



Instituto Federal de Educação, Ciência e Tecnologia Goiano – Campus Urutaí
Programa de Pós-Graduação em Conservação de
Recursos Naturais do Cerrado

RESPOSTA DE ABELHAS A CENÁRIOS FUTUROS DE MUDANÇAS CLIMÁTICAS UTILIZANDO MODELOS DE NICHOS ECOLÓGICO

MILTON FERREIRA ALVES JÚNIOR

Orientador: Prof. Dr. Daniel Paiva Silva

Coorientador: Prof. Dr. Bruno Villela de Moraes e Silva

Coorientador: Prof. Dr. Matheus Souza Lima-Ribeiro

Urutaí (GO)
Fevereiro de 2019



Instituto Federal de Educação, Ciência e Tecnologia Goiano

Reitor

Prof. Dr. Vicente Pereira Almeida

Pró-Reitor de Pesquisa e Pós-Graduação e Inovação

Prof. Dr. Fabiano Guimarães Silva

Campus Urutaí

Diretor Geral

Prof. Dr. Gilson Dourado da Silva

Diretor de Pesquisa, Pós-Graduação e Inovação

Prof. Dr. André Luís da Silva Castro

Programa de Pós-Graduação em Conservação de Recursos Naturais do Cerrado

Coordenador

Prof. Dr. Ivandilson Pessoa Pinto de Menezes

Urutaí (GO)
Fevereiro de 2019

MILTON FERREIRA ALVES JÚNIOR

**RESPOSTA DE ABELHAS A CENÁRIOS
FUTUROS DE MUDANÇAS CLIMÁTICAS
UTILIZANDO MODELOS DE NICHO
ECOLÓGICO**

Orientador

Prof. Dr. Daniel Paiva Silva

Coorientador

Prof. Dr. Bruno Vilela de Moraes e Silva

Coorientador

Prof. Dr. Matheus Souza Lima-Ribeiro

Dissertação apresentada ao Instituto Federal Goiano –
Campus Urutaí, como parte das exigências do Programa
de Pós-Graduação em Conservação de Recursos Naturais
do Cerrado para obtenção do título de Mestre.

Urutaí (GO)
Fevereiro de 2019

Os direitos de tradução e reprodução são reservados.

Nenhuma parte desta publicação poderá ser gravada, armazenada em sistemas eletrônicos, fotocopiada ou reproduzida por meios mecânicos ou eletrônicos ou utilizada sem a observância das normas de direito autoral.

Dados Internacionais de Catalogação na Publicação (CIP)
Sistema Integrado de Bibliotecas – SIB/IF Goiano

A474r Alves, Milton.

Resposta de abelhas a cenários futuros de mudanças climáticas utilizando modelos de nicho ecológico. Milton Alves. -- Urutaí, GO: IF Goiano, 2019.
85 fls.

Orientador: Prof. Dr. Daniel Paiva Silva.

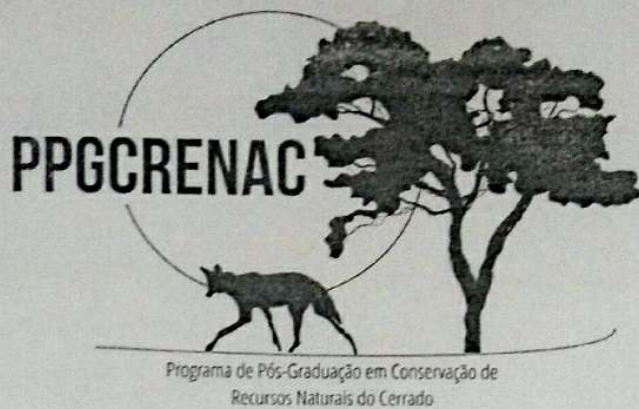
Coorientador: Prof. Dr. Bruno Vilela de Moraes e Silva

Coorientador: Prof. Dr. Matheus Souza Lima Ribeiro

Dissertação (Programa de Pós-Graduação em Conservação de Recursos Naturais do Cerrado) – *Campus* Urutaí do Instituto Federal Goiano, 2019.

1. Interações Ecológicas. 2. Serviços Ecossistêmicos. 3. Espécies Exóticas. 4. Áreas Progradadas. 5. Xylocopini. 6. Lithurgini. 7. Modelos de Nicho Ecológico. I. Silva, Daniel Paiva. II. Moraes e Silva, Bruno Vilela de. III. Ribeiro, Matheus Souza Lima. IV. Título.

CDU 57



FICHA DE APROVAÇÃO DA DISSERTAÇÃO

Título da dissertação:	Resposta de Abelhas a cenários futuros de mudanças climáticas utilizando modelos do nicho ecológico
Orientador:	Prof. Dr. Daniel Paiva Silva
Coorientadores:	Prof. Dr. Bruno Vilela de Moraes e Silva e Prof. Dr. Matheus Silva Lima Ribeiro
Autor:	Milton Ferreira Alves Júnior

Dissertação de Mestrado **APROVADA** em 15 de fevereiro de 2019, como parte das exigências para obtenção do Título de **MESTRE EM CONSERVAÇÃO DE RECURSOS NATURAIS DO CERRADO**, pela Banca Examinadora especificada a seguir:

Prof. Dr. Daniel Paiva Silva
Instituto Federal Goiano – Campus Urutaí
Presidente

Prof. Dr. André Luis da Silva Castro
Instituto Federal Goiano – Campus Urutaí
Membro titular

Prof. Dr. João Carlos Nabout
Universidade Estadual de Goiás – Campus Anápolis
Membro titular

Aos meus filhos, Raul e Cecília, cujos sorrisos foram essenciais para manutenção de minha estrutura capilar durante este processo de aprendizado.

“Você tem direito a suas próprias opiniões, não a seus próprios fatos.”

Daniel Patrick Moynihan

AGRADECIMENTOS

À minha esposa, Silvia, agradeço, primeiramente, pelo olhar crítico à redação técnica, desde a primeira versão do pré-projeto para a seleção deste programa de mestrado, sempre me auxiliando a solidificar conceitos e teorias ecológicas fundamentais ao escopo deste trabalho. Em todos os níveis da avalanche de emoções desses dois últimos anos, seu apoio, compreensão, estímulos e mesmo cutucões, foram imprescindíveis para a construção de minha mentalidade científica e formação como ser humano.

Ao meu orientador, Daniel Paiva Silva, por ter estimulado meu potencial e vontade de me aventurar nos universos da lógica e linguagem de programação, da estatística, e das modernas teorias ecológicas. A confiança dispensada em mim, alguém sem experiência laboratorial anterior nessas grandes áreas, foi força motivadora nos momentos em que até meus próprios neurônios, em choque, se colocavam inacessíveis para calibragem cognitiva. Em várias etapas da redação técnica, você assumiu o papel de parceria na redação, sem nunca perder oportunidade de passar algum aprendizado, de autocorrelação espacial ao uso de preposições. Escrever meu texto em inglês foi um deleite que me encheu de orgulho. Seu auxílio na construção de orações lógicas, diretas e com propriedade técnico-gramatical, foram essenciais na fluidez dos capítulos. Agradeço por despertar em mim a curiosidade e a paixão pela ciência, pela ecologia e pelo livre pensamento crítico. Sua parceria, paciência e doação intelectual foram, e continuaram sendo, essenciais à minha formação profissional.

Aos co-orientadores agradeço pelas sugestões, críticas, pela disposição, pela paciência e por todas as lições sobre a estruturação dos códigos em R. Ao Professor Matheus Souza Lima-Ribeiro, pela disciplina “Modelagem de Distribuição de Espécies”, essencial para roteirização dos códigos e para a correta aplicação dos conceitos teóricos pertinentes. A todos os e-mails respondidos com muito interesse e intensidade e a todas as ligações via Skype, fundamentais para a alavancagem dos trabalhos em momentos que as sombras de *Mordor* ofuscavam a viabilidade dos meus códigos. Ao professor Bruno Vilela de Moraes e Silva, por ter se doado, mesmo quando em trânsito, nas viagens de ida e volta de seu laboratório no Pós-doutoramento nos Estados Unidos ao Brasil. O incentivo em utilizar o *GitHub* e em aprender novas sintaxes em R, levaram este os códigos desenvolvidos para este trabalho a um nível de reprodutibilidade

impecável. Sem a prontidão de vocês dois, várias das análises e formas de apresentação dos dados, seriam comprometidas. Muito obrigado!

Aos meus pais, Rute e Milton, pelo suporte emocional, cuidados e incentivos. Todo meu esforço individual na carreira acadêmica só foi possível porque vocês me propiciaram boa formação pessoal dentro do máximo de suas capacidades. Muito obrigado pela doação de parte de suas vidas a mim.

Ao Professor Fernando Amaral Silveira, do departamento de Zoologia do *campus* Viçosa da Universidade Federal de Minas Gerais (UFMG), por ter cedido ocorrências que compuseram parte do banco de dados das abelhas utilizadas do capítulo 3.

Aos programas de pós-graduação em Conservação do Cerrado do IF Goiano, em Ecologia e Evolução da Universidade Federal de Goiás (UFG) e Zoologia da Universidade Federal do Pará (UFPA), pelas disciplinas integrantes de meu currículo de pós-graduado.

Aos colegas do laboratório COBIMA pelos inúmeros auxílios, como ao rodar os códigos dos modelos remotamente.

Ao Instituto Federal do Tocantins pela agilidade administrativa em analisar e me conceder o afastamento para pós-graduação.

