "Realised" STAR scores are "ex-post," or scores that represent actual gains or losses accrued by a conservation intervention after it has been implemented in the AOI (IBAT, 2021). In other words, "Realised" STAR aims to track and verify an intervention's effects on biodiversity over time. "Achieved" STARt, as presented in this thesis, is essentially a theoretical prediction of the "Realised" STARt score that could be achieved by abating a specific threat under ideal conditions. Importantly, "Achieved" STARt scores are what I use to predict and map the areas where biodiversity would benefit the most from intervention.

Raster Creation and Analysis (Steps 11-12). For each scenario, I calculated the difference in STARt scores for each threat between the "Agroforestry" condition and the "Actual" condition to estimate an "Achieved" STARt score representing the benefit of the agroforestry implementation. All calculations and analyses were performed in Microsoft Excel (Version 2307), RStudio (Version 2023.06.1+524), and ArcGIS Pro (Version 3.1).

To estimate the spatially explicit distribution of expected biodiversity returns from different agricultural land use choices, I created rasters that applied the calculations described above across the AOI for each scenario. For each scenario, I generated 100 meter resolution rasters for each of my 131 species for the following 6 measures: mean projected population decline for the "Actual" condition, mean projected population decline for the "Agroforestry" condition, reduction in mean projected population decline between "Actual" and "Agroforestry" conditions, STARt score for the "Actual" condition, STARt score for the "Agroforestry" condition, and "Achieved" STARt score. To create these, I used the AOH rasters from Lumbierres et al. (2022), clipped to each scenario's respective AOI extent, as baseline rasters. The pixels representing a species' AOH all originally held a value of one, while pixels outside the AOH boundaries held a value of zero. I changed all pixels with "zero" values to "No Data" so that I would be able to differentiate between values of zero that I purposefully calculated from those that Lumbierres et al. (2022) originally used to classify their rasters. All values of one were changed to reflect the reclassifications described in detail below. In total, I created 131 rasters for each of the 6 listed measures within each of the three scenarios, for a total of 18 sets of 131 reclassified species AOH rasters (or 2,358 reclassified AOH rasters in total). In this case, "reclassifying" a raster means changing its pixel values and refers to the software command I used.

To create the three raster sets in each scenario representing mean projected population decline measures, I reclassified each species' baseline AOH raster three times. I used each species' respective mean projected population decline value across threats to reclassify the rasters. For the "Actual" condition's raster, I used the mean projected population decline value I previously calculated for the species under that condition. Subsequently, each pixel value that previously was 1 in the AOH was set to be equal to the overall mean projected population decline percentage for the species under the "Actual" condition. I then performed the same process for each species using the "Agroforestry" condition and its respective average population decline percentages, generating my second set of rasters. Finally, I performed the same process for each species, this time using the reduction in mean projected population decline from the "Actual" to the "Agroforestry" condition that I calculated for each species. In total, this made 9 sets of 131 rasters, with 3 sets for each scenario.

To create the three raster sets in each scenario representing each STARt measure, I again reclassified each species' baseline AOH raster three times. Unlike the population decline rasters, I did not make the raster values equivalent to each species' total estimated STARt score. Instead, I individually divided each species' total "Actual," "Agroforestry," and "Achieved" STARt scores by the number of pixels from its AOH raster that overlapped with the AOI. For instance, a total estimated STARt score of 400 for a species whose AOH overlaps with the AOI by 100 pixels would result in pixel values of 4. This accounted for the size of a species AOH in how it is weighted in raster creation for

STARt scores. In other words, it weighted species with restricted ranges more heavily than those with expansive ranges. For the “Actual” condition’s raster, I used this calculated pixel value for each species to reclassify each species’ baseline raster. This step, following from Mair et al. (2021), reflects the size of each species AOH in the STARt raster values and is particularly important for depicting the relative weight endemic species contribute to STARt scores. For the second set of rasters in each scenario, I performed the same process for each species under the “Agroforestry” condition using that species’ “Agroforestry” STARt scores. Finally, I performed the same process for each species, this time using the “Achieved” STARt scores for each species to produce my third set of rasters in each scenario. In total, this made 9 sets of 131 rasters, with 3 sets for each scenario.

I then mosaiced the reclassified AOH rasters for each scenario condition across 131 species to produce six final rasters for each scenario. The mosaic function in ArcGIS Pro (Version 3.1) merges rasters and performs calculations on overlapping pixels to produce a single, final raster. For the sets of rasters reclassified using mean projected population decline, I used the “Mean” function to mosaic each set of rasters to produce a spatially explicit estimate of the mean population decline across the 131 bird species at the 100m resolution. For the sets of rasters reclassified using STARt scores, I used the “Sum” function to mosaic each set of rasters and produce a spatially explicit estimate of the total expected opportunity for threat reduction available for the 131 bird species (e.g. STARt scores) at a 100 meter resolution. Within these rasters, the STARt value varies from pixel to pixel based on which species’ AOH files overlap. This last, crucial step produced 18 final rasters–6 for each scenario, to reflect the 6 measures described above–which are key deliverables for this study.

These rasters resulted in detailed, interactive TIFF files that could be summarized and compared to one another to understand how the study system and its bird biodiversity would be expected to fare if agroforestry was or was not widely present. I used them to explore the regions where agroforestry would be expected to yield the greatest benefit to threatened and near threatened birds in the Peruvian Amazon. To do so, I overlaid the first-level country subdivision administrative boundaries of Peru over 1) the reduction in mean projected population decline raster and 2) the achieved STARt raster for each scenario. I then used zonal statistics in ArcGIS Pro to calculate the 1) mean reduction in mean projected population decline and 2) sum Achieved STARt value for each administrative region for each scenario. I also used zonal statistics to calculate total STARt values per region for the "Actual" and "Agroforestry" conditions in each scenario. Finally, to calculate the benefit of converting agriculture to agroforestry in each region, I divided the "Achieved" STARt value for each region by its "Actual" STARt value, then converted this decimal to a percentage. This percentage can be used to understand the benefit of agroforestry to my study species, as it is less arbitrary and more intuitive than Achieved STARt values.

I then ranked the administrative regions based on which would yield the highest benefits to biodiversity if agroforestry were to be implemented on a mass scale. The regions that occur in the Peruvian Amazon are ranked such that higher rankings indicate greater biodiversity benefits based on the relevant metric (e.g. projected population decline or STAR). All seventeen regions that occur in the Peruvian Amazon were ranked in Scenarios 1 and 2; Apurimac is excluded from the Scenario 3 rankings, as agricultural areas have not been officially recorded there by The Ministry of Environment of Peru. I explored how rankings differed by condition and scenario, to understand how modifications to the STAR metric will affect its output.

Finally, using the total STARt scores that I calculated for each threat and each species in Scenario 1's Actual condition, I ranked each threat category and each species based on how much they contributed to the total STARt score for that condition. I then graphically displayed these ranks to explore how much benefit addressing each threat and each species would yield, based on the current, "real world" data hosted by the IUCN Red List.

RESULTS

Contribution of Individual Threats and Species to STARt Scores. In the Peruvian Amazon, some threats stand out as particularly egregious for the imperiled birds in my study. The most severe threat to these species was agriculture, according to their IUCN RedList assessments (Figure 6). In particular, agro-industry farming of annual and perennial non-timber crops and agro-industry livestock farming and ranching were the two most significant threats, although smallholder impacts were by no means negligible.

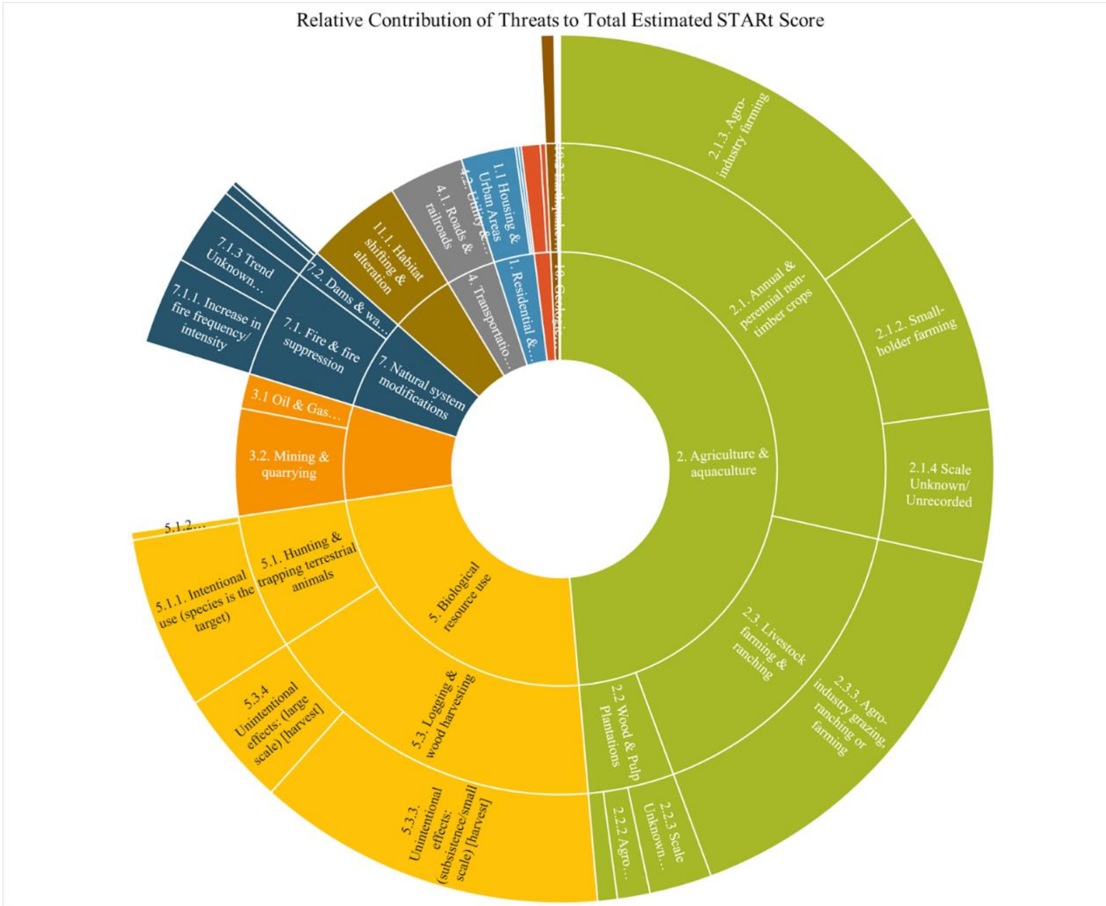

Figure 6. Relative contribution of threats to total estimated STARt score for "Actual" condition in Scenario 1*,* representing the current real world situation according to the STAR metric.

Some species contributed relatively more to the total estimated STARt score in my study region. In other words, certain species–due to restricted AOH extent or Red List status (e.g. risk of extinction), or both–contribute relatively more to the total estimated STARt scores produced in each scenario. This ranking reflects the data for the Actual condition in Scenario 1, which uses up-to-date, unmodified Red List data, thus representing the "real world" as it currently is. In particular, the endemic, critically endangered species *Cinclodes palliatus*, *Synallaxis maranonica*, and *Pauxi koepckeae* contribute the most to the total estimated STARt score (Figure 7). Notably, these species are all threatened by agriculture. This demonstrates how species that are more imperiled or that are endemic within the AOI are weighted more heavily when using the STAR metric.

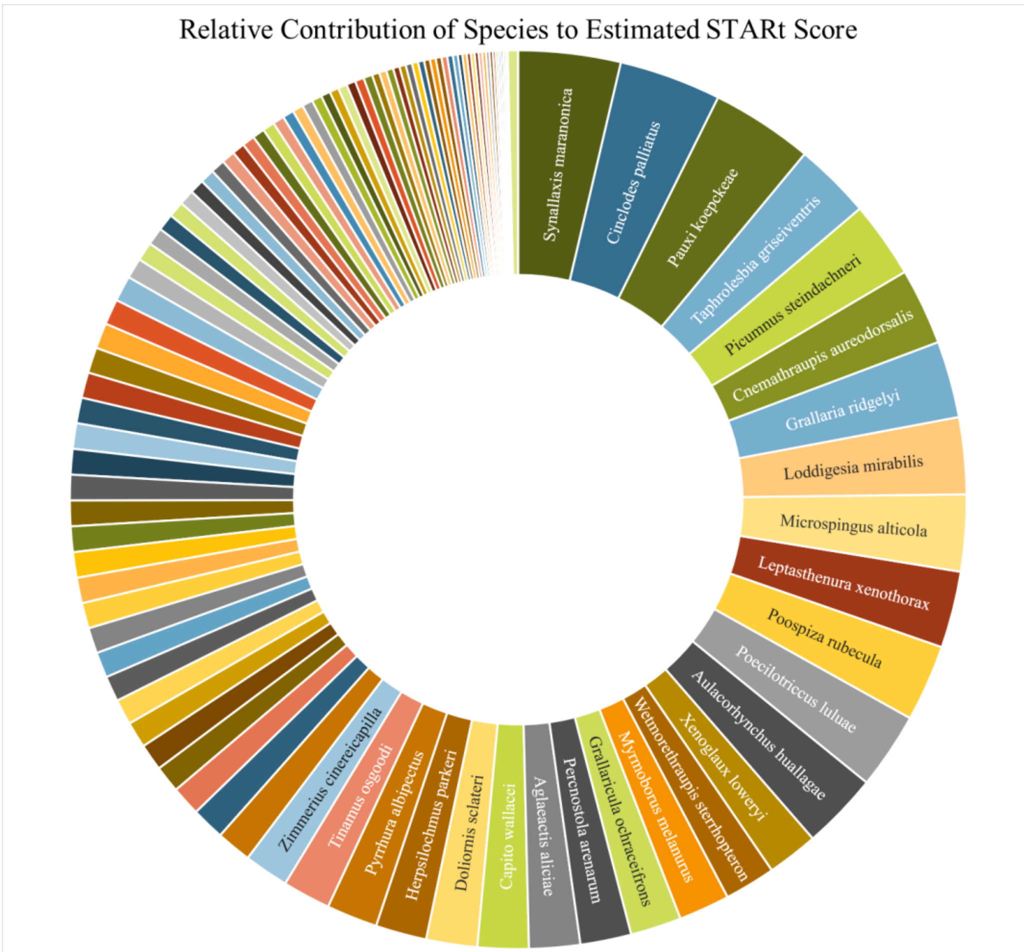

Figure 7. Relative contribution of species to total estimated STARt score for the "Actual" condition in Scenario 1, representing the current real world situation according to the STAR metric and the most up to date IUCN Red List data for my study species.

Scenario 1 Results. In this scenario, my AOI was the Peruvian Amazon and I incorporated threat data for my study species from all twelve of the IUCN's major threat categories into my analysis. The Actual condition for this scenario represents the STAR metric in its traditional, unmodified form. The mean projected population decline range for imperiled Peruvian Amazon bird species was 7.76%, with a range of 1.25% to 20.01%, according to my “Actual” condition calculations. Implementation of agroforestry would reduce this mean to 4.32%, with a range of 0.01% to 14.67%, according to my “Agroforestry” condition calculations. The expected reduction in mean projected population decline for the studied birds was 3.44%, ranging from 0% to 11.15%, with variation in where the benefits occur. In some areas–particularly the northwestern Amazon–as high as an 11.15% reduction in mean projected population decline across threatened bird species was estimated to be achieved through agroforestry (Figure 8).

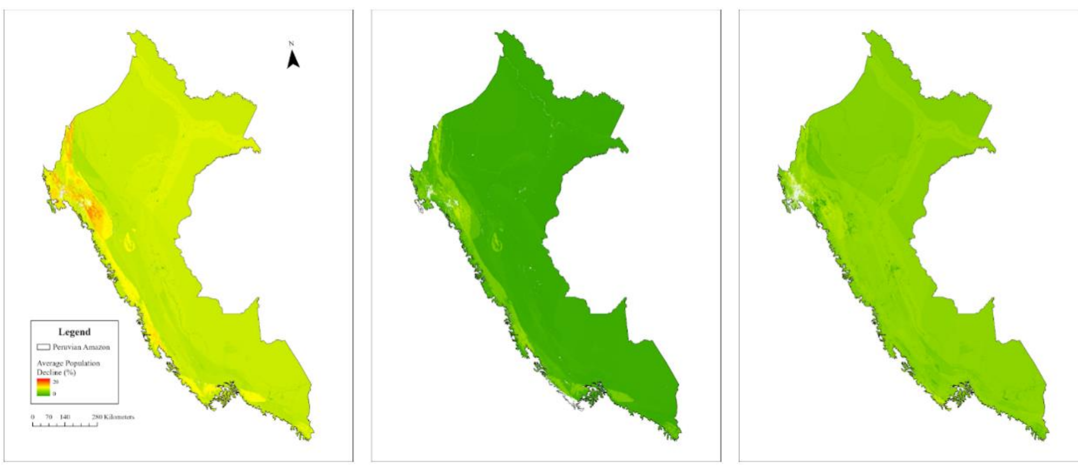

Figure 8. From left to right, mean projected population decline for 1) Actual condition, 2) Agroforestry condition, and 3) reduction from Actual to Agroforestry condition in Scenario 1.

In my maps of the STAR metric, a higher value indicated a greater potential for benefit to biodiversity if threats were abated. In the Actual condition, the maximum pixel STARt value was 0.85, again occurring in the northwestern portion of the region, though high STARt values were present in the entire western half of the region. The STARt scores in the Agroforestry condition were much lower, with a maximum STARt value of only 0.28. These values represented the theoretical remaining contribution of threats to species status after agroforestry implementation in the region. The Achieved STARt values (difference between the Actual to Agroforestry condition)–which in some areas was as high as 0.57–suggest the benefit conferred by agroforestry (Figure 9). These scores are only meaningful when compared to one another, both within and across conditions. Though these values may appear small, this is only because the rasters have a very fine resolution of 100 meters. Aggregating the rasters to a coarser resolution would yield higher values per pixel, but would not change the total estimated STARt scores calculated for each condition.

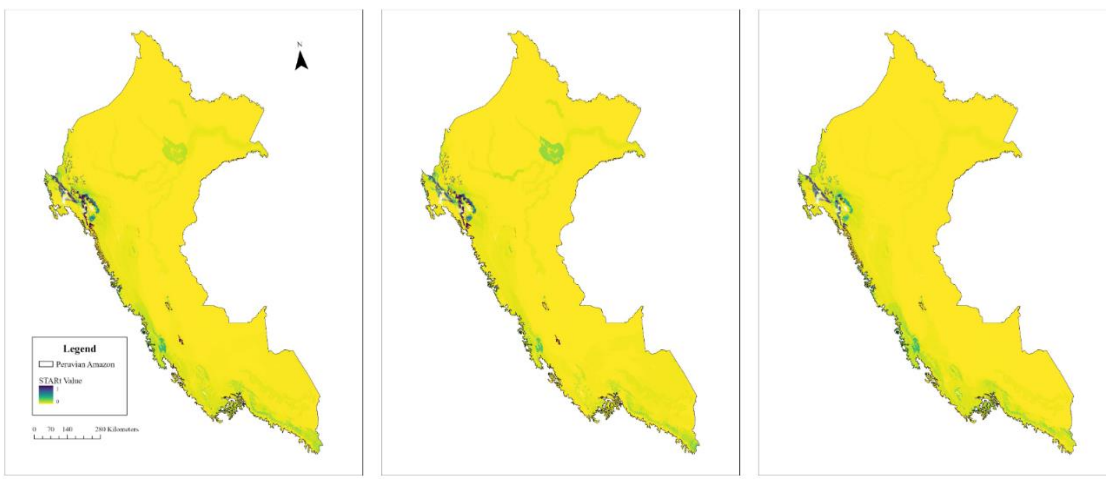

Figure 9. Total estimated STARt scores for imperiled birds in the Peruvian Amazon representing, from left to right, 1) the Actual condition, 2) the Agroforestry condition, and 3) Achieved STARt scores in Scenario 1.

Scenario 2 Results. For Scenario 2, my AOI was the Peruvian Amazon and I only incorporated threat data for the IUCN's agriculture threat category into my analysis. The Actual condition in this scenario again represents the STAR metric in its traditional form, with the exception that this scenario exclusively considers agricultural threats and is therefore “disaggregated” in a way that Scenario 1 is not. The mean projected population decline range for imperiled Peruvian Amazon bird species was 7.76%, with a range of 1.25% to 19.96%, according to my “Actual” condition calculations. Implementation of agroforestry would reduce the mean to 4.32%, with a range of 0.09% to 14.67%, according to my “Agroforestry” condition calculations. The expected reduction in mean projected population decline for the studied birds was 3.44%, ranging from 0% to 11.15%, with variation in where the benefits occur. In some areas–particularly the northwestern Amazon–as high as an 11.15% reduction in mean projected population decline across threatened bird species was estimated to be achieved through agroforestry (Figure 11).