RESPOSTA DE ABELHAS A CENÁRIOS FUTUROS DE MUDANÇAS CLIMÁTICAS UTILIZANDO MODELOS DE NICHOS ECOLÓGICOS

RESUMO

Mudanças globais como perda de habitat, invasões de espécies exóticas e mudanças climáticas têm sido sugeridas como as principais causas desse declínio dos polinizadores. Assim, entender como as abelhas responderão às mudanças climáticas futuras pode nos mostrar como os serviços ecossistêmicos de polinização podem mudar, com consequências tanto para a agricultura, para o funcionamento dos ecossistemas, bem como para as atividades econômicas influenciadas pela polinização. No capítulo um, intitulado “**Integrando preditores bióticos em modelos de nicho: resposta de espécie exótica na América do Sul a mudanças climáticas globais**”, avaliamos o efeito da inclusão de componentes bióticos (distribuições potenciais das plantas associadas) sobre a distribuição potencial da abelha exótica *Lithurgus huberi* Ducke (1907) na América do Sul. Nossos resultados mostraram que a inclusão do componente biótico melhorou nosso modelo. Além disso, a distribuição de áreas adequadas a *L. huberi* no futuro tende a diminuir com significativa mudança das áreas atualmente ocupadas. Em nosso segundo capítulo, intitulado “**Mudanças climáticas retrairão a faixa de distribuição adequada de abelhas carpinteiras da região Neotropical**”, o principal objetivo foi avaliar os efeitos das mudanças climáticas globais sobre a distribuição futura, e sua sobreposição a áreas de proteção ambiental da América do Sul, para três espécies de abelhas carpinteiras nativas do Cerrado brasileiro, *Xylocopa abbreviata* Hurd & Moure (1963), *Xylocopa truxali* Hurd & Moure (1963) e *Xylocopa vestita* Hurd & Moure (1963). Nossos resultados mostraram redução significativa da área de distribuição futura de todas as *Xylocopa* avaliadas.

Keywords: Interações Ecológicas, Serviços Ecossistêmicos, Espécies Exóticas, Áreas Protegidas, Xylocopini, Lithurgini.

RESPOSTA DE ABELHAS A CENÁRIOS FUTUROS DE MUDANÇAS CLIMÁTICAS UTILIZANDO MODELOS DE NICHOS ECOLÓGICOS

ABSTRACT

Pollinators, especially bees, are threatened by environmental degradation, demanding effective strategies and public policies to protect them from the ongoing decline. Global changes such as loss of habitat, invasion of exotic species and climate change have been suggested as the main causes of this decline. Above all, climate change is of greater concern in the scientific world, since climate is the primary control of species distribution and ecological processes. Thus, understanding how bees respond to future climate change can show us how ecosystem services can change, with consequences for both agriculture, ecosystem functioning, and the economic activity involved in pollination. In chapter one entitled "**Integrating biotic predictors into niche models: response of an exotic species in South America climate change**", we evaluated the effect of inclusion of biotic components, the predictive variables derived from potential plant distributions, upon the potential distribution of the exotic bee *Lithurgus huberi* Ducke (1907) in South America. Our results showed that the inclusion of the biotic component partially improved our model and that of *L. huberi*. Besides, the bee's distribution tends to decrease in the future, regardless of the scenario considered, but especially in the most pessimistic one. Our main objective in the second chapter, entitled "**Climate change will contract the distribution range of Neotropical carpenter bees**", was to assess the effects of global climate change on future distribution by underlying areas of environmental protection for *Xylocopa abbreviata* Hurd & Moure (1963), *Xylocopa truxali* Hurd & Moure (1963), and *Xylocopa vestita* Hurd & Moure (1963) in South America. Our results showed a significant reduction of the future distribution area of all *Xylocopa* species evaluated as well in protected areas

Keywords: Ecological Interactions, Ecological Services, Biotic Components, Exotic Species, Protected Areas, Lithurgini, Xylocopini.

SUMÁRIO

AGRADECIMENTOS.....	vii
RESUMO	ix
ABSTRACT.....	x
SUMÁRIO	xi
LISTA DE FIGURAS.....	xii
LISTA DE TABELAS.....	xiii
CAPÍTULO 1	15
1.1 INTRODUÇÃO GERAL.....	15
1.2 REFERÊNCIAS.....	18
CAPÍTULO 2.....	21
2. INTEGRANDO PREDITORES BIÓTICOS EM MODELOS DE NICHOS ECOLÓGICOS.....	21
ABSTRACT.....	22
2.1 INTRODUCTION	23
2.2 METHODS	26
2.2.1 Occurrence data.....	26
2.2.2 Selecting environmental variables and processing occurrences.....	26
2.2.3 Experiments procedures and analysis of biotic interactions	30
2.2.4 Evaluation and ensembles	32
2.3 RESULTS	34
2.4 DISCUSSION.....	39
2.5 SUPPORTING INFORMATION.....	42
2.6 REFERENCES	43
2.7 SUPPLEMENTARY MATERIALS	52
CAPÍTULO 3.....	59
3. O IMPACTO DAS MUDANÇAS CLIMÁTICAS NA DISTRIBUIÇÃO DE ABELHAS NATIVAS DA REGIÃO NEOTROPICAL.....	59
ABSTRACT.....	60
3.1 INTRODUCTION	61
3.2 METHODS	63
3.2.1 Occurrence data.....	63
3.2.2 Selecting environmental variables and processing occurrences.....	63
3.2.3 Modelling procedures and evaluation	67
3.3 RESULTS	70
3.4 DISCUSSION.....	75
3.5 REFERENCES	78
CAPÍTULO 4.....	85
CONCLUSÕES GERAIS	85

LISTA DE FIGURAS

FIGURE 2-1 HIERARCHICAL CLUSTERING OF THE 11 AOGCMS ACCORDING TO THE CORRELATION BETWEEN ALL 19 CLIMATIC VARIABLES FOR THE FUTURE SCENARIOS IN A) RCP 2.6, B) RCP 4.5, C) RCP 6.0, AND D) RCP 8.5. ▼ INDICATES THE SELECTED AOGCMS IN ALL SCENARIOS: CCSM4, IPSL-CMSA-LR AND MIROC-ESM. RCP: REPRESENTATIVE CARBON PATHWAY. 29

FIGURE 2-2 FLOWCHART AND SUMMARY OF THE MODELING EXPERIMENTS PERFORMED IN THIS STUDY. EXPERIMENT # 1 MODELS THE DISTRIBUTION OF *L. HUBERI* BEE AND ASSOCIATED PLANTS IN THE PRESENT: (A) OCCURRENCES DATASETS; (B) FILTERING OCCURRENCES IN THE GEOGRAPHIC SPACE; (C) PARTITION OF OCCURRENCES INTO TEST-TRAINING SUBSETS; (D) PARAMETERIZATION OF GENERAL MODELS AND MODELING PROCEDURES; (E) EVALUATION OF THE RESULTING PREDICTIONS AND ENSEMBLES OF ALL PREDICTIONS AND METHODS BY SCENARIO; (F) ADDITIONAL STAGES OF EXPERIMENT # 1 - (F.1) GENERATION OF BIOTIC COMPONENTS FROM PLANT PREDICTIONS AND (F.2) COMPARISON OF *L. HUBERI* DISTRIBUTION WITHOUT AND WITH BIOTIC COMPONENTS. EXPERIMENT # 2 MODELS THE POTENTIAL DISTRIBUTION OF *L. HUBERI* IN THE FOUR FUTURE CLIMATE SCENARIOS, USING THE SAME METHODS FROM (A) TO (E) EMPLOYED IN EXPERIMENT # 1..... 32

FIGURE 2-3 RESULTS OF THE MODELING EXPERIMENT #1. (A) EVALUATION OF D VALUES FOR EACH TREATMENT BY PREDICTIVE METHOD, WHICH WE USED TO SUPPORT OUR CHOICE FOR THE SEP-PA EXPERIMENT; (B) PROPORTION OF OCCUPIED EXTENT OF *LITHURGUS HUBERI*'S POTENTIAL DISTRIBUTIONS ACCORDING TO EACH PREDICTIVE METHOD IN PROPORTION TO THE STUDY AREA. CENTRAL VALUES CORRESPOND TO THE MEANS, WHILE THE BARS CORRESPOND TO THE 95% CONFIDENCE INTERVAL. DIFFERENT LETTERS ARE STATISTICALLY DIFFERENT. THE SEP-PA TREATMENT IS HIGHLIGHTED IN BOTH FIGURES. 35

FIGURE 2-4 THINNED OCCURRENCES FOR *LITHURGUS HUBERI* (BLUE DOTS) AND ENSEMBLES OF DISTRIBUTION RANGE OF ITS PREDICTIONS FOR THE CURRENT SCENARIO IN ALL TREATMENTS. THE ENSEMBLE DISTRIBUTIONS WERE PRODUCED USING ALL THREE METHODS ACCORDING TO EACH TREATMENT IN MODELING EXPERIMENT #1: , ABIOTIC VARIABLES ONLY; SEP-PA, ABIOTIC VARIABLES PLUS MAPS OF PRESENCE AND ABSENCE OF THE ASSOCIATED PLANT SPECIES; SEP-SUIT, ABIOTIC VARIABLES PLUS PLANT SPECIES SUITABILITY; STK-PA, ABIOTIC VARIABLES PLUS SUMMED PRESENCE AND ABSENCE MAPS OF THE PLANTS; STK-SUIT, AVERAGE OF THE SUITABILITY OF THE ASSOCIATED PLANTS. THE COLOR SCALE CORRESPONDS TO THE SUITABILITY VALUES FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATE SCENARIOS CONSIDERED. 36

FIGURE 2-5 SIZE OF THE *LITHURGUS HUBERI*'S DISTRIBUTION CONSIDERING THE PREDICTIVE METHODS, ALL AOGCMS, AND FUTURE SCENARIOS (RCPs 2.6 TO 8.5). THE RANGE SIZE IS REPRESENTED BY THE NUMBER OF GRID CELLS OCCUPIED IN EACH PREDICTIVE METHOD (X 1000) PER SCENARIO. CENTRAL VALUES CORRESPOND TO THE MEANS AND THE BARS CORRESPOND TO THE 95% CONFIDENCE INTERVAL. ○, ■, ● REPRESENT, RESPECTIVELY, THE METHODS: BIOCLIM, MAXENT, SVM. THE NUMBERING “.1”, “.2”, AND “.3” REPRESENT, RESPECTIVELY, THE FOLLOWING AOGCMS: CCSM4, IPSL-CMSA-LR AND MIROC-ESM. 37

FIGURE 2-6 FINAL DISTRIBUTION OF *LITHURGUS HUBERI* BEE FOR CURRENT AND FUTURE SCENARIOS (RCPs 2.6 TO 8.5). THE MAPS FOR THE FUTURE SCENARIOS WERE GENERATED BY THE WEIGHTED MEAN OF ALL THREE METHODS (BIOCLIM, MAXENT, SVM) IN ALL AOGCMS. THE COLOR SCALE CORRESPONDS TO THE VALUES OF SUITABILITY FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATIC SCENARIOS. RCP: REPRESENTATIVE CARBON PATHWAY. 38

FIGURE 3-1 TOTAL OCCURRENCE DATA FOR THE MODELED BEES *XYLOCOPA ABBREVIATA*, *XYLOCOPA TRUXALI*, AND *XYLOCOPA VESTITA*, INCLUDING ALL SOURCES COMPOSING THE DATABASE. THE NAMES OF THE BRAZILIAN STATES CITED ALONG THE TEXT ARE SHOWN IN THE FIGURE..... 63

FIGURE 3-2 HIERARCHICAL CLUSTERING OF THE 11 AOGCMs ACCORDING TO THE CORRELATION BETWEEN ALL 19 CLIMATIC VARIABLES FOR THE FUTURE SCENARIOS IN A) RCP 2.6, B) RCP 4.5, C) RCP 6.0, AND D) RCP 8.5. ▼ INDICATES THE SELECTED AOGCMs IN ALL SCENARIOS: CCSM4, IPSL-CMSA-LR AND MIROC-ESM. RCP: REPRESENTATIVE CARBON PATHWAY. 67

FIGURE 3-3 SUMMARY OF THE MODELING PROCEDURES. (A) OCCURRENCES DATASETS. (B) FILTERING OF OCCURRENCES IN THE GEOGRAPHIC SPACE. (C) PARTITIONING OCCURRENCES IN TEST TRAINING SUBSETS. (D) MODELS PARAMETERIZATION AND GENERAL MODELING PROCEDURES. (E) PREDICTIONS EVALUATION. (F) ENSEMBLES OF ALL PREDICTIONS PRODUCED BY ALL METHODS BY SCENARIO. 68

FIGURE 3-4 OCCURRENCES AND DISTRIBUTION PREDICTIONS FOR *XYLOCOPA ABBREVIATA*, *XYLOCOPA TRUXALI*, AND *XYLOCOPA VESTITA*. THE COLOR SCALE CORRESPONDS TO THE SUITABILITY VALUES FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATE SCENARIOS (RCPs 2.6 TO 8.5) CONSIDERED. THE MAPS FOR THE CURRENT SCENARIO WERE GENERATED BY THE WEIGHTED MEAN OF ALL PREDICTIVE METHODS. THE MAPS FOR THE FOR THE FUTURE SCENARIOS WERE GENERATED BY THE WEIGHTED MEAN OF ALL FOUR PREDICTIVE METHODS (BIOCLIM, GOWER, MAXENT, SVM) IN ALL AOGCMs. RCP: REPRESENTATIVE CARBON PATHWAY. 71

FIGURE 3-5 COMPARISON OF CURRENT AND ENSEMBLE FUTURE PREDICTIONS FOR *XYLOCOPA ABBREVIATA*, *XYLOCOPA TRUXALI*, AND *XYLOCOPA VESTITA*. THE MAPS FOR THE FUTURE WERE GENERATED BY THE AVERAGE SUITABILITY OF THE FOUR RCP SCENARIOS, FOR EACH SPECIES. THE COLOR SCALE CORRESPONDS TO THE SUITABILITY VALUES FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATE SCENARIOS CONSIDERED. 72

FIGURE 3-6 CURRENT AND FUTURE DISTRIBUTION RANGES FOR *XYLOCOPA ABBREVIATA* (A AND B), *XYLOCOPA TRUXALI* (C AND D), AND *XYLOCOPA VESTITA* (E AND F) OVERLAPPED WITH BRAZILIAN'S STRICT USE PROTECTED AREAS NETWORK (IUCN'S CLASSES I TO IV). THE THREE MAPS FOR THE FUTURE SCENARIO REPRESENT THE CONSENSUAL DISTRIBUTION ALL MAPS OBTAINED FROM THE ENSEMBLES OF EACH REPRESENTATIVE CONCENTRATION PATHWAY. GREEN POLYGONS REFER TO THE SUITABLE AREA ABOVE THE THRESHOLD NO-OMISSION OBTAIN FROM THE PRESENT ENSEMBLE BY EACH SPECIES. YELLOW POLYGONS REFER TO BRAZILIAN'S PROTECTED AREAS OVERLAPPING WITH THE SPECIES' PREDICTED RANGE. RED POLYGONS REFER TO THE PROTECTED AREAS NOT SUITABLE FOR THE SPECIES.. 74

LISTA DE TABELAS

TABLE 2-1 RESULTS OF THE EXPLORATORY FACTOR ANALYSIS WITH VARIMAX AXIS ROTATION AMONG THE 19 WORLDCLIM VARIABLES. BOLD VALUES REPRESENT LOADING GREATER THAN 0.8. VARIABLES IN BOLD REPRESENT THOSE THAT WE MAINTAINED IN OUR STUDY..... 28

TABLE 2-2 RESULTS OF THE REPEATED MEASURES ANOVA PERFORMED WITH TREATMENTS IN OUR MODELS. (A) THE RESULTS CONSIDERING THE VALUES OF D FOR *LITHURGUS HUBERI*'S PREDICTIONS; (B) THE RESULTS CONSIDERING *LITHURGUS HUBERI*'S RANGE SIZE. 34

TABLE 3-1 RESULTS OF THE EXPLORATORY FACTOR ANALYSIS, WITH VARIMAX AXIS ROTATION, AMONG THE 19 WORLDCLIM VARIABLES. BOLD VALUES REPRESENT LOADING GREATER THAN 0.8. VARIABLES IN BOLD REPRESENT THOSE THAT WE MAINTAINED IN OUR STUDY..... 65

TABLE 3-2 RESULTS OBTAINED FOR EACH METHOD BY PREDICTING THE CURRENT POTENTIAL DISTRIBUTION OF *XYLOCOPA ABBREVIATA*, *XYLOCOPA VESTITA* AND *XYLOCOPA TRUXALI*, MODELED WITH WORLDCLIM INTERPOLATIONS OF OBSERVED DATA, REPRESENTATIVE OF 1960-1990..... 70

TABLE 3-3 DISTRIBUTION RANGE SIZE (IN GRID CELLS) IN BOTH PRESENT AND FUTURE ENSEMBLE DISTRIBUTIONS (ALL SCENARIOS) AND PERCENTAGE OF DISTRIBUTION RANGE AND PROTECTED AREAS LOSS IN BOTH PRESENT AND FUTURE SCENARIOS FOR *XYLOCOPA ABBREVIATA*, *XYLOCOPA TRUXALI*, AND *XYLOCOPA VESTITA*. THE NUMBERS WITHIN BRACKETS IN THE COLUMNS REGARDING THE PERCENTAGE OF PROTECTED DISTRIBUTION RANGE FOR EACH SPECIES REFER TO THE RAW AMOUNT OF GRID CELLS PREDICTED WITHIN PROTECTED AREAS..... 73

1.1 INTRODUÇÃO GERAL

Polinizadores, sobretudo abelhas, estão ameaçados pela degradação ambiental, exigindo estratégias eficazes e políticas públicas para protegê-los (Potts et al., 2016; Settele et al., 2016). As mudanças climáticas globais têm sido consideradas um dos mais preocupantes condutores do declínio dos polinizadores em todo o mundo (Ghazoul, 2005; Hegland et al., 2009; Potts et al., 2010; Steffan-Dewenter et al., 2005; Winfree et al., 2009). Essas mudanças podem comprometer a riqueza e abundância de espécies de abelhas (Papanikolaou et al., 2016), a sincronização de fenologia e padrões de atividade diurna de polinizadores (Stevenson et al., 2015), modificar redes de interação polinizadores-plantas (Hegland et al., 2009; Memmott et al., 2010; Pecl et al., 2017) e alterar as áreas de ocupação adequadas dessas espécies (Giannini et al., 2012; Parmesan and Yohe, 2003). Isto é particularmente importante, uma vez que os serviços de polinização fornecidos pelas abelhas são importantes para a manutenção da diversidade dos ecossistemas naturais e também da agricultura e produção de alimentos (Costanza et al., 2014).

As mudanças observadas nos padrões fenológicos de espécies demonstram que as mudanças climáticas globais estão, de fato, afetando os ecossistemas (Parmesan, 2006; Parmesan and Yohe, 2003; Pecl et al., 2017; Visser and Both, 2005). Isso pode ser observado à medida em que o nível trófico diretamente abaixo, e.g. planta associada, apresenta seu desenvolvimento atrasado ou adiantado, se o nível trófico superior, e.g. polinizador, não conseguir alterar seus padrões fenológicos em igual proporção, levando ao desacoplamento fenológico de suas atividades sazonais. (Kuntner et al., 2014; Ovalle-Rivera et al., 2015; Parmesan, 2006; Schweiger et al., 2008; Visser et al., 2004). Além disso, o padrão de distribuição geográfica das espécies pode ser alterado pelas mudanças climáticas tendo em vista suas necessidades climáticas intrínsecas, levando a possível desencontro de espécies no espaço geográfico (Parmesan and Yohe, 2003; Schweiger et al., 2012, 2008). Assim, o desacoplamento fenológico e o deslocamento geográfico inesperados podem afetar as interações bióticas tanto por alterarem as distribuições e abundâncias das espécies quanto por causarem extinções (Blois et al., 2013; Schweiger et al., 2008).

O uso de modelos de nicho ecológico (MNE; também chamados Modelos de Distribuição Potencial – mas veja Peterson and Soberón, 2012) é abordagem comum na literatura tanto para avaliar o impacto das mudanças climáticas na potencial distribuição de futura de espécies (Araújo and Peterson, 2012; Giannini et al., 2017a; Silva et al., 2018), quanto para avaliar o estabelecimento de espécies exóticas (Jiménez-Valverde et al., 2011; Silva et al., 2014).