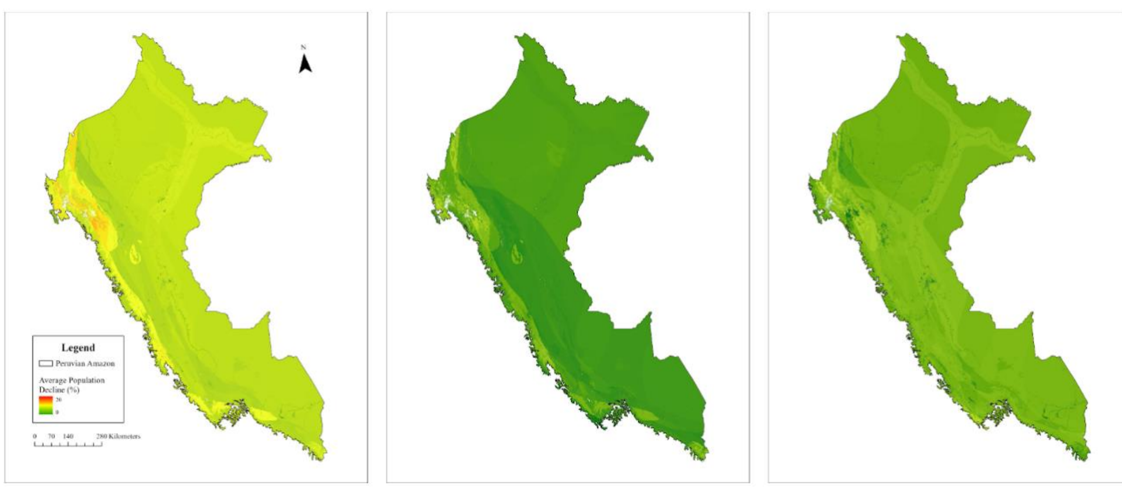

Figure 10. From left to right, mean projected population decline for 1) Actual condition, 2) Agroforestry condition, and 3) reduction from Actual to Agroforestry condition in Scenario 2.

In the Actual condition, the maximum STARt value was 1.14, again occurring in the northwestern portion of the region, though high STARt values were present in the entire western half of the region. The STARt scores in the Agroforestry condition were much lower, with a maximum STARt value of only 0.007. These values represented the theoretical remaining contribution of threats to species status after agroforestry implementation in the region. The reduction in total estimated STARt values from the Actual to Agroforestry condition is again as high as 0.57 in some areas (Figure 11). The "Achieved" STAR values are consistent across Scenarios 1 and 2. The major difference lies in the total estimated STARt score map and the remaining STARt map, which represents what threats are "leftover" after agroforestry implementation and must still be resolved.

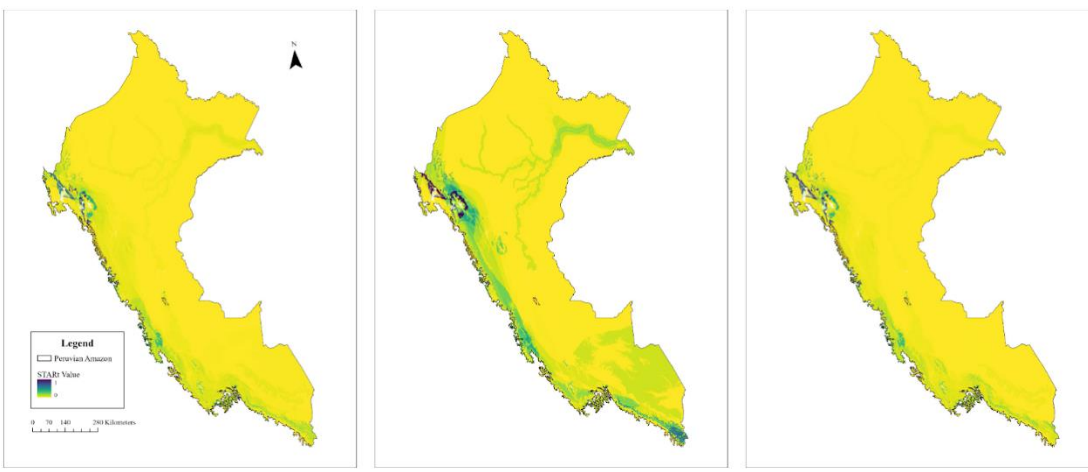

Figure 11. Total estimated STARt scores for imperiled birds in the Peruvian Amazon representing, from left to right, 1) the Actual condition, 2) the Agroforestry condition, and 3) Achieved STARt scores in Scenario 2.

Scenario 3 Results. For Scenario 3, my AOI was recorded agricultural areas in the Peruvian Amazon and I only incorporated threat data for the IUCN's agriculture threat category into my analysis. Importantly, the AOI in this scenario is modified such that it only considers the extent of recorded agricultural areas, which is a modification from the original STAR metric. The mean projected population decline range for imperiled Peruvian Amazon bird species was 7.36%, with a range of 0% to 27.28%, according to my "Actual" condition calculations. Implementation of agroforestry would reduce the mean to 1.69%, with a range of 0% to 14.67%, according to my "Agroforestry" condition calculations. The expected reduction in mean projected population decline for the studied birds was 5.65%, with a range from 0% to 18.68%, with variation in where the benefits occur. As high as an 11.15% reduction in mean projected population decline across imperiled bird species was estimated to be achieved through agroforestry (Figure 12).

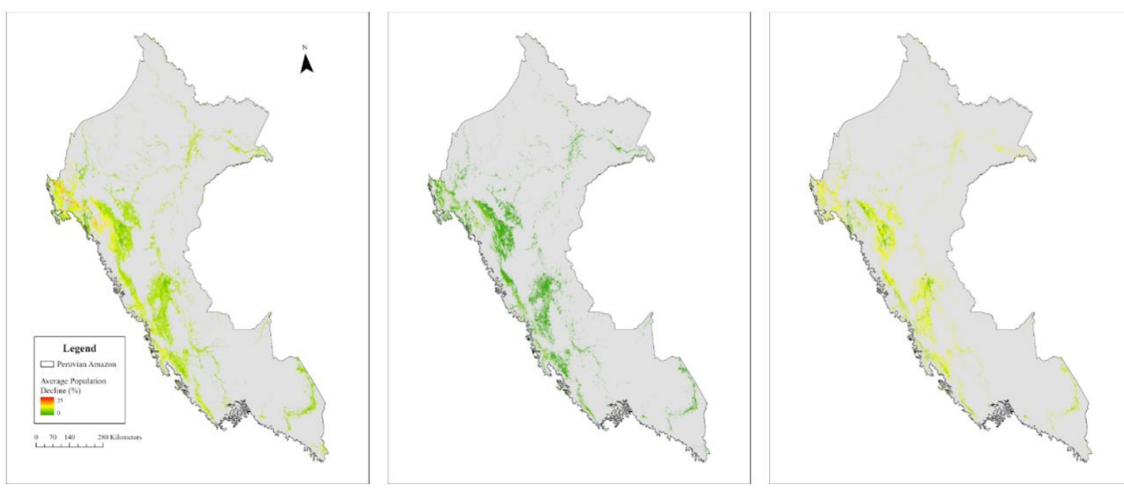

Figure 12. From left to right, mean projected population decline for 1) Actual condition, 2) Agroforestry condition, and 3) reduction from Actual to Agroforestry condition in Scenario 3.

In the Actual condition, the maximum STARt value per pixel was 1.7, again occurring in the northwestern portion of the region, though high STARt values were present in the entire western half of the region. The STARt scores in the Agroforestry condition were much lower, with a maximum STARt value per pixel of only 1.01. These values represented the theoretical remaining contribution of threats to species status after agroforestry implementation in the region. The reduction in total estimated STARt values from the Actual to Agroforestry condition is as high as 0.85 in some pixels (Figure 13).

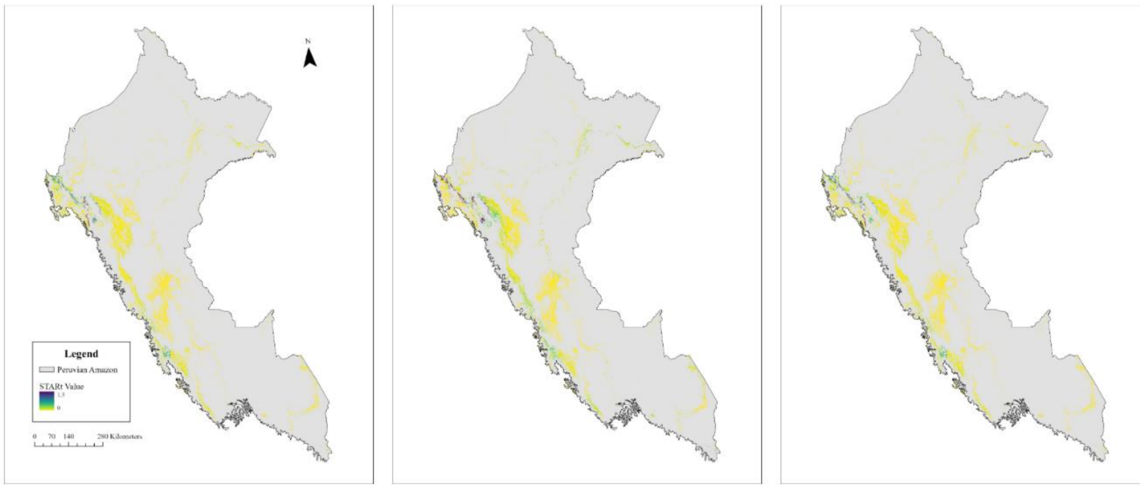

Figure 13. Total estimated STARt scores for imperiled birds in the Peruvian Amazon representing, from left to right, 1) the Actual condition, 2) the Agroforestry condition, and 3) Achieved STARt scores in Scenario 3.

Region Prioritization Results. Based on the mapped Achieved STARt results for all three scenarios, the greatest opportunity for threatened bird biodiversity protection appears to be in the western portion of the Peruvian Amazon, followed by the southern portion of the area. Three particular “hotspots” are identifiable in Scenarios 1 and 2: 1) around the border between Amazonas and San Martin, 2) bisecting Huanuco, Pasco, and Junin, and 3) along the southwestern border of Madre de Dios. Scenario 3 only exhibits high STARt scores around the first two of the listed “hotspots.” The first two spots notably occur in areas where extensive agriculture has been documented by the Peruvian government. The third spot in Madre de Dios does not significantly overlap with recorded agricultural land, so when the AOI is restricted to the extent of agricultural activity–as was done in Scenario 3–it no longer presents as an area that would accrue meaningful potential benefit from agroforestry implementation.

The final region rankings indicate which regions in the Peruvian Amazon would benefit the most from agroforestry implementation (Table 5). The rankings are different based on the metric used, meaning that using mean projected population decline to rank the regions yields a different order than using achieved STARt score. Moreover, for each metric, rankings differ between scenarios.

Ranking the regions based on mean reduction in mean projected population decline yields fairly variable results between scenarios, with Ayacucho, Apurimac, and Cajamarca emerging as the top ranked regions for Scenarios 1, 2, and 3, respectively. Some regions, such as San Martin, Ucayali, Pasco, and Cajamarca consistently occur in the top half of the rankings across scenarios.

Ranking the regions based on sum Achieved STARt score yields more consistent results across scenarios, with Amazonas emerging as the most consistently top ranked region for all three scenarios. Notably, the rankings for Scenarios 1 and 2 are the same. The ranking for Scenario 3 differs, but some regions consistently rank in the top 50% across scenarios, including Cajamarca, Junin, San Martin, Huanuco, and Pasco. Others consistently occur in the bottom 50%, including Apurimac, Lambayeque, and Huancavelica.

Table 5

Region Prioritization Rankings

Mean % Reduction in Average Projected Population Decline, Ranked Greatest to Least						Sum Achieved STARt Score, Ranked Greatest to Least					
Scenario 1		Scenario 2		Scenario 3		Scenario 1		Scenario 2		Scenario 3	
Rank	Name	Rank	Name	Rank	Name	Rank	Name	Rank	Name	Rank	Name
1	Ayacucho	1	Apurimac	1	Cajamarca	1	San Martin	1	San Martin	1	Amazonas
2	San Martin	2	Ayacucho	2	Loreto	2	Amazonas	2	Amazonas	2	Cajamarca
3	Ucayali	3	San Martin	3	Ucayali	3	Cusco	3	Cusco	3	Junin
4	Pasco	4	Ucayali	4	Puno	4	Junin	4	Junin	4	San Martin
5	Madre de Dios	5	Pasco	5	Junin	5	Huanuco	5	Huanuco	5	Huanuco
6	Cajamarca	6	Madre de Dios	6	Pasco	6	Cajamarca	6	Cajamarca	6	Pasco
7	Amazonas	7	Cajamarca	7	San Martin	7	Loreto	7	Loreto	7	Piura
8	Huanuco	8	Amazonas	8	Huanuco	8	Pasco	8	Pasco	8	Ayacucho
9	Cusco	9	Huanuco	9	Amazonas	9	Madre de Dios	9	Madre de Dios	9	Loreto
10	Loreto	10	Cusco	10	Madre de Dios	10	Puno	10	Puno	10	Ucayali
11	Puno	11	Loreto	11	Cusco	11	Ucayali	11	Ucayali	11	Cusco
12	Junin	12	Puno	12	Piura	12	La Libertad	12	La Libertad	12	Lambayeque
13	La Libertad	13	Junin	13	Ayacucho	13	Ayacucho	13	Ayacucho	13	Madre de Dios
14	Huancavelica	14	La Libertad	14	Huancavelica	14	Piura	14	Piura	14	Puno
15	Piura	15	Huancavelica	15	Lambayeque	15	Huancavelica	15	Huancavelica	15	Huancavelica
16	Lambayeque	16	Piura	16	La Libertad	16	Lambayeque	16	Lambayeque	16	La Libertad
17	Apurimac	17	Lambayeque			17	Apurimac	17	Apurimac		

Note. This table shows my ranking of priority regions for each scenario.

To better understand the benefits represented by “Achieved” STARt, I calculated the benefit percentage that “Achieved” STARt represents for each scenario. A higher percentage indicates a higher magnitude change from the total “Actual” STARt value across regions to the “Agroforestry” STARt value across regions. In other words, a higher benefit percentage a greater benefit from converting to agroforestry.

Table 6

Benefit of Agroforestry, Represented as Percentage

Scenario 1			
Sum STARt Score			Benefit Across Regions (%)
"Actual"	"Agroforestry"	Achieved	
10882.99	6401.88	4481.11	41%

Scenario 2			
Sum STARt Score			Benefit Across Regions (%)
"Actual"	"Agroforestry"	Achieved	
5748.33	4481.11	4481.11	78%

Scenario 3			
Sum STARt Score			Benefit Across Regions (%)
"Actual"	"Agroforestry"	Achieved	
4083.71	696.40	3387.31	83%

Note. This table shows the benefit of moving from the "Actual" to "Agroforestry" condition for each scenario, expressed as a percentage and highlighted in green. This percentage is obtained by dividing the "Achieved" STARt score by the "Actual" STARt score for each scenario.

When mapped spatially, sum achieved STARt score rankings for Scenario 3 demonstrate that the greatest benefit to bird biodiversity from agroforestry implementation can be achieved in the western Peruvian Amazon, particularly Amazonas and Cajamarca (Figure 14). Considerable bird biodiversity benefits would also be gained through interventions that promote agroforestry in in Junin, San Martin, Huanuco, and Pasco. The final map in Figure 14 makes the results shown in Figure 13 more digestible by demonstrating which regions have the highest collective STARt scores.

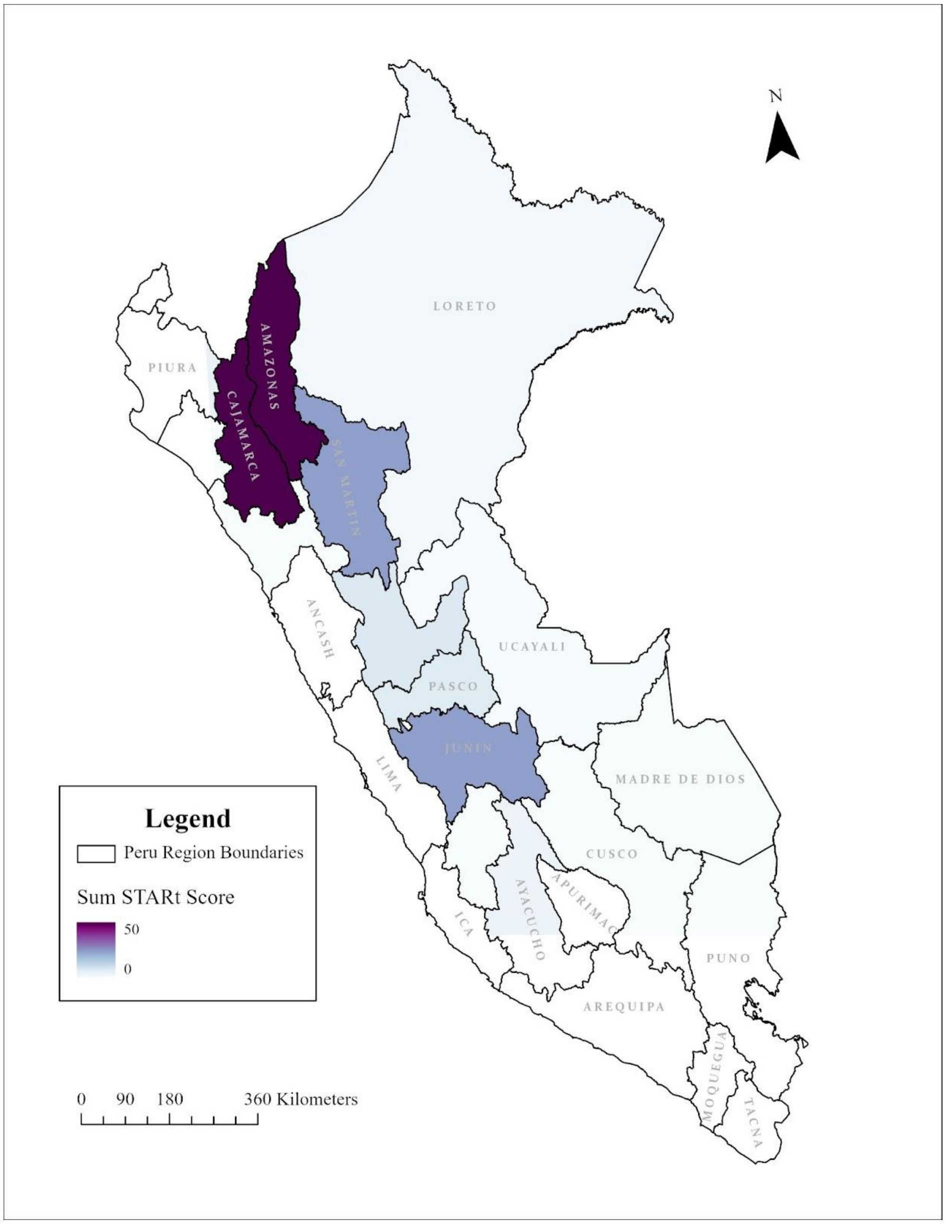

Figure 14. Spatial ranking of regions by priority, using the "Achieved" STARt values for Scenario 3.

DISCUSSION

Benefit of Agroforestry to Imperiled Birds in the Peruvian Amazon. My results demonstrate where agroforestry is likely to yield the greatest benefit to imperiled bird biodiversity in the Peruvian Amazon. My results not only show where the greatest biodiversity benefits from agroforestry implementation can be expected, but also elucidate differences in those expected benefits from place to place. This standardization–for both mean projected population decline and STARt scores–means regions can meaningfully be compared to one another during analysis. From a decision making perspective, this standardization is critical. Although I present my final results at a regional scale, the underlying data rasters can just as easily be analyzed using smaller administrative scales (e.g. at the province or district level), based on the needs of decision makers.

Amazonas consistently stands out as the region that would produce the most bird conservation benefit if agroforestry was promoted, which logically follows when population and land use trends are considered. The key characteristics that cause Amazonas to stand out are its agriculture patterns and number of highly imperiled species. A relatively high proportion of Amazonas' land in the Amazon is also covered by agriculture–almost 10%–meaning there is more opportunity to abate this threat (Table 1; MINAM, 2018). Finally, Amazonas contains one of the four critically endangered endemic bird species included in this thesis' dataset (*Synallaxis maranonica*). Additionally, regions in the western Peruvian Amazon, like Amazonas, generally have larger human populations and greater human population density, which is likely contributing to the scale and intensity of agriculture occurring in these areas (INEI, 2017). In combination, these factors cause Amazonas to rank highly in potential benefit to imperiled birds from agroforestry implementation. Other regions that rank in the top 50%–such as Cajamarca, San Martin, and Junin–display similar trends across these categories. Collectively, these regions all occur in the western Peruvian Amazon, which is closer to major population centers than the eastern Peruvian Amazon.

From a decision making perspective, these results can help conservationists, policy makers, and other critical stakeholders direct their efforts towards targeted interventions in the top-ranked regions. Conservationists and local communities can also point to these results to justify investment in Peruvian Amazon communities, particularly through sustainable agriculture initiatives. The prioritization rankings do not indicate that action should not be taken in regions that rank lower (e.g. Lambayeque, Madre de Dios), but that these regions are currently experiencing less severe and immediate threats to imperiled bird biodiversity due to agriculture. The raster that depicts Actual STARt scores in Scenario 1 shows that imperiled bird biodiversity in Madre de Dios would meaningfully benefit from conservation action (Figure 9). However, Achieved STARt scores for Scenario 1 show limited benefit in this region as a result of agroforestry implementation. Meaningful threats to biodiversity are present in Madre de Dios and other regions ranked lower in my results (Table 5, Figure 14), but they are not agricultural in nature and are thus not ones that can be resolved through agroforestry.

In light of limited resources for abating agriculture-related threats are limited, they would likely best be spent in the regions identified in the west (e.g. Amazonas) (Figure 14). However, the complexity of this system cannot be ignored. Although I have identified regions that should be prioritized for agroforestry implementation in this thesis, conservationists must understand that all of these regions are interconnected and highly dependent on one another. Bird biodiversity in Amazonas affects bird biodiversity in La Libertad, and vice versa. Ultimately, effective conservation planning means implementing solutions at multiple scales and acknowledging the complexity and coupling of the systems within which we work.