Uma característica marcante dos MNE é a dependência do conceito de nicho ecológico (Elith et al., 2006; Guisan and Thuiller, 2005; Guisan and Zimmermann, 2000; Soberón, 2007). Os primeiros conceitos de nicho adotados pela comunidade científica foram propostos por (1) Grinnell (1924), que levava em consideração as condições do ambiente e (2) Elton (1927) propôs que as interações entre espécies eram fatores cruciais na delimitação do nicho das espécies. O conceito moderno de Hutchinson (1957) abarca esses dois conceitos e define nicho ecológico como “um hipervolume, n-dimensional, cujos eixos abrangem condições, recursos e interações nos quais os indivíduos de uma espécie são capazes de sobreviver, crescer e reproduzir” (Peterson et al., 1999). Após este longo processo de amadurecimento do termo ecológico, Soberón (2007) ressalta que o nicho utilizado em MNE é o nicho Grinnelliano. Tanto os nichos de Elton (1927) quanto o de Grinnell (1924) são relevantes para a compreensão da distribuição dos indivíduos de dada espécie. Entretanto, enquanto as interações que compõem o nicho Eltoniano são geralmente observadas em resoluções espaciais finas ($<1\text{km}^2$), o nicho Grinnelliano é mais adequado aos MNE quando se trabalha em resoluções espaciais amplas. Nestes métodos, as variáveis abióticas (cenopoéticas) são preponderantes na modulação da distribuição espacial das espécies ($>1\text{km}^2$) (Hortal et al., 2010; Soberón, 2007). Apesar das interações ecológicas também serem importantes na determinação da distribuição das espécies (em micro-escalas), a disponibilização de vasta quantidade de variáveis abióticas em bancos de dados *online* (e.g. Hijmans et al., 2005) permitiu a popularização dos métodos de MNE e seu uso em questões relacionadas á conservação de espécies (Guisan et al., 2013).

Nesse contexto, em nosso primeiro capítulo, intitulado “**Integrando preditores bióticos em modelos de nicho: resposta de espécie exótica na américa do sul a cenários futuros de mudanças climáticas**”, avaliamos o efeito da inclusão de componentes bióticos (distribuições potenciais das plantas associadas) para gerar a distribuição potencial da abelha exótica *Lithurgus huberi* Ducke (1907) na América do Sul. Adicionalmente, ao se considerar as mudanças climáticas globais, avaliamos como

a distribuição da espécie e sua interação com as plantas polinizadas se dará no futuro. As plantas foram consideradas como recursos alimentares para as abelhas e introduzidas no modelo como componentes bióticos na previsão de distribuição. Realizamos comparações entre modelos com e sem a incorporação dos componentes bióticos em nossos procedimentos de modelagem. Analisamos qual desses procedimentos melhora a capacidade preditiva do modelo. Por fim, avaliamos os padrões de adequabilidade futura da abelha, avaliando a quantidade de áreas perdidas e ou ganhas quando comparado com a distribuição potencial da abelha no presente. Nossos resultados mostraram que a inclusão do componente biótico no nosso modelo em um dos métodos preditivos avaliados. Além disso, observamos que a distribuição potencial de *L. huberi* tende a diminuir no futuro, do cenário considerado, mas especialmente no cenário mais pessimista.

Em nosso segundo capítulo, intitulado “**Mudanças climáticas retrairão a faixa de distribuição adequada de abelhas carpinteiras da região Neotropical**”, o principal objetivo foi avaliar os efeitos das mudanças climáticas globais sobre a distribuição futura de três espécies de abelhas carpinteiras nativas do Cerrado brasileiro, *Xylocopa abbreviata* Hurd & Moure (1963), *X. Truxali* Hurd & Moure (1963) e *X. vestita* Hurd & Moure (1963). Utilizamos diversos métodos de MNE para prever áreas de ocorrência potencial dessas espécies. Por fim, também estimamos a proporção da área predita de cada espécie ocorrendo dentro de unidades de proteção ambiental, comparando o cenário climático presente com quatro cenários futuros de emissões de carbono atmosférico, do mais otimista ao mais pessimista, para o ano de 2070. Mostramos redução da área potencialmente adequada para as três espécies de abelhas carpinteiras nos quatro cenários de futuro. Ademais, a quantidade de áreas protegidas foi consideravelmente reduzida nos cenários de futuro.

1.2 REFERÊNCIAS

- Araújo, M. B., & Peterson, A. T. (2012). Uses and misuses of bioclimatic envelope modeling. *Ecology*, *93*(7), 1527–1539. <https://doi.org/10.1890/07-1861.1>
- Blois, J. L., Zarnetzke, P. L., Fitzpatrick, M. C., & Finnegan, S. (2013). Climate Change and the Past, Present, and Future of Biotic Interactions. *Science*, *341*(2013), 499–504. <https://doi.org/10.1126/science.1237184>
- Costanza, R., de Groot, R., Sutton, P., van der Ploeg, S., Anderson, S. J., Kubiszewski, I., ... Turner, R. K. (2014). Changes in the global value of ecosystem services. *Global Environmental Change*, *26*(1), 152–158. <https://doi.org/10.1016/j.gloenvcha.2014.04.002>
- Elith, J., Graham, C. H., Anderson, R. P., Dudik, M., Ferrier, S., Guisan, A., ... Zimmermann, N. E. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, *29*(2), 129–151. <https://doi.org/10.1111/j.2006.0906-7590.04596.x>
- Elton, C. (1927). *Animal ecology*. Sidgwick and Jackson.
- Ghazoul, J. (2005). Buzziness as usual? Questioning the global pollination crisis. *Trends in Ecology and Evolution*, *20*(7), 367–373. <https://doi.org/10.1016/j.tree.2005.04.026>
- Giannini, T. C., Acosta, A. L., Garófalo, C. A., Saraiva, A. M., Alves-dos-Santos, I., & Imperatriz-Fonseca, V. L. (2012). Pollination services at risk: Bee habitats will decrease owing to climate change in Brazil. *Ecological Modelling*, *244*, 127–131.
- Giannini, T. C., Costa, W. F., Cordeiro, G. D., Imperatriz-Fonseca, V. L., Saraiva, A. M., Biesmeijer, J., & Garibaldi, L. A. (2017). Projected climate change threatens pollinators and crop production in Brazil. *PloS One*, *12*(8), e0182274. <https://doi.org/10.1371/journal.pone.0182274>
- Grinnell, J. (1924). Geography and Evolution. *Ecology*, *5*(3), 225–229. <https://doi.org/10.2307/1929447>
- Guisan, A., & Thuiller, W. (2005). Predicting species distribution: Offering more than simple habitat models. *Ecology Letters*, *8*(9), 993–1009. <https://doi.org/10.1111/j.1461-0248.2005.00792.x>
- Guisan, A., Tingley, R., Baumgartner, J. B., Naujokaitis-Lewis, I., Sutcliffe, P. R., Tulloch, A. I. T., ... Buckley, Y. M. (2013). Predicting species distributions for conservation decisions. *Ecology Letters*, *16*(12), 1424–1435. <https://doi.org/10.1111/ele.12189>
- Guisan, A., & Zimmermann, N. E. (2000). Predictive habitat distribution models in ecology. *Ecological Modelling*, *135*(2–3), 147–186. [https://doi.org/10.1016/S0304-3800\(00\)00354-9](https://doi.org/10.1016/S0304-3800(00)00354-9)
- Hegland, S. J., Nielsen, A., Lázaro, A., Bjerknes, A. L., & Totland, Ø. (2009). How does climate warming affect plant-pollinator interactions? *Ecology Letters*, *12*(2), 184–195. <https://doi.org/10.1111/j.1461-0248.2008.01269.x>
- Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., & Jarvis, A. (2005). Very high

- resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, 25, 1965–1978.
- Hortal, J., Roura-Pascual, N., Sanders, N. J., & Rahbek, C. (2010). Understanding (insect) species distributions across spatial scales. *Ecography*, 33(1), 51–53. <https://doi.org/10.1111/j.1600-0587.2009.06428.x>
- Hutchinson, G. E. (1957). Concluding remarks. *Cold Spring Harbor Symposia on Quantitative Biology*, 22, 415–427. <https://doi.org/10.1101/SQB.1957.022.01.039>
- Jiménez-Valverde, A., Peterson, A. T., Soberón, J., Overton, J. M., Aragón, P., Lobo, J. M., ... Lobo, J. M. (2011). Use of niche models in invasive species risk assessments. *Biological Invasions*, 13(12), 2785–2797. <https://doi.org/10.1007/s10530-011-9963-4>
- Kuntner, M., Năpăruș, M., Li, D., & Coddington, J. A. (2014). Phylogeny predicts future habitat shifts due to climate change. *PLoS ONE*, 9(6). <https://doi.org/10.1371/journal.pone.0098907>
- Memmott, J., Carvell, C., Pywell, R. F., & Craze, P. G. (2010). The potential impact of global warming on the efficacy of field margins sown for the conservation of bumble-bees. *Philosophical Transactions of the Royal Society B-Biological Sciences*, 365(1549), 2071–2079. <https://doi.org/10.1098/rstb.2010.0015>
- Ovalle-Rivera, O., Läderach, P., Bunn, C., Obersteiner, M., & Schroth, G. (2015). Projected shifts in *Coffea arabica* suitability among major global producing regions due to climate change. *PLoS ONE*, 10(4). <https://doi.org/10.1371/journal.pone.0124155>
- Papanikolaou, A. D., Kühn, I., Frenzel, M., & Schweiger, O. (2016). Semi-natural habitats mitigate the effects of temperature rise on wild bees. *Journal of Applied Ecology*, 54(2), 527–536. <https://doi.org/10.1111/1365-2664.12763>
- Parmesan, C. (2006). Ecological and evolutionary responses to recent climate change. *Annual Review of Ecology and Systematics*, 37(1), 637–669. <https://doi.org/10.1146/annurev.ecolsys.37.091305.110100>
- Parmesan, C., & Yohe, G. (2003). A globally coherent fingerprint of climate change impacts across natural systems. *Nature*, 421, 37. <https://doi.org/10.1038/nature01286>
- Pecl, G. T., Araújo, M. B., Bell, J. D., Blanchard, J., Bonebrake, T. C., Chen, I. C., ... Williams, S. E. (2017). Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science*, 355(6332). <https://doi.org/10.1126/science.aai9214>
- Peterson, A. T., & Soberón, J. (2012). Species distribution modeling and ecological niche modeling: Getting the Concepts Right. *Natureza a Conservacao*, 10(2), 102–107. <https://doi.org/10.4322/natcon.2012.019>
- Peterson, A. T., Soberón, J., & Sánchez-Cordero, V. (1999). Conservatism of Ecological Niches in Evolutionary Time. *Science*, 285(5431), 1265–1267. <https://doi.org/10.1126/science.285.5431.1265>
- Potts, S. G., Biesmeijer, J. C., Kremen, C., Neumann, P., Schweiger, O., & Kunin, W. E. (2010). Global pollinator declines: trends, impacts and drivers. *Trends in Ecology & Evolution*,

- 25(6), 345–353. <https://doi.org/10.1016/j.tree.2010.01.007>
- Potts, S. G., Imperatriz-Fonseca, V., Ngo, H. T., Aizen, M. A., Biesmeijer, J. C., Breeze, T. D., ... Vanbergen, A. J. (2016). Safeguarding pollinators and their values to human well-being. *Nature*, *540*(7632), 220–229. <https://doi.org/10.1038/nature20588>
- Schweiger, O., Heikkinen, R. K., Harpke, A., Hickler, T., Klotz, S., Kudrna, O., ... Settele, J. (2012). Increasing range mismatching of interacting species under global change is related to their ecological characteristics. *Global Ecology and Biogeography*, *21*(1), 88–99. <https://doi.org/10.1111/j.1466-8238.2010.00607.x>
- Schweiger, O., Settele, J., Kudrna, O., Klotz, S., & Kuhn, I. (2008). Climate change can cause spatial mismatch of trophically interacting species. *Ecology*, *89*(12), 3472–3479. <https://doi.org/10.1890/07-1748.1>
- Settele, J., Bishop, J., & Potts, S. G. (2016). Climate change impacts on pollination. *Nature Plants*, *2*(July), 16092.
- Silva, D. P., Dew, R. M., Vilela, B., Stevens, M. I., & Schwarz, M. P. (2018). No deaths in the desert: predicted responses of an arid-adapted bee and its two nesting trees suggest resilience in the face of warming climates. *Insect Conservation and Diversity*. <https://doi.org/10.1111/icad.12318>
- Silva, D. P., Gonzalez, V. H., Melo, G. A. R., Lucia, M., Alvarez, L. J., & De Marco, P. (2014). Seeking the flowers for the bees: Integrating biotic interactions into niche models to assess the distribution of the exotic bee species *Lithurgus huberi* in South America. *Ecological Modelling*, *273*, 200–209. <https://doi.org/10.1016/j.ecolmodel.2013.11.016>
- Soberón, J. (2007). Grinnellian and Eltonian niches and geographic distributions of species. *Ecology Letters*, *10*(12), 1115–1123. <https://doi.org/10.1111/j.1461-0248.2007.01107.x>
- Steffan-Dewenter, I., Potts, S. G., Packer, L., & Ghazoul, J. (2005). Pollinator diversity and crop pollination services are at risk [3] (multiple letters). *Trends in Ecology and Evolution*, *20*(12), 651–653. <https://doi.org/10.1016/j.tree.2005.09.004>
- Stevenson, T. J., Visser, M. E., Arnold, W., Barrett, P., Biello, S., Dawson, A., ... Helm, B. (2015). Disrupted seasonal biology impacts health, food security and ecosystems. *Proceedings of the Royal Society B: Biological Sciences*, *282*(1817). <https://doi.org/10.1098/rspb.2015.1453>
- Visser, M. E., & Both, C. (2005). Shifts in phenology due to global climate change : the need for a yardstick. *Proceedings of the Royal Society B*, *272*(November), 2561–2569.
- Visser, M. E., Both, C., & Lambrechts, M. M. (2004). Global Climate Change Leads to Mistimed Avian Reproduction. *Advances in Ecological Research*, *35*, 89–110. [https://doi.org/10.1016/S0065-2504\(04\)35005-1](https://doi.org/10.1016/S0065-2504(04)35005-1)
- Winfree, R., Aguilar, R., Vázquez, D. P., LeBuhn, G., & Aizen, M. A. (2009). A Meta-Analysis of Bees' Responses to Anthropogenic Disturbance, *90*(8), 2068–2076.

**INTEGRANDO PREDITORES BIÓTICOS EM MODELOS DE
NICHOS ECOLÓGICOS**

Periódico a ser submetido:

Ecological Modelling

INTEGRATING BIOTIC PREDICTORS IN ECOLOGICAL NICHE MODELLING: RESPONSE OF AN EXOTIC BEE IN SOUTH AMERICA TO CLIMATE CHANGES

ABSTRACT

Biotic interactions can influence species' distribution range. Considering the effects of global climate changes, many studies attempted to integrate them into Ecological Niche Models (ENM) procedures. However, there is a lack of studies evaluating the effects of the inclusion of such interactions upon the distribution of species in scenarios of climate change. Here we evaluated the predicted range of an exotic bee species in future scenarios, including its associated plants as predictor variables. The bee *Lithurgus huberi* Ducke, 1907 (Apidae: Megachilinae: Lithurgini) is an exotic species in South America. Because it is oligolectic to flowers with large pollen grains, we evaluated whether the integration of the biotic component (relationship plants-bee) improves the predictive capacity of its ENM in both current and in the future range distributions. We used all climate models of the four representative concentration pathway (RCP). To reduce uncertainty in our results, we selected three models of each RCP by means of cluster analysis. We then use plant predictions for the present as additional predictor variables to predict the future distribution of *L. huberi* in all RCPs. Our evaluation index was a statistical test based on the True Presence Rate estimated by each prediction. Our results show that the inclusion of the biotic component improved our models in one of the predictive methods evaluated. In addition, we observed that the potential distribution of *L. huberi* tends to decrease in the future, regardless of the RCP considered, but especially in RCP8.5, the most pessimistic scenario.

Keywords: Lithurgini, Species Interactions, Pollination, Exotic Species, Phenology, Biotic Component.

2.1.1 INTRODUCTION

The atmospheric concentration of CO₂ and other greenhouse gases recorded successive increases after the industrial revolution, causing rise in global temperature averages, changes in precipitation patterns, elevation in the average sea level, and changes to the frequency and intensity of extremes climatic events (Blois et al., 2013; Hughes, 2000; Parmesan, 2006). Several possible impacts on biological systems have been investigated such as: 1) changes in the structure and composition of communities, leading to the progressive impoverishment of some communities and relative advancement of opportunistic species (Thuiller et al., 2007); 2) interferences in species' dispersal abilities (Travis et al., 2013); 3) changes in interspecific interactions, for instance in parasitoid-host interactions (Tylianakis and Binzer, 2014); 4) changes in metabolic rates and physiological processes (Dillon et al., 2010); and 5) increasing the probability of species extinction (Thomas et al., 2004). The spatial distribution of species is determined by both abiotic and biotic conditions as well by their ability to reach regions in the geographic space (Soberón, 2007; Soberón and Peterson, 2005). Hence, it is possible that changes in climatic conditions lead to changes in these patterns of distribution, since species should "pursue" the isotherms that guarantee them better physiological tolerance (Parmesan, 2006; Schweiger et al., 2008).

Biotic interactions concern a central part of the ecological framework, as their effects on the distribution of species and communities are utmost important (Araújo and Luoto, 2007; Blois et al., 2013; Silva et al., 2018; Soberón, 2010; Staniczenko et al., 2017). The observed changes in phenological patterns of species demonstrate that climate change is, in fact, affecting such interactions of living systems (Parmesan, 2006; Parmesan and Yohe, 2003; Pecl et al., 2017; Visser and Both, 2005). This may be observed since a trophic the level directly below (e.g. associated plants) delay or advance their phenological/developmental events and if the upper trophic (e.g. pollinators) cannot change their phenological patterns accordingly (Visser et al., 2004). Hence, unexpected phenological and geographical decoupling may affect biotic interactions both by altering species' distributions (Schweiger et al., 2008) and by leading to species' extinctions (Blois et al., 2013).

While considering exotic species, their potential to occupy new regions may be positively affected by the action of climate change (Lockwood et al., 2009). Generally,

the invasion process of exotic species is characterized by three stages (Richardson et al., 2000): introduction, naturalization, and species dissemination. In the first stage, the species reach its new distribution areas and climatic ranges. In the second stage, some individuals from self-sustaining populations arrive and establish other populations in the new geographic range. Eventually, given the right conditions, in the third stage, they will spread in the geographic space, causing further expansion of their distribution area. Exotic species who are successful in the "naturalization" stage, tend not to have very refined requirements to occur, which increases the probability of success of these species in scenarios of global climate change (Lockwood et al., 2009; Parmesan, 2006; Pecl et al., 2017; Richardson et al., 2000).

Ecological Niche Modeling (ENM; also known as Potential Distribution Models - but see Peterson and Soberón, 2012) compose an array of approaches that may be used to assess the invasion potential and establishment of exotic species (Jiménez-Valverde et al., 2011), as well to assess the impact of climate change on their distributions (Araújo and Peterson, 2012). These models relate the species' known occurrences with the present climate to predict the potential distribution of a given species by the intercession of these biotic and abiotic elements (Soberón, 2007; Soberón and Peterson, 2005). The ENM establishes a multidimensional environmental space (Elith et al., 2006), where it is possible to estimate species' niche parameters to estimate their potential distribution in areas climatically similar to those of the species' known occurrences (Peterson et al., 2011; Soberón, 2007; Soberón and Peterson, 2005). Therefore, it is possible to obtain distribution range estimates of species in areas where their distribution is still unknown (Soberón and Peterson, 2005).

Eltonian niches are generally observed in narrow spatial resolutions ($<1\text{Km}^2$), while the Grinnelian niches are ruling in wide spatial resolutions ($>1\text{Km}^2$) (Hortal et al., 2010). Considering that Grinnelian niches are easier to deal with when considering the EMNs, abiotic variables (classified as "*scenopoetic*" by Grinnell) are preponderant in the modulation of the potential species distribution (Soberón, 2007) in relation to the biotic ones (classified by Grinnell as the "*interactive*" variables). Nevertheless, among the ecological/predictor variables used in these methods, resulting in both the success of the establishment of exotic species and in the reduction of predicted areas as suitable ones, it is generally expected that the biotic components of the ecological niches have the most significant effects on the distribution of the modeled species (Jiménez-

Valverde et al., 2011; Soberón, 2007; Soberón and Peterson, 2005). However, the strategy of including biotic components in ENM, as well the understanding of which spatial scale in which they are relevant, are not yet consolidated in the literature (Anderson, 2016; Hortal et al., 2010; Soberón, 2010, 2007; Soberón and Peterson, 2005).