Mechanisms Behind Scenario Prioritization Outcomes. Across scenarios, the benefit of converting agricultural land to agroforestry across regions was as high as 83% (Table 6). The benefit percentages were 41% for Scenario 1, 78% for Scenario 2, and 83% for Scenario 3. The value for Scenario 1 is much lower than the others because the total estimated STARt score for the “Actual” condition included STARt calculations for all threats, whereas the “Achieved” STARt score only represented change to agricultural threats. However, in Scenarios 2 and 3, only agricultural threat data was used. These results emphasize why using the STAR metric to analyze individual, disaggregated threats can be useful. Additionally, representing the overall benefit as a percentage, rather than an arbitrary “Achieved” STARt score, may help decision makers better understand and interpret the results I have presented.

The differences in prioritization rankings for the regions is a result of the different calculation mechanisms shown in the Methods. These differences offer important insight into how the metrics chosen by conservationists can affect conservation decision making. Whether conservation decision makers use projected population decline or STARt scores to plan their interventions depends on their goals. Mean projected population decline may offer an acceptable understanding of biodiversity loss in the region, particularly if conservationists are concerned exclusively with population decline, irrespective of endemism and Red List status. In some decision making scenarios, this level of analysis may be sufficient or even desired. However, when relying exclusively on projected population decline as a metric, the lack of consideration for population proportions in the

AOI and Red List status of species could be deficiencies in many decision making situations for conservationists.

The traditional usage of the STAR metric, and my associated rankings, overcomes these deficiencies by accounting for endemism and species threat status. My modified usage of the STAR metric goes further by considering threats independently and restricting the AOI to the spatial extent of the threat (e.g. agriculture). The traditional STAR metric allows conservation decision makers to consider how imperiled species are within a given area in their intervention planning calculus, which is critical if those decision makers are not only concerned with overall population decline, but with directing resources towards species that are the most imperiled. My modified version of the STAR metric goes further by restricting the metric's analysis to areas where the threat is actually occurring. For decision making purposes, this is critical, as it ensures that regions where agricultural threats actually occur are weighted more heavily in the region rankings than those where agriculture is sparse.

Ultimately, the rankings for Achieved STARt scores in Scenario 3 are likely to be better than that of Scenarios 1 and 2 for decision making purposes, as the spatial analysis allows more precision and accuracy with regards to the extent of agricultural threats. Although the region rankings do not meaningfully vary between Scenarios 1 and 2, the rasters for Scenario 2 would be more helpful than those of Scenario 1 for decision making regarding agroforestry implementation, as they exclusively convey information about agricultural threats. However, Scenario 2 lacks the specificity in terms of threat extent and presence that Scenario 3 incorporates. Scenario 1 results would be most helpful to decision makers who are interested in the broader threats at play in the

Peruvian Amazon and would like to know how broad threat categories interact within the system. Of the rankings shown, the Scenario 3 ranking (and the associated rasters) offer the best visualization of potential bird biodiversity benefits from agroforestry in the Peruvian Amazon, as Scenario 3 incorporates spatially explicit threat information. Therefore, Scenario 3 likely offers the most useful results for the intended goals of this thesis.

Implications of Modified STAR Metric Usage. The results of this study show how the STAR metric can be modified to make threats spatially explicit and to model possible alternative scenarios. Although this analysis focused exclusively on the benefits of changing agricultural practices to benefit biodiversity–and modifying the STAR metric accordingly–the same methodology can be applied to other spatially explicit threats impacting species within and beyond the Peruvian Amazon. Ultimately, were all threats impacting threatened species within a given AOI made spatially explicit, the STAR metric would likely yield different yet more meaningful results, at least from a decision making perspective. The methodology outlined in this paper should be applied to other threats, taxons, and geographical contexts to refine it and confirm its usefulness. Moreover, on-the-ground ecological experiments could be carried out in the study region to verify my predictions and catalog the differences between the expected benefits I calculated for Achieved STARt, versus the real, post biodiversity benefits–measured as Realised STARt–that agroforestry would bring.

Overall, this analysis reinforces the utility of the STAR metric as a tool for conservation decision making. Broadly, this thesis also demonstrates how the level of spatial analysis (e.g. scale and extent) and the metrics chosen by conservation decision makers can affect research outputs and, subsequently, decision making and intervention outcomes. This is a well documented principle in landscape ecology that should be accounted for in conservation planning processes.

Obstacles to Uptake and Solutions. Although this analysis reinforces the potential benefits of agroforestry, government policies and perverse incentives likely stand in the way of voluntary widespread adoption of agroforestry in the Amazon (Pokorny et al., 2021). The Peruvian government may consider subsidization of sustainable agricultural practices to incentivize uptake and meet sustainability goals (Rode et al., 2023). However, such reworking of national agricultural policies risks being a politically arduous and slow process. In the absence of government subsidization, NGOs and private entities have the opportunity to fill this niche. Some pilot initiatives to promote agroforestry in the Amazon are underway, including Conservation International's Amazon Business Alliance, which seeks to promote green growth in the Peruvian Amazon and Amazonia more broadly (Conservation International, n.d.). However, the capacity and authority of non-governmental organizations is limited, preventing them from making the sweeping systemic changes necessary to prevent widespread bird biodiversity loss and ecological collapse in Peru's Amazon rainforest.

Outlining an evidence-based logic model for imperiled bird conservation in the Peruvian Amazon can help make conservation planning more efficient and effective and can demonstrate where my analysis using the STAR metric should be viewed in this region's broader conservation decision making context (Figure 15). Notice that the coupling of wildlife and human wellbeing become apparent when long-term outcomes are the focus: win-win solutions that protect wildlife while enhancing human wellbeing exist, but sufficient resources must be allocated by governing bodies to achieve these outcomes. If left unaddressed, biodiversity loss and habitat destruction will continue to degrade the ecosystem services upon which Amazonian communities depend. Considering how integral nature is to livelihoods in the Peruvian Amazon, the continual deforestation occurring in this region due to agriculture not only threatens wildlife, but in the long-term could have severe consequences for local communities.

Logic Model: Peruvian bird Conservation Through Agroforestry

Process			Outcomes		
Inputs	**Activities**	**Outputs**	**Short Term**	**Intermediate**	**Long Term**
Data collection for imperiled bird species that occur in the Peruvian Amazon.	Synthesis and analysis of data using the STAR metric.	Evidence-based recommendations on where bird conservation is most needed and would yield the greatest biodiversity return on investment.	Improved bird conservation planning and prioritization.	Implementation of evidence-based bird conservation recommendations in Peruvian Amazon communities.	Stabilization and increase of Amazonian bird populations in Peru.
Collection of peer-reviewed published research relevant to agroforestry in Amazonia.	Synthesis and analysis of current body of literature.	Evidence-based recommendations on where agroforestry could feasibly and profitably be implemented.	Uptake of recommendations by stakeholders and funding bodies.	Widespread conversion of agricultural systems to agroforestry in the Peruvian Amazon.	Increased biodiversity in the Peruvian Amazon.
Agricultural policy modification at multiple levels of government in Peru.	Government subsidization and private sector investment in Peruvian agroforestry programs.	Direct payments to and indirect benefits (e.g. tax breaks) for Peruvian farmers practicing agroforestry.	Voluntary uptake of agroforestry practices by Peruvian farmers.		Economic empowerment of smallholder farmers, improved food and job security, and reduced poverty.
	Educational programs targeting Peruvian farmers.	Low or no-cost educational workshops that engage Peruvian farmers and provide resources for human-wildlife conflict resolution, agroforestry implementation, biodiversity conservation, and ecosystem service importance .	Improvement in farmer knowledge related to wildlife and conservation.	Increased stakeholder engagement and desire to achieve coexistence with wildlife, especially apex predators.	
Resources allocated towards program evaluation by funding bodies.	Post facto program monitoring and evaluation.	Assessment of program efficiency and effectiveness. Answers the question: have program activities achieved their stated goals? If not, how should they be modified?	Understanding of program efficacy by administrators and funders (e.g. Peruvian government, NGOs).	Modification of program, where recommended by evaluators.	Improvement in Amazonian wildlife conservation practices.

Assumptions	Contextual Factors
Smallholder farmers would voluntarily uptake conservation and agroforestry practices if financially incentivized. birds and their prey populations would respond positively to agroforestry adoption in in deforested areas. Agroforestry is a viable livelihood alternative to current agricultural practices that would not result in a decrease in annual income or quality of life.	Expansion of agriculture into primary forest in the Amazon, rapid deforestation, illegal land uses (e.g. mining, logging, wildlife take, and prohibited crop production), megadiverse ecosystems, consistent population declines across bird species, loss of wildlife habitat necessary and feeding and breeding, human-wildlife conflict, predator persecution, ineffectual enforcement of environmental regulations.

Figure 15. *Logic Model for Peruvian Amazon Bird Conservation Through Agroforestry.* This logic model outlines the practical process needed to achieve the conservation outcomes outlined in the theory of change shown in Figure 3.

Despite these sociopolitical and economic barriers, conservation decision makers have the ability to uptake the STAR metric and the modifications I have presented here in their decision making and intervention planning processes. The results of analyses like the one presented here can bolster conservationists' arguments in favor of more biodiversity conscious, nature positive policies. My analysis, including the rasters I produced for each scenario, can create clarity for conservationists, policymakers, and other stakeholders on where agroforestry would be most likely to benefit bird biodiversity in the Peruvian Amazon. Moreover, my results can provide justification for investment in agroforestry and related community initiatives, particularly in the regions that ranked highest for mean achieved STARt scores as a result of agroforestry implementation (Figure 28).

Limitations. Some limitations are inherent to the STAR metric, and those limitations are reflected in this thesis. First, the STAR metric uses area of habitat (AoH) as a proxy for population. As a proxy, this is more precise than a species' range, as it accounts for elevation limits, habitat associations, and land cover; however, it fails to account for population density and may be less precise for migratory species' whose nesting, breeding, and resident AOH extents significantly differ. The STAR metric also traditionally has a habitat restoration component, STARr, which can be used to measure the potential benefit of habitat restoration to species within the AOI. However, for the purpose of this analysis, I did not calculate STARr scores, as I was primarily concerned with determining the potential threat abatement benefit of converting agriculture to agroforestry within the AOI.

Practical application of agroforestry as a conservation measure would also require that species and threat presences are verified within the AoI. A species does not necessarily have individuals occupying its entire AOH, nor are its threats distributed uniformly across that range. In some cases, particularly where illegal land use practices are occurring, the full extent of a threat may not be officially recorded or understood. Finally, some data involved with this analysis is up to 10 years old (e.g. IUCN Red List species assessments), meaning that incorporating more up-to-date data may change the case study results slightly. Models, though extremely helpful in research, planning, and decision making contexts, are ultimately simplified approximations of the real world. They should be used appropriately as tools, but must be accompanied by other data, knowledge, and expertise when making decisions in complex systems.

CONCLUSION

The Amazon rainforest is a unique landscape that hosts considerable biodiversity and provides invaluable ecosystem services. The Peruvian Amazon provides an illuminating regional case study due to its high rate of deforestation, enmeshment between people and wildlife, and projected human population growth. Agroforestry presents one alternative for achieving landscape sustainability while meeting the needs of people, but obstacles to implementation exist. Because the Amazon spans multiple countries, broader governance challenges persist. Ultimately, recovering bird populations in Peru's Amazon rainforest–and restoring biodiversity in the broader Amazonian landscape–will probably require targeted investment, cooperation between stakeholders, and careful evidence-based conservation planning. This process can be assisted and supported by the STAR metric and the modifications to it laid out in this thesis, which is in itself critical to quantifying return on investment for biodiversity.

REFERENCES

Arévalo-Gardini, E., Farfán, A., Barraza, F., Arévalo-Hernández, C. O., Zúñiga-Cernades, L. B., Alegre, J., & Baligar, V. C. (2021). Growth, Physiological, Nutrient-Uptake-Efficiency and Shade-Tolerance Responses of Cacao Genotypes under Different Shades. *Agronomy*, *11*(8), 1536. https://doi.org/10.3390/agronomy11081536

Bachman, S. P., Field, R., Reader, T., Raimondo, D., Donaldson, J. S., Schatz, G. E., & Lughadha, E. N. (2019). Progress, challenges and opportunities for Red Listing. *Biological Conservation*, *234*, 45–55. https://doi.org/10.1016/j.biocon.2019.03.002

Beillouin, D., Ben-Ari, T., Malézieux, E., Seufert, V., & Makowski, D. (2021). Positive but variable effects of crop diversification on biodiversity and ecosystem services. *Global Change Biology*, *27*(19), 4697–4710. https://doi.org/10.1111/gcb.15747

BirdLife International (BirdLife International). (2017). *IUCN Red List of Threatened Species: Hemitriccus cohnhafti*. IUCN Red List of Threatened Species. https://www.iucnredlist.org/species/103680575/112426729

BirdLife International. (2022, January 12). *New growth in Peru*. https://www.birdlife.org/news/2022/01/13/new-growth-in-peru/

Blare, T., & Donovan, J. (2016). Building value chains for indigenous fruits: lessons from camu-camu in Peru. *Renewable Agriculture and Food Systems*, *33*(1), 6–18. https://doi.org/10.1017/s1742170516000181

Bohada-Murillo, M., Castaño-Villa, G. J., & Fontúrbel, F. E. (2019). The effects of forestry and agroforestry plantations on bird diversity: A global synthesis. *Land Degradation & Development*, *31*(5), 646–654. https://doi.org/10.1002/ldr.3478

Bottrill, M. C., Joseph, L. N., Carwardine, J., Bode, M. F., Cook, C. N., Game, E. T., Grantham, H. S., Kark, S., Linke, S., McDonald-Madden, E., Pressey, R. L., Walker, S., Wilson, K. A., & Possingham, H. P. (2008). Is conservation triage just smart decision making? *Trends in Ecology and Evolution*, *23*(12), 649–654. https://doi.org/10.1016/j.tree.2008.07.007

Caro, T., Rowe, Z., Berger, J., Wholey, P., & Dobson, A. (2022). An inconvenient misconception: Climate change is not the principal driver of biodiversity loss. *Conservation Letters*, *15*(3). https://doi.org/10.1111/conl.12868

Carrete, M., Tella, J. L., Blanco, G., & Bertellotti, M. (2009). Effects of habitat degradation on the abundance, richness and diversity of raptors across

Neotropical biomes. *Biological Conservation*, *142*(10), 2002–2011. https://doi.org/10.1016/j.biocon.2009.02.012

Castro-Nunez, A. C., Villarino, M. E. J., Bax, V., Ganzenmüller, R., & Francesconi, W. (2021). Broadening the Perspective of Zero-Deforestation Interventions in Peru by Incorporating Concepts from the Global Value Chain Literature. *Sustainability*, *13*(21), 12138. https://doi.org/10.3390/su132112138

Clavo Peralta, Z. M., Vela Alvarado, J. W., & Alvez-Valles, C. M. (2022). Biodiversity Islands and Dominant Species in Agricultural Landscapes of the South Western Amazon, Perú. *Biodiversity Islands: Strategies for Conservation in Human-Dominated Environments*, 207–235. https://doi.org/10.1007/978-3-030-92234-4_9

Conservation International. (n.d.). *Amazon Business Alliance*. https://www.conservation.org/peru/iniciativas-actuales/amazon-business-alliance

De Beenhouwer, M., Aerts, R., & Honnay, O. (2013). A global meta-analysis of the biodiversity and ecosystem service benefits of coffee and cacao agroforestry. *Agriculture, Ecosystems & Environment*, *175*, 1–7. https://doi.org/10.1016/j.agee.2013.05.003

Dudley, N., & Alexander, S. (2017). Agriculture and biodiversity: a review. *Biodiversity*, *18*(2–3), 45–49. https://doi.org/10.1080/14888386.2017.1351892

Dumont, E. S., Bonhomme, S., Pagella, T., & Sinclair, F. (2017). Structured Stakeholder Engagement Leads to Development of More Diverse and Inclusive Agroforestry Options. *Experimental Agriculture*, *55*(S1), 252–274. https://doi.org/10.1017/s0014479716000788

European Space Agency. (2017). *Land Cover CCI Product User Guide Version 2*. ESA Climate Change Initiative. Retrieved June 1, 2023, from http://maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf

Fajardo, J., Lessmann, J., Bonaccorso, E., Devenish, C., & Muñoz, J. (2014). Combined Use of Systematic Conservation Planning, Species Distribution Modelling, and Connectivity Analysis Reveals Severe Conservation Gaps in a Megadiverse Country (Peru). *PLoS ONE*, *9*(12), e114367. https://doi.org/10.1371/journal.pone.0114367

González, N. C., & Kröger, M. (2020). The potential of Amazon indigenous agroforestry practices and ontologies for rethinking global forest governance. *Forest Policy and Economics*, *118*, 102257. https://doi.org/10.1016/j.forpol.2020.102257

Hawkins, F., Beatty, & Tognelli. (2018). *Assessment of potential reduction in likelihood of species extinctions for Bukit Tigapuluh Sustainable Landscape and Livelihoods Project*. International Union for the Conservation of Nature US.

Hemmelgarn, H., & Gold, M. A. (2021). Agroforestry education and training. *ASSA, CSSA and SSSA*, 543–554. https://doi.org/10.1002/9780891183785.ch19

Hernandez-Aguilera, J. N., Conrad, J. M., Gómez, M. I., & Rodewald, A. D. (2019). The Economics and Ecology of Shade-grown Coffee: A Model to Incentivize Shade and Bird Conservation. *Ecological Economics*, *159*, 110–121. https://doi.org/10.1016/j.ecolecon.2019.01.015

International Union for Conservation of Nature. (n.d.). *The IUCN Red List of Threatened Species*. IUCN Red List of Threatened Species. https://www.iucnredlist.org/

IPBES. (2019). Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. E. S. Brondizio, J. Settele, S. Díaz, and H. T. Ngo (editors). IPBES secretariat, Bonn, Germany. 1148 pages. https://doi.org/10.5281/zenodo.3831673

IUCN. (2020, October 30). *Peru - IUCN Green List*. IUCN Green List. https://iucngreenlist.org/country/peru/

IUCN. (2022). *The IUCN Red List Threat Classification Scheme Version 3.3*. IUCN Red List of Threatened Species. https://www.iucnredlist.org/resources/threat-classification-scheme

Kaonga, M., & Place, F. (2012). *Agroforestry for Biodiversity and Ecosystem Services: Science and Practice*. BoD – Books on Demand.

Lumbierres, M., Dahal, P. R., Soria, C. D., Di Marco, M., Butchart, S. H. M., Donald, P. F., & Rondinini, C. (2022). Area of Habitat maps for the world's terrestrial birds and mammals. *Scientific Data*, *9*(1). https://doi.org/10.1038/s41597-022-01838-w

Lumbierres, M., Dahal, P. R., Soria, C. D., Di Marco, M., Butchart, S. H. M., Donald, P. F., & Rondinini, C. (2022, December 15). *Area of Habitat maps for the world's terrestrial birds and mammals*. Dryad. Retrieved June 1, 2023, from https://doi.org/10.5061/dryad.02v6wwq48

Machovina, B., Feeley, K. J., & Ripple, W. J. (2015). Biodiversity conservation: The key is reducing meat consumption. *Science of the Total Environment*, *536*, 419–431. https://doi.org/10.1016/j.scitotenv.2015.07.022

Mair, L., Bennun, L. A., Brooks, T. M., Butchart, S. H. M., Bolam, F. C., Burgess, N. D., Ekstrom, J. M. M., Milner-Gulland, E. J., Hoffmann, M., Ma, K., Macfarlane, N.

B. W., Raimondo, D. C., Rodrigues, A. S. L., Shen, X., Strassburg, B. B. N., Beatty, C. R., Gómez-Creutzberg, C., Iribarrem, A., Irmadhiany, M., . . . McGowan, P. J. K. (2021). A metric for spatially explicit contributions to science-based species targets. *Nature Ecology & Evolution*, *5*(6), 836–844. https://doi.org/10.1038/s41559-021-01432-0

McCallum, M. L. (2015). Vertebrate biodiversity losses point to a sixth mass extinction. *Biodiversity and Conservation*, *24*(10), 2497–2519. https://doi.org/10.1007/s10531-015-0940-6

MINAM. (2018). *Cobertura y uso de la tierra – Geoservidor*. MINAM Geoservidor. Retrieved January 1, 2023, from https://geoservidor.minam.gob.pe/monitoreo-y-evaluacion/cobertura-y-uso-de-la-tierra/

Miranda, E. B. P. (2018). Prey Composition of Harpy Eagles (*Harpia harpyja*) in Raleighvallen, Suriname. *Tropical Conservation Science*, *11*, 194008291880078. https://doi.org/10.1177/1940082918800789

Palm, C. (2006). Slash-and-burn agriculture: the search for alternatives. *Choice Reviews Online*, *43*(07), 43–4013. https://doi.org/10.5860/choice.43-4013

Pereira, J. C., & Viola, E. (2021). *Climate change and biodiversity governance in the Amazon: At the Edge of Ecological Collapse?* Routledge.

Perry, J., Lojka, B., Ruiz, L., Van Damme, P., Houška, J., & Cusimamani, E. F. (2016). How natural Forest Conversion Affects Insect Biodiversity in the Peruvian Amazon: Can Agroforestry Help? *Forests*, *7*(12), 82. https://doi.org/10.3390/f7040082

Peru Ministry of Foreign Trade and Tourism. (2020, February 23). *Peru is one of the most biodiverse countries on the planet*. Perú Info. https://peru.info/en-us/tourism/news/3/18/peru-is-one-of-the-most-biodiverse-countries-on-the-planet

Peru National Institute of Statistics and Informatics. (2017). *Peru Population and Housing Census*.