The bee *Lithurgus huberi* Ducke, 1907 (Apidae: Megachilinae: Lithurgini) is considered to be an exotic species in South America (Snelling, 1983) due to their morphological similarities with *Lithurgus antratus* Smith, 1853, representative of an Indo-Australian complex of eight species, which were grouped to represent a single taxonomic unit (Michener, 1965). This bee is univoltine and nests in powdery wood, allowing the dispersion of its individuals over great distances (Camillo et al., 1994, 1983). In addition, as in other cases in the genus *Lithurgus*, it appears to be oligolectic to plants with large pollen grains (Pick and Schlindwein, 2011). While, in its natural range, *L. huberi* was observed collecting pollen from Asteraceae and, specially, Malvaceae (Michener, 2007), in its invaded area, it was observed collecting pollen from both Convolvulaceae (particularly from *Ipomoea* e *Merremia*) and Malvaceae (*Sida* sp. e *Gossypium* spp.) (Camillo et al., 1994, 1983; Michener, 2007; Pick and Schlindwein, 2011).

Here we extend the study done by Silva *et al.* (2014) while modeling the potential distribution of the same exotic bee. Nonetheless, we made use of several future climatic scenarios to evaluate how the potential interaction of the bee and the pollen plants may take place in the future. In this context, we evaluated the effect of considering biotic predictors derived from the potential distributions of *L. huberi*'s associated plants on its potential distribution in South America. In addition, we evaluated how this species' distribution and interactions with such plants may take place in the future. For that, we included the predicted ranges of the associated plants as biotic components of *L. huberi*'s current and future distributions. We performed modelling experiments comparing models with and without these biotic components to assess if such procedures improve our models' predictive ability to estimates *L. huberi*'s ranges. Finally, considering the bee's future distribution range, we also, measured the amount of lost and/or gained range areas in comparison to its the potential current distribution.

2.2 METHODS

2.2.1 Occurrence data

We obtained the geographic occurrences of the bee and its associated plant species from the database structured by Silva *et al.* (2014). This database consists of occurrences obtained from different sources: 1) the internet accessible databases Global Biological Information Facility (GBIF; <http://www.gbif.org>), Species Link of the Reference Center on Environmental Information (CRIA; <http://www.splink.cria.org.br>), Inter-American Biodiversity Information Network (<http://www.iabin.databasin.org>) and Discover Life Bee Species Guide and World Checklist (<http://www.discoverlife.org>); 2) scientific articles and environmental reports published in specific literature and internet; 4) published literature and 5) field surveys.

We collected data on the occurrences of all plant species reported to be used by *L. huberi* as pollen resources in South America (Camillo *et al.*, 1994, 1983; Pick and Schlindwein, 2011). We gathered all the available information from *Ipomoea nil* (L.) Roth, *Ipomoea bahiensis* (L.) Roth, *Ipomoea purpurea* (L.) Roth, *Ipomoea indica* (Burm. F.) Merril, *Ipomoea cairica* (L.) Doce, *Ipomoea asarifolia* (Desr.) Roemer & Schultes and *Merremia aegyptia* (L.) Urban from CRIAS' Species Link, as well from GBIF. We disregarded the records obtained for *Sida* sp. e *Gossypium* spp. because at the time of the construction of the database there were no species-specific records of both these genera and *L. huberi* reported in the literature. Thus, the species that we modeled in this work were: the exotic bee *L. huberi*, and seven plants, six *Ipomoea* and one *Merremia*, associated with it in South America.

2.2.2 Selecting environmental variables and processing occurrences

We encoded all data preparation processes and variables selection, occurrences processing, and predictive methods operationalization in the open source language R (Development Core Team, 2018). We delimited the extension of the grid cells of our predictor variables to South America, with the resolution of 2.5 arcmin (cells with ~4 km² on the equator). We collected all 19 climatic variables (abiotic component), both for the current (interpolations of observed data, representative of 1960-1990) and for each one of the 11 Atmospheric Oceanic Global Circulation Models (AGOCMs hereon)

common at all four IPCC's Representative Concentration Pathways (RCP hereon) (RCP2.6, RCP4.5, RCP6.0 e RCP8.5), with projections for 2070 (average interpolations for 2061-2080). Such variables are freely available in the online database WorldClim (www.worldclim.org; Hijmans et al., 2005).

Modelling with all climatic variables may produce overfitted models (Jiménez-Valverde et al., 2011). Thus, we selected our predictor variables using an Exploratory Factor Analysis (EFA hereon) with VARIMAX axis rotation type. The EFA is a method commonly used in the social sciences to identify the factors (structure or axes) that highlights the correlation of each raw variable with each one of these factors (Distefano et al., 2009; Lawley and Maxwell, 1962). We defined the number of factors in the EFA graphically, by performing a scree test (Cattell, 1966) and analyzing the resulting plot generated via the function `fa.parallel` from the *psych* package (Revelle, 2018). This test showed us that only five factors, that reached observed eigenvalues higher than a random expectation, were needed as environmental predictors for South America. Each one of these factors provide a specific loading value, ranging from -1 to 1, for each variable, where 1 represents the maximum correlation value to the factor (Cattell, 1966; Distefano et al., 2009). Starting from our initial set of 19 abiotic variables for the present scenario, we selected the variables with the highest loading value to represent each one of the five EFA axes (Tab. 2-1). Therefore, our set of abiotic components was composed by: Mean Diurnal Range (Bio02); Isothermality (Bio03); Mean Temperature of Warmest Quarter (Bio10); Precipitation of Driest Month (Bio14); Precipitation of Wettest Quarter (Bio16).

Usually, the climatic variables derived for future scenarios and widely used in ENMs studies are generated by the production of several AOGCMs by independent research organizations. Broadly speaking, these models are mathematical representations of physical processes operating in the atmosphere, ocean, cryosphere, and on the earth's surface (Stocker et al., 2013). Each AOGCM has its peculiarities, since each one uses a unique set of equations to simulate the climatic dynamics. Thus, differences in the initial configuration and in the algorithms that generate this model inevitably lead to different environmental predictions (McGuffie and Henderson-Sellers, 2014). In contrast to the current scenario, where we modeled the species with only one AOGCM available in Worldclim, for the future scenarios, we used several AOGCMs available for the four RCPs available in WorldClim. To reduce the repeatability between

models that are similar and that may increase the uncertainty of the predictions (Varela et al., 2015), we used a hierarchical clustering analysis (HCA hereon) to select the appropriate AOGCMs along all four RCPs.

Table 2-1 Results of the Exploratory Factor Analysis with VARIMAX axis rotation among the 19 WorldClim variables. Bold values represent loading greater than 0.8. Variables in bold represent those that we maintained in our study.

VARIABLES	COD.	FACTORS				
		1	2	3	4	5
Annual Mean Temperature	bio01	0.914	0.042	0.315	0.223	-0.103
Mean Diurnal Range	bio02	-0.121	-0.358	-0.238	-0.194	0.865
Isothermality	bio03	0.312	0.109	0.842	0.278	-0.008
Temperature Seasonality	bio04	-0.294	-0.014	-0.856	-0.376	0.177
Max Temperature of Warmest Month	bio05	0.982	-0.040	-0.058	0.115	0.101
Min Temperature of Coldest Month	bio06	0.782	0.124	0.451	0.279	-0.299
Temperature Annual Range	bio07	-0.223	-0.220	-0.720	-0.302	0.536
Mean Temperature of Wettest Quarter	bio08	0.920	0.045	0.193	0.141	0.024
Mean Temperature of Driest Quarter	bio09	0.777	0.039	0.420	0.275	-0.247
Mean Temperature of Warmest Quarter	bio10	0.985	0.051	0.046	0.130	-0.071
Mean Temperature of Coldest Quarter	bio11	0.821	0.041	0.474	0.281	-0.137
Annual Precipitation	bio12	0.280	0.527	0.303	0.720	-0.129
Precipitation of Wettest Month	bio13	0.351	0.190	0.342	0.835	-0.127
Precipitation of Driest Month	bio14	-0.010	0.956	0.142	0.209	-0.106
Precipitation Seasonality	bio15	0.039	-0.686	0.222	0.032	0.282
Precipitation of Wettest Quarter	bio16	0.349	0.207	0.340	0.837	-0.119
Precipitation of Driest Quarter	bio17	0.009	0.946	0.150	0.250	-0.120
Precipitation of Warmest Quarter	bio18	0.136	0.548	0.181	0.415	0.138
Precipitation of Coldest Quarter	bio19	0.153	0.430	0.185	0.551	-0.297

To maintain the models' comparability, we initially selected only the 11 AOGCMs common to the four RCPs. Then, we built four initial arrays, one for each RCP, with the 19 variables of the 11 AOGCMs, using the *abind* function from the package *abind* (Plate and Heiberger, 2016). We classified the models into groups using

the correlation between their predictions. Finally, we used the `hcluster` function from the package `amap` (Lucas, 2018) to proceed with our HCA, ordering the similarities among the predictions of the models based on the correlation between the predictions in the AOGCMs among the same variables. We set the maximum number of clusters to four. Finally, we analyzed all AOGCM from the four resulting dendrograms following the criteria of 1) be in only one of the four groups of the individual cluster and 2) be present in all four dendrograms referring to each RCP. Hence, we selected the AOGCMs CCSM4, IPSL-CMSA-LR and MIROC-ESM in all RCPs as our future variable sets, to represent the future distribution of our modeled species (Fig 2-1).