Pickett, S. T. A., & Cadenasso, M. L. (1995). Landscape Ecology: Spatial Heterogeneity in Ecological Systems. *Science*, *269*(5222), 331–334. https://doi.org/10.1126/science.269.5222.331

Pokorny, B., Robiglio, V., Reyes, M., Vargas, R., & Patiño Carrera, C. F. (2021). The potential of agroforestry concessions to stabilize Amazonian forest frontiers: a case study on the economic and environmental robustness of informally settled small-scale cocoa farmers in Peru. *Land Use Policy*, *102*, 105242. https://doi.org/10.1016/j.landusepol.2020.105242

Porro, R., Lopez-Feldman, A., & Vela-Alvarado, J. W. (2015). Forest use and agriculture in Ucayali, Peru: Livelihood strategies, poverty and wealth in an Amazon frontier. *Forest Policy and Economics*, *51*, 47–56. https://doi.org/10.1016/j.forpol.2014.12.001

Power, M. E., Tilman, D., Estes, J. A., Menge, B. A., Bond, W. J., Mills, L. S., Daily, G., Castilla, J. C., Lubchenco, J., & Paine, R. T. (1996). Challenges in the Quest for Keystones. *BioScience*, *46*(8), 609–620. https://doi.org/10.2307/1312990

RAISG. (2022). *Maps*. Retrieved June 1, 2023, from https://www.raisg.org/en/maps/

Ravikumar, A., Sears, R. R., Cronkleton, P., Menton, M., & Pérez-Ojeda del Arco, M. (2016). Is small-scale agriculture really the main driver of deforestation in the Peruvian Amazon? Moving beyond the prevailing narrative. *Conservation Letters*, *10*(2), 170–177. https://doi.org/10.1111/conl.12264

Recanati, F., Allievi, F., Scaccabarozzi, G., Espinosa, T., Dotelli, G., & Saini, M. (2015). Global Meat Consumption Trends and Local Deforestation in Madre de Dios: Assessing Land Use Changes and other Environmental Impacts. *Procedia Engineering*, *118*, 630–638. https://doi.org/10.1016/j.proeng.2015.08.496

Ritchie, H. (2013, November 13). *Land Use*. Our World in Data. https://ourworldindata.org/land-use?fbclid=IwAR1OnVSd1Rhj7PKzA4xCejkIPKfiKJf84AXumZ2KvC4FXUBi7aLVzDwgbY4

Rode, J., Escobar, M. M., Khan, S. J., Borasino, E., Kihumuro, P., Okia, C. A., Robiglio, V., & Zinngrebe, Y. (2023). Providing targeted incentives for trees on farms: A transdisciplinary research methodology applied in Uganda and Peru. *Earth System Governance*, *16*, 100172. https://doi.org/10.1016/j.esg.2023.100172

Roth, T., & Weber, D. (2007). Top predators as indicators for species richness? Prey species are just as useful. *Journal of Applied Ecology*, *45*(3), 987–991. https://doi.org/10.1111/j.1365-2664.2007.01435.x

Sánchez-Cuervo, A. M., de Lima, L. S., Dallmeier, F., Garate, P., Bravo, A., & Vanthomme, H. (2020). Twenty years of land cover change in the southeastern Peruvian Amazon: implications for biodiversity conservation. *Regional Environmental Change*, *20*(1). https://doi.org/10.1007/s10113-020-01603-y

Sergio, F., Schmitz, O. J., Krebs, C. J., Holt, R. D., Heithaus, M. R., Wirsing, A. J., Ripple, W. J., Ritchie, E., Ainley, D., Oro, D., Jhala, Y., Hiraldo, F., & Korpimäki, E. (2014). Towards a cohesive, holistic view of top predation: a definition, synthesis and perspective. *Oikos*, *123*(10), 1234–1243. https://doi.org/10.1111/oik.01468

Torralba, M., Fagerholm, N., Burgess, P. J., Moreno, G., & Plieninger, T. (2016). Do European agroforestry systems enhance biodiversity and ecosystem services? A meta-analysis. *Agriculture, Ecosystems & Environment*, *230*, 150–161. https://doi.org/10.1016/j.agee.2016.06.002

Tscharntke, T., Milder, J. C., Schroth, G., Clough, Y., DeClerck, F., Waldron, A., Rice, R., & Ghazoul, J. (2014). Conserving Biodiversity Through Certification of Tropical Agroforestry Crops at Local and Landscape Scales. *Conservation Letters*, *8*(1), 14–23. https://doi.org/10.1111/conl.12110

Udawatta, R. P., Rankoth, L., & Jose, S. (2019). Agroforestry and Biodiversity. *Sustainability*, *11*(10), 2879. https://doi.org/10.3390/su11102879

USAID. (2018, June 19). *Peru*. LandLinks. https://www.land-links.org/country-profile/peru/
Vargas González, J. D. J., McCabe, J. D., Anderson, D. L., Curti, M., Cárdenas, D. C., & Vargas, F. H. (2020). Predictive Habitat Model Reveals Specificity in a Broadly Distributed Forest Raptor, The Harpy Eagle. *Journal of Raptor Research*, *54*(4). https://doi.org/10.3356/0892-1016-54.4.349

APPENDIX A

STUDY SPECIES LIST

Scientific Name	**Red List Status**	**Population Trend**	**Year Assessment Published**	**Assessment Scope**
Aburria aburri	Near Threatened	Decreasing	2016	Global
Accipiter poliogaster	Near Threatened	Decreasing	2022	Global
Agamia agami	Vulnerable	Unknown	2016	Global
Aglaeactis aliciae	Vulnerable	Decreasing	2020	Global
Aglaeactis castelnaudii	Near Threatened	Decreasing	2017	Global
Agriornis albicauda	Vulnerable	Decreasing	2021	Global
Ampelornis griseiceps	Vulnerable	Decreasing	2016	Global
Anairetes alpinus	Endangered	Decreasing	2016	Global
Andigena hypoglauca	Near Threatened	Decreasing	2016	Global
Ara militaris	Vulnerable	Decreasing	2020	Global
Arremon castaneiceps	Near Threatened	Decreasing	2018	Global
Asthenes urubambensis	Near Threatened	Decreasing	2021	Global
Atlapetes melanopsis	Near Threatened	Decreasing	2021	Global
Atlapetes terborghi	Near Threatened	Stable	2022	Global
Aulacorhynchus huallagae	Endangered	Decreasing	2019	Global

Buteogallus solitarius	Near Threatened	Decreasing	2020	Global
Cacicus koepckeae	Near Threatened	Decreasing	2020	Global
Campylopterus villaviscensio	Near Threatened	Decreasing	2016	Global
Capito fitzpatricki	Near Threatened	Stable	2020	Global
Capito wallacei	Vulnerable	Stable	2016	Global
Chaetocercus bombus	Near Threatened	Decreasing	2021	Global
Chaetura pelagica	Vulnerable	Decreasing	2018	Global
Cichlopsis peruviana	Near Threatened	Decreasing	2017	Global
Cinclodes aricomae	Critically Endangered	Decreasing	2018	Global
Cinclodes palliatus	Critically Endangered	Decreasing	2021	Global
Cnemathraupis aureodorsalis	Endangered	Decreasing	2016	Global
Cnipodectes superrufus	Vulnerable	Increasing	2017	Global
Conirostrum bicolor	Near Threatened	Decreasing	2018	Global
Conirostrum binghami	Near Threatened	Decreasing	2021	Global
Conirostrum margaritae	Vulnerable	Decreasing	2018	Global
Conopias cinchoneti	Vulnerable	Stable	2017	Global

Contopus cooperi	Near Threatened	Decreasing	2017	Global
Coryphaspiza melanotis	Vulnerable	Decreasing	2018	Global
Cranioleuca berlepschi	Near Threatened	Decreasing	2022	Global
Crax globulosa	Endangered	Decreasing	2016	Global
Cyanolyca viridicyanus	Near Threatened	Decreasing	2016	Global
Deconychura pallida	Near Threatened	Decreasing	2016	Global
Dendroplex kienerii	Near Threatened	Decreasing	2017	Global
Doliornis sclateri	Vulnerable	Decreasing	2016	Global
Drymotoxeres pucheranii	Near Threatened	Decreasing	2017	Global
Dysithamnus occidentalis	Near Threatened	Decreasing	2022	Global
Eubucco glaucogularis	Near Threatened	Decreasing	2021	Global
Euchrepomis sharpei	Endangered	Decreasing	2016	Global
Falco deiroleucus	Near Threatened	Decreasing	2016	Global
Formicarius rufifrons	Near Threatened	Decreasing	2016	Global
Forpus xanthops	Vulnerable	Stable	2021	Global
Gallinago imperialis	Near Threatened	Decreasing	2016	Global

Gallinago nobilis	Near Threatened	Decreasing	2016	Global
Grallaria ridgelyi	Endangered	Decreasing	2021	Global
Grallaricula ochraceifrons	Vulnerable	Decreasing	2022	Global
Grallaricula peruviana	Near Threatened	Decreasing	2022	Global
Harpia harpyja	Vulnerable	Decreasing	2021	Global
Heliangelus regalis	Near Threatened	Decreasing	2022	Global
Hemitriccus cohnhafti	Near Threatened	Decreasing	2017	Global
Hemitriccus rufigularis	Near Threatened	Decreasing	2017	Global
Herpsilochmus axillaris	Vulnerable	Decreasing	2016	Global
Herpsilochmus motacilloides	Near Threatened	Decreasing	2016	Global
Herpsilochmus parkeri	Vulnerable	Decreasing	2022	Global
Incaspiza watkinsi	Vulnerable	Decreasing	2022	Global
Kleinothraupis parodii	Near Threatened	Decreasing	2017	Global
Laniisoma buckleyi	Near Threatened	Decreasing	2016	Global
Lathrotriccus griseipectus	Vulnerable	Decreasing	2016	Global
Leptasthenura xenothorax	Endangered	Decreasing	2016	Global
Leptopogon taczanowskii	Near Threatened	Decreasing	2016	Global

Leptotila ochraceiventris	Vulnerable	Decreasing	2020	Global
Lipaugus uropygialis	Vulnerable	Decreasing	2021	Global
Loddigesia mirabilis	Endangered	Decreasing	2016	Global
Megascops marshalli	Near Threatened	Stable	2016	Global
Microspingus alticola	Endangered	Decreasing	2016	Global
Mitu tuberosum	Near Threatened	Decreasing	2021	Global
Morphnus guianensis	Near Threatened	Decreasing	2017	Global
Myrmoborus lugubris	Vulnerable	Decreasing	2016	Global
Myrmoborus melanurus	Vulnerable	Decreasing	2016	Global
Myrmoderus eowilsoni	Near Threatened	Decreasing	2020	Global
Neochen jubata	Near Threatened	Decreasing	2016	Global
Neomorphus geoffroyi	Vulnerable	Decreasing	2021	Global
Nephelomyias lintoni	Near Threatened	Decreasing	2016	Global
Nothoprocta taczanowskii	Vulnerable	Decreasing	2018	Global
Pachyramphus spodiurus	Vulnerable	Decreasing	2019	Global
Patagioenas oenops	Near Threatened	Decreasing	2022	Global
Pauxi koepckeae	Critically Endangered	Decreasing	2018	Global

Penelope barbata	Near Threatened	Decreasing	2019	Global
Percnostola arenarum	Vulnerable	Decreasing	2018	Global
Phacellodomus dorsalis	Near Threatened	Decreasing	2020	Global
Phaethornis koepckeae	Near Threatened	Decreasing	2016	Global
Phegornis mitchellii	Near Threatened	Decreasing	2016	Global
Phyllomyias weedeni	Vulnerable	Decreasing	2016	Global
Phylloscartes gualaquizae	Near Threatened	Decreasing	2016	Global
Picumnus steindachneri	Endangered	Decreasing	2016	Global
Pipile grayi	Near Threatened	Decreasing	2021	Global
Pithys castaneus	Near Threatened	Decreasing	2018	Global
Podiceps juninensis	Near Threatened	Decreasing	2020	Global
Poecilotriccus luluae	Endangered	Decreasing	2016	Global
Poospiza rubecula	Endangered	Decreasing	2017	Global
Primolius couloni	Vulnerable	Decreasing	2021	Global
Psittacara frontatus	Near Threatened	Decreasing	2021	Global
Psophia leucoptera	Near Threatened	Decreasing	2016	Global
Pyrrhura albipectus	Vulnerable	Decreasing	2021	Global

Ramphastos ambiguus	Near Threatened	Decreasing	2016	Global
Sclerurus albigularis	Near Threatened	Stable	2016	Global
Scytalopus gettyae	Near Threatened	Stable	2021	Global
Scytalopus unicolor	Near Threatened	Decreasing	2022	Global
Sericossypha albocristata	Vulnerable	Decreasing	2018	Global
Setophaga cerulea	Near Threatened	Decreasing	2021	Global
Setophaga striata	Near Threatened	Decreasing	2018	Global
Spizaetus isidori	Endangered	Decreasing	2016	Global
Spizaetus ornatus	Near Threatened	Decreasing	2022	Global
Synallaxis courseni	Vulnerable	Stable	2016	Global
Synallaxis hypochondriaca	Near Threatened	Decreasing	2021	Global
Synallaxis maranonica	Critically Endangered	Decreasing	2018	Global
Syndactyla ruficollis	Vulnerable	Decreasing	2016	Global
Syndactyla ucayalae	Near Threatened	Decreasing	2016	Global
Tangara argyrofenges	Vulnerable	Decreasing	2018	Global
Tangara meyerdeschauenseei	Near Threatened	Increasing	2018	Global

Taphrolesbia griseiventris	Endangered	Decreasing	2020	Global
Tephrophilus wetmorei	Vulnerable	Decreasing	2018	Global
Thamnophilus cryptoleucus	Near Threatened	Decreasing	2016	Global
Thamnophilus praecox	Near Threatened	Decreasing	2017	Global
Thamnophilus shumbae	Vulnerable	Decreasing	2020	Global
Thamnophilus tenuepunctatus	Vulnerable	Decreasing	2016	Global
Theristicus branickii	Near Threatened	Decreasing	2017	Global
Tinamus guttatus	Near Threatened	Decreasing	2019	Global
Tinamus osgoodi	Vulnerable	Decreasing	2019	Global
Tinamus tao	Vulnerable	Decreasing	2019	Global
Touit stictopterus	Near Threatened	Decreasing	2021	Global
Vultur gryphus	Vulnerable	Decreasing	2020	Global
Wetmorethraupis sterrhopteron	Vulnerable	Decreasing	2016	Global
Xenerpestes singularis	Near Threatened	Decreasing	2016	Global
Xenoglaux loweryi	Vulnerable	Stable	2020	Global
Zaratornis stresemanni	Vulnerable	Decreasing	2016	Global
Zimmerius cinereicapilla	Vulnerable	Decreasing	2016	Global

Note. The data from this table was derived from the IUCN Red List's online data portal (2022).

APPENDIX B

IUCN THREATS CLASSIFICATION SCHEME (VERSION 3.3)

1 Residential & commercial development

- 1.1 Housing & urban areas
- 1.2 Commercial & industrial areas
- 1.3 Tourism & recreation areas

2 Agriculture & aquaculture

- 2.1 Annual & perennial non-timber crops
  - 2.1.1 Shifting agriculture
  - 2.1.2 Small-holder farming
  - 2.1.3 Agro-industry farming
  - 2.1.4 Scale Unknown/Unrecorded
- 2.2 Wood & pulp plantations
  - 2.2.1 Small-holder plantations
  - 2.2.2 Agro-industry plantations
  - 2.2.3 Scale Unknown/Unrecorded
- 2.3 Livestock farming & ranching
  - 2.3.1 Nomadic grazing
  - 2.3.2 Small-holder grazing, ranching or farming
  - 2.3.3 Agro-industry grazing, ranching or farming
  - 2.3.4 Scale Unknown/Unrecorded
- 2.4 Marine & freshwater aquaculture
  - 2.4.1 Subsistence/artisanal aquaculture
  - 2.4.2 Industrial aquaculture
  - 2.4.3 Scale Unknown/Unrecorded

3 Energy production & mining

- 3.1 Oil & gas drilling
- 3.2 Mining & quarrying
- 3.3 Renewable energy

4 Transportation & service corridors

- 4.1 Roads & railroads
- 4.2 Utility & service lines
- 4.3 Shipping lanes
- 4.4 Flight paths

5 Biological resource use

- 5.1 Hunting & collecting terrestrial animals
  - 5.1.1 Intentional use (species being assessed is the target)

5.1.2 Unintentional effects (species being assessed is not the target)
5.1.3 Persecution/control
5.1.4 Motivation Unknown/Unrecorded

5.2 Gathering terrestrial plants
5.2.1 Intentional use (species being assessed is the target)
5.2.2 Unintentional effects (species being assessed is not the target)
5.2.3 Persecution/control
5.2.4 Motivation Unknown/Unrecorded

5.3 Logging & wood harvesting
5.3.1 Intentional use: subsistence/small scale (species being assessed is the target [harvest]
5.3.2 Intentional use: large scale (species being assessed is the target)[harvest]
5.3.3 Unintentional effects: subsistence/small scale (species being assessed is not the target)[harvest]
5.3.4 Unintentional effects: large scale (species being assessed is not the target)[harvest]
5.3.5 Motivation Unknown/Unrecorded

5.4 Fishing & harvesting aquatic resources
5.4.1 Intentional use: subsistence/small scale (species being assessed is the target)[harvest]
5.4.2 Intentional use: large scale (species being assessed is the target)[harvest]
5.4.3 Unintentional effects: subsistence/small scale (species being assessed is not the target)[harvest]
5.4.4 Unintentional effects: large scale (species being assessed is not the target)[harvest]
5.4.5 Persecution/control
5.4.6 Motivation Unknown/Unrecorded

6 Human intrusions & disturbance

6.1 Recreational activities
6.2 War, civil unrest & military exercises
6.3 Work & other activities

7 Natural system modifications

7.1 Fire & fire suppression
7.1.1 Increase in fire frequency/intensity
7.1.2 Suppression in fire frequency/intensity
7.1.3 Trend Unknown/Unrecorded

7.2 Dams & water management/use
7.2.1 Abstraction of surface water (domestic use)
7.2.2 Abstraction of surface water (commercial use)
7.2.3 Abstraction of surface water (agricultural use)
7.2.4 Abstraction of surface water (unknown use)
7.2.5 Abstraction of ground water (domestic use)

7.2.6 Abstraction of ground water (commercial use)
7.2.7 Abstraction of ground water (agricultural use)
7.2.8 Abstraction of ground water (unknown use)
7.2.9 Small dams
7.2.10 Large dams
7.2.11 Dams (size unknown)
7.3 Other ecosystem modifications

8 Invasive & other problematic species, genes & diseases

8.1 Invasive non-native/alien species/diseases
8.1.1 Unspecified species
8.1.2 Named species
8.2 Problematic native species/diseases
8.2.1 Unspecified species
8.2.2 Named species
8.3 Introduced genetic material
8.4 Problematic species/diseases of unknown origin
8.4.1 Unspecified species
8.4.2 Named species
8.5 Viral/prion-induced diseases
8.5.1 Unspecified "species" (disease)
8.5.2 Named "species" (disease)
8.6 Diseases of unknown cause

9 Pollution

9.1 Domestic & urban waste water
9.1.1 Sewage
9.1.2 Run-off
9.1.3 Type Unknown/Unrecorded
9.2 Industrial & military effluents
9.2.1 Oil spills
9.2.2 Seepage from mining
9.2.3 Type Unknown/Unrecorded
9.3 Agricultural & forestry effluents
9.3.1 Nutrient loads
9.3.2 Soil erosion, sedimentation
9.3.3 Herbicides & pesticides
9.3.4 Type Unknown/Unrecorded
9.4 Garbage & solid waste
9.5 Air-borne pollutants
9.5.1 Acid rain
9.5.2 Smog
9.5.3 Ozone
9.5.4 Type Unknown/Unrecorded
9.6 Excess energy
9.6.1 Light pollution

9.6.2 Thermal pollution
9.6.3 Noise pollution
9.6.4 Type Unknown/Unrecorded

10 Geological events

10.1 Volcanoes
10.2 Earthquakes/tsunamis
10.3 Avalanches/landslides

11 Climate change & severe weather

11.1 Habitat shifting & alteration
11.2 Droughts
11.3 Temperature extremes
11.4 Storms & flooding
11.5 Other impacts

12 Other options

12.1 Other threat

Note. This scheme was produced by the IUCN (2022).

APPENDIX C

IUCN THREAT IMPACT SCORING SYSTEM (VERSION 1.0)

Threat Impact Scoring System (based on additive scores and defined thresholds)

Version 1.0 [revised version based on implementation in SIS]

a) Ongoing threat (score = 3)

Scope		Severity:	*Very rapid* Score 3	*Rapid* Score 2	*Slow* Score 1	*Fluctuating* Score 1	*Negligible/No* Score 0
Whole	Score	3	9	8	7	7	6
Majority	Score	2	8	7	6	6	5
Minority	Score	1	7	6	5	5	4

b) Future threat (long term) (score = 1)

Scope		Severity:	*Very rapid* Score 3	*Rapid* Score 2	*Slow* Score 1	*Fluctuating* Score 1	*Negligible/No* Score 0
Whole	Score	3	7	6	5	5	4
Majority	Score	2	6	5	4	4	3
Minority	Score	1	5	4	3	3	2

Impact Coding:

- High impact
- Medium impact
- Low impact
- Negligible / No impact

Note. This figure was produced by the IUCN (2022).

APPENDIX D

MEAN PROJECTED POPULATION DECLINE MATRIX

		Severity						
		Unknown/ Unrecorded	Very Rapid Declines	Rapid Declines	Slow, Significant Declines	Causing/could cause fluctuations	Negligible Declines	No Decline
Scope	Whole (>90%)	18	63	24	10	10	1	1
	Majority (50-90%)	15	52	18	9	9	0	0
	Minority (<50%)	7	24	7	5	5	0	0
	Unknown/ Unrecorded	13	46	16	8	8	0	0

Note. This figure is based on the work of Hawkins et al. (2018).