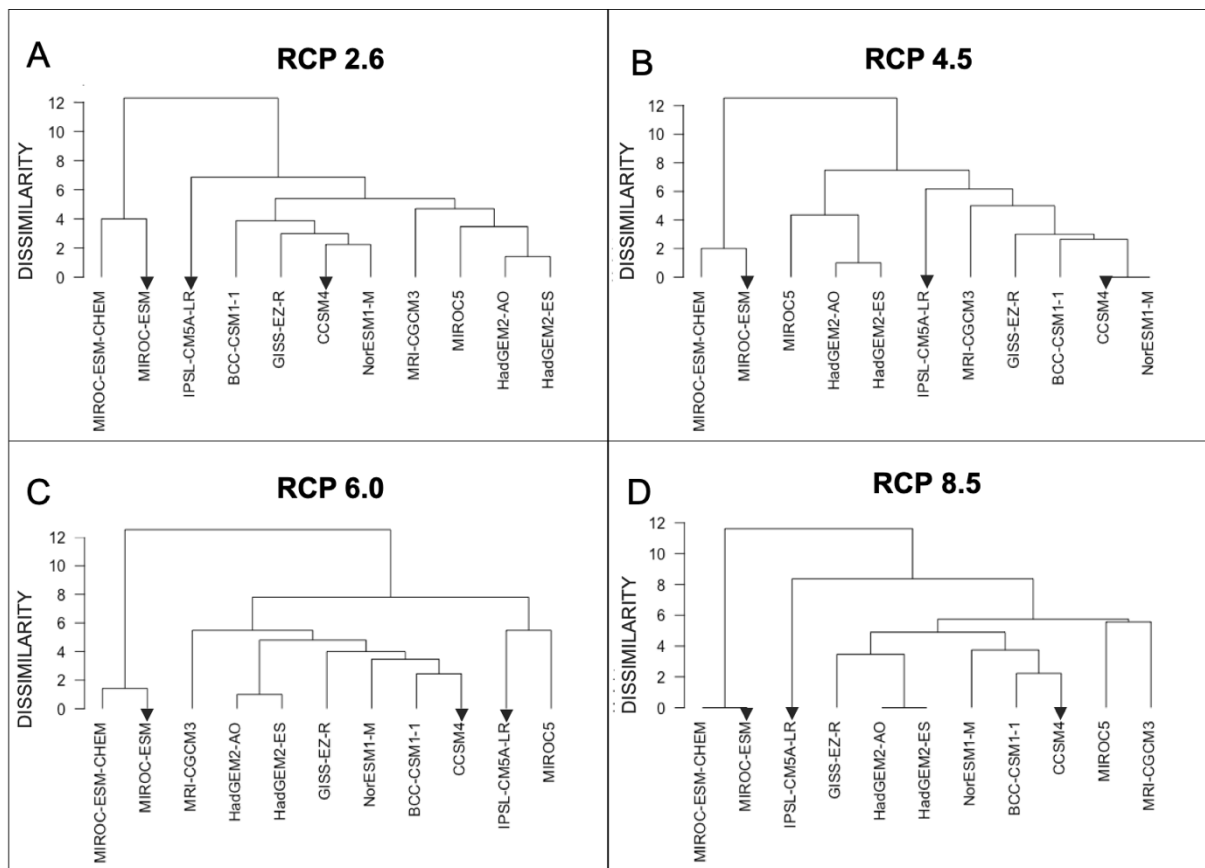


Figure 2-1 Hierarchical clustering of the 11 AOGCMs according to the correlation between all 19 climatic variables for the future scenarios in A) RCP 2.6, B) RCP 4.5, C) RCP 6.0, and D) RCP 8.5. ▼ indicates the selected AOGCMs in all scenarios: CCSM4, IPSL-CMSA-LR and MIROC-ESM. RCP: Representative Carbon Pathway.

To avoid potential effects of spatial autocorrelation between the occurrences of the eight species (one bee and seven host plants), we used the `spThin` package (Aiello-Lammens et al., 2015) to eliminate occurrences that were very close to each other. We only kept the occurrences that were at a minimum distance of 20 km from one another

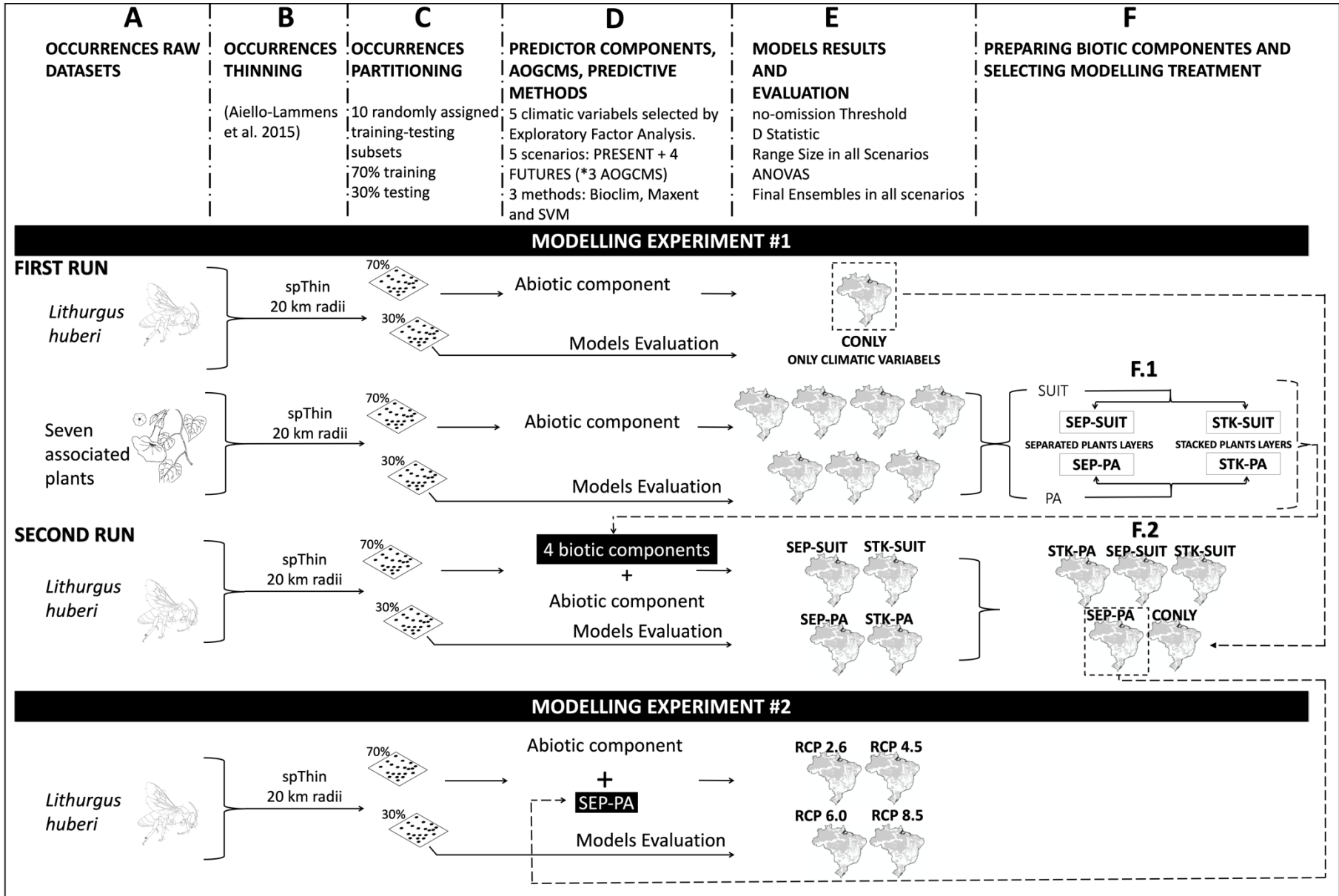
in each species' occurrence dataset used in our models (Fig. 2-2 B). After the geographic space filtering process, the total of spatially unique occurrences remaining for each species was: 50 for *L. huberi*, 170 for *I. asarifolia*, 160 for *I. bahiensis*, 157 for *I. cairica*, 215 for *I. indica*, 338 for *I. nil*, 232 for *I. purpurea* e 239 for *M. aegyptia*.

We divided the occurrences of all species into 10 training-testing subsets, where in each of these subsets, 70% of the occurrence records randomly assigned to the training subsets and the remaining 30% were assigned to the testing subsets (Fig 2-2 C). We used the same subsets in the same order in all our modelling runs for all climatic scenarios considered here.

2.2.3 Experiments procedures and analysis of biotic interactions

Given the predictive ENM methods' individual biases and the uncertainty natures, they may result in different distribution patterns for the modeled species (Barry and Elith, 2006; Rocchini et al., 2011). Thus, we predicted *L. huberi*'s distribution and those of its associated plants using three different predictive methods (Fig 2-2 D): 1) BIOCLIM (Booth et al., 2014; Nix, 1986), implemented by the *bioclim* function from *dismo* package (Hijmans et al., 2017); 2) Maximum Entropy (MaxEnt; Phillips et al., 2006; Phillips and Dudík, 2008), using the MaxEnt function from *dismo* package, loaded within the package by the MaxEnt standalone program installation; and 3) *Support Vector Machines* (SVM; Schölkopf et al., 2001; Tax and Duin, 2004), by using the *ksvm* function from *kernelab* package (Karatzoglou et al., 2004).

Our first modelling experiment consisted of a set of different treatments. In the initial treatment (CLIMA hereon), we model the potential distribution of *L. huberi* and its seven associated plant species for the current scenario, using only the abiotic/climatic variables. From the modeled suitabilities of *L. huberi*'s associated plants, we generated four sets of biotic components that we used in the other treatments of this first modeling experiment (Fig. 2-2 F.1). Then, we model the potential distribution of *L. huberi*, now having as predictors, in addition to the abiotic variables, four sets of biotic components, one specific to each new treatment. Each of these generated biotic components contains a specific amount of predictor variables, being: 1) the suitability of each species of plant cut into presence-absence maps (SEP-PA hereon); 2) the raw suitability for each plant species (SEP-SUIT); 3) sum of the presence and absence values of all plant species by grid cells (STK-PA); 4) the average plant species suitability per grid cell (STK-SUIT).



SEP-SUIT STK-SUIT






F.2

STK-PA SEP-SUIT STK-SUIT





SEP-PA CONLY




MODELLING EXPERIMENT #2

Lithurgus huberi



spThin
20 km radii

70%
30%



Abiotic component
+
SEP-PA

Models Evaluation

RCP 2.6 RCP 4.5




RCP 6.0 RCP 8.5




Figure 2-2 Flowchart and summary of the modeling experiments performed in this study. Experiment # 1 models the distribution of *L. huberi* bee and associated plants in the present: (A) occurrences datasets; (B) filtering occurrences in the geographic space; (C) partition of occurrences into test-training subsets; (D) parameterization of general models and modeling procedures; (E) evaluation of the resulting predictions and ensembles of all predictions and methods by scenario; (F) additional stages of Experiment # 1 - (F.1) generation of biotic components from plant predictions and (F.2) comparison of *L. huberi* distribution without and with biotic components. Experiment # 2 models the potential distribution of *L. huberi* in the four future climate scenarios, using the same methods from (A) to (E) employed in experiment # 1.

Lastly, before we proceeded to our second modeling experiment, we compared the potential distribution of *L. huberi* in the current scenario among the five treatments (CLIMA, SEP-PA, SEP-SUIT, STK-PA, STK-SUIT) (Fig. 2-2 F.2). Then, we used the treatment that best represented *L. huberi*'s suitability in the current scenario to generate *L. huberi*'s predictions for the four future RCPs (Fig 2-3).

2.2.4 Evaluation and ensembles

One way of evaluating the predictions, commonly used by ecological niche modelers, is through metrics associated with pseudo-absences, where absence data is generated to fill the lack of knowledge regarding real absences. In this type of evaluation, after the determination of the predictions by using thresholds that makes the balance between the errors of omission and commission (e.g. the ROC threshold; Liu et al., 2011, 2005), the predictions are evaluated by a metric compatible with pseudo-absences (e.g. true skill statistic; TSS; Allouche et al., 2006). This type of evaluation may represent conceptually flawed analyses given the unreal nature of pseudo-absence data (Golicher et al., 2012; Hirzel et al., 2006; Lobo, 2016; VanDerWal et al., 2009). Moreover, different scales applied in the creation of distribution maps using pseudo-absences may generate divergent final results, depending on the proximity to the occurrences of the known species (Lobo and Tognelli, 2011; VanDerWal et al., 2009). Thus, to avoid these potential setbacks, we grounded our modelling procedures in using presence only methods. The statistical test we adopted here, D, was adapted from Pearson et al., 2007, defined simply as

$$D = TPR * (1 - pi)$$

Where, TPR refers to the True Presence Rate (TPR), and pi refers to the proportion of the area predicted as presence for the species.

Here, we only changed the logic of weighting success binarily (hit/miss), described by Pearson *et al.* (2007),), for a percentage rate of success, i.e. ranging from 0 to 1. Models that predict the entire area of study as the presence of the species are trivial, as they also predict all occurrence points as true (Golicher *et al.*, 2012; Pearson *et al.*, 2007). We used this metric as the weight for assembling the predictions from all predictive methods (Fig. 2-2 E). Thus, low values of D indicate models of low predictive ability and assume a negligible weight in the ensemble, since they are reflected directly in the final weighted suitability. On the other hand, models with high predictive ability would be those that predict a relatively small area as the presence of the species and, even so, they hit the points of occurrence of the species. These models with higher D values contribute with greater importance for the final ensemble (Hirzel *et al.*, 2006; Pearson *et al.*, 2007; Peterson *et al.*, 2011; Shcheglovitova and Anderson, 2013).

We ensemble the 10 prediction replicates, both for the current as well for all four future scenarios, into a single map for each scenario, via a weighted average with all predictions made from each predictive method. We repeated this process in all modeling experiments for *L. huberi* in the different treatments of predictor variables and modeled climatic scenarios.

We used Repeated Measures ANOVAs to: 1) select the most representative treatment of the *L. huberi* current distribution, and with it model and analyze *L. huberi*'s future distribution in the four RCPs; 2) describe the pattern of retraction or expansion of the exotic bee's predicted range in the future. All R scripts written for our modelling procedures are available at <https://github.com/miltonmta/huberi>.

2.3 RESULTS

The D values obtained for the distribution of *L. huberi* in each modeling method were 0.398 ± 0.067 (average \pm standard deviation) for Bioclim, 0.468 ± 0.078 for MaxEnt, and 0.614 ± 0.053 for SVM. In general, the average values of D, considering all methods together, were 0.501 ± 0.112 for *L. huberi*, 0.581 ± 0.141 for *I. asarifolia*, 0.555 ± 0.140 for *I. bahiensis*, 0.700 ± 0.100 for *I. cairica*, 0.495 ± 0.165 for *I. indica*, 0.353 ± 0.146 for *I. nil*, 0.359 ± 0.142 for *I. purpurea*, and 0.459 ± 0.134 for *M. aegyptia*.

Considering the different treatments used to determine *L. huberi*'s distribution in our models, the treatment SEP-PA (modeled with the suitability of each plant species cut into presence-absence maps) was that which obtained the best performance, while comparing it with the other methods we use. For MaxEnt, this treatment reached the higher values in comparison to the others, with D values around 0.6 and 0.7. For SVM, the SEP-PA treatment only showed prediction improvement when compared to the CLIMA treatment, while all other treatments achieved similar results to SEP-PA. For Bioclim, SEP-PA was only better than the STK-SUIT treatment (Fig. 2-3A and Tab. 2-2A). On the other hand, our ANOVA results show that the effect of treatments on the predicted area of the bee depends on the modeling method used. In general, the SEP-PA treatment showed good performance in both MaxEnt and SVM (Fig. 2-3A), while Bioclim overpredicted the bee's distribution in all treatments. Thus, we selected the SEP-PA treatment to analyze the future predictions of *L. huberi* due to its performance in the MaxEnt method, as well for considering that biotic information may make the overall model more realistic.

Table 2-2 Results of the Repeated Measures ANOVA performed with treatments in our models. (A) The results considering the values of D for *Lithurgus huberi*'s predictions; (B) The results considering *Lithurgus huberi*'s range size. XP: modelling treatment

	Variables	Sum of Squares	Degrees of freedom	Mean squares	F value	Adjusted P
	treatment	0.119	4	0.030	1.60	< 0.185
A)	method	3.435	2	1.718	118.60	< 0.000*
	method vs. xp	0.122	8	0.015	1.10	< 0.403
	treatment	0.126	4	0.032	6.01	< 0.001*
B)	method	0.954	2	0.477	89.55	< 0.000*
	method vs. xp	0.281	8	0.035	6.59	< 0.000*

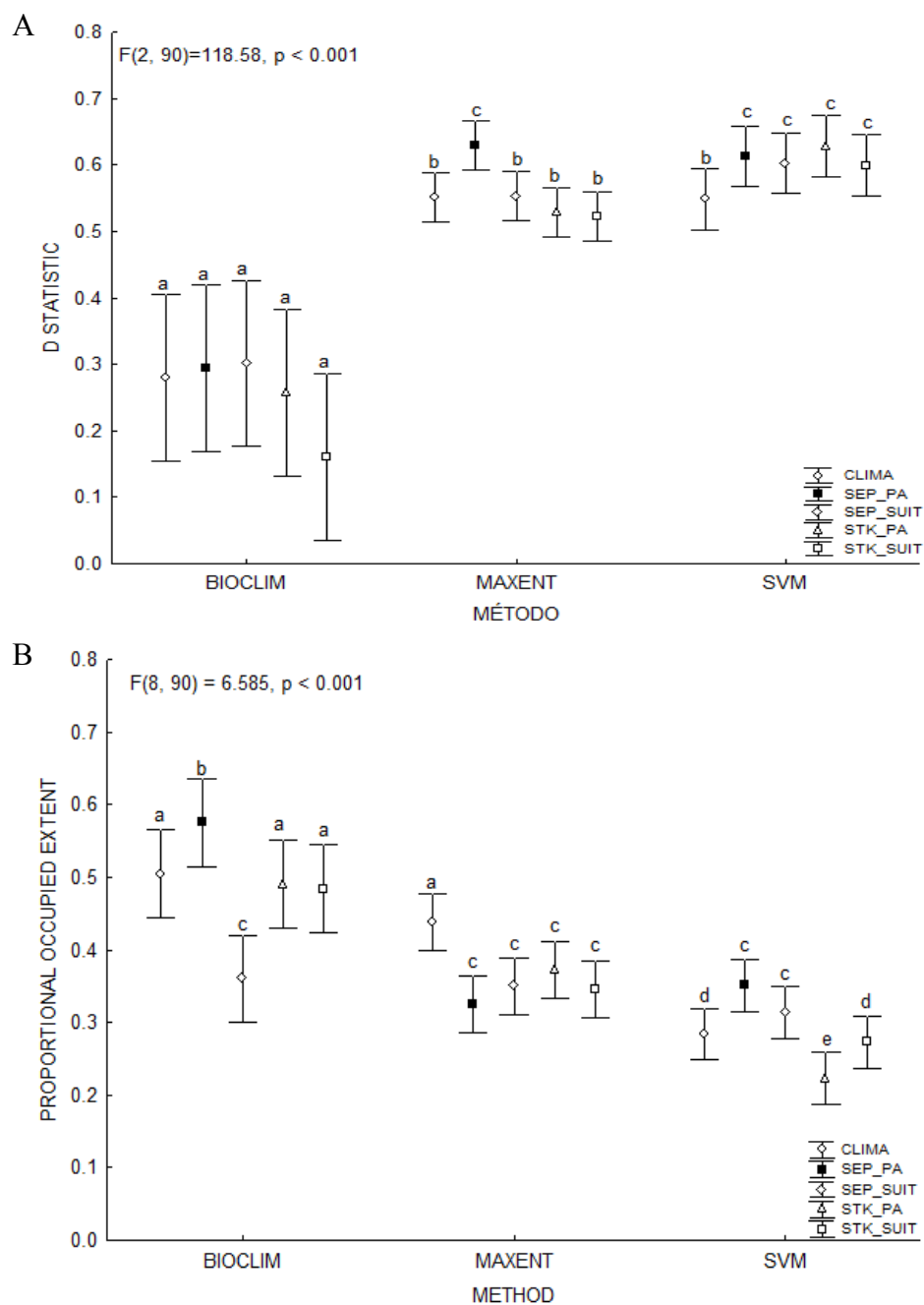


Figure 2-3 Results of the modeling experiment #1. (A) evaluation of D values for each treatment by predictive method, which we used to support our choice for the SEP-PA experiment; (B) Proportion of occupied extent of *Lithurgus huberi*'s potential distributions according to each predictive method in proportion to the study area. Central values correspond to the means, while the bars correspond to the 95% confidence interval. Different letters are statistically different. The SEP-PA treatment is highlighted in both figures.

We can infer an inversely proportional relationship between D results and the size of the distribution. We observed that high values of D may incur in a low predicted distribution area. The Bioclim method, for example, predicted larger areas for *L. huberi* than both MaxEnt and SVM methods, which reached higher values of D on the other hand (Fig. 2-3A and 2-3B).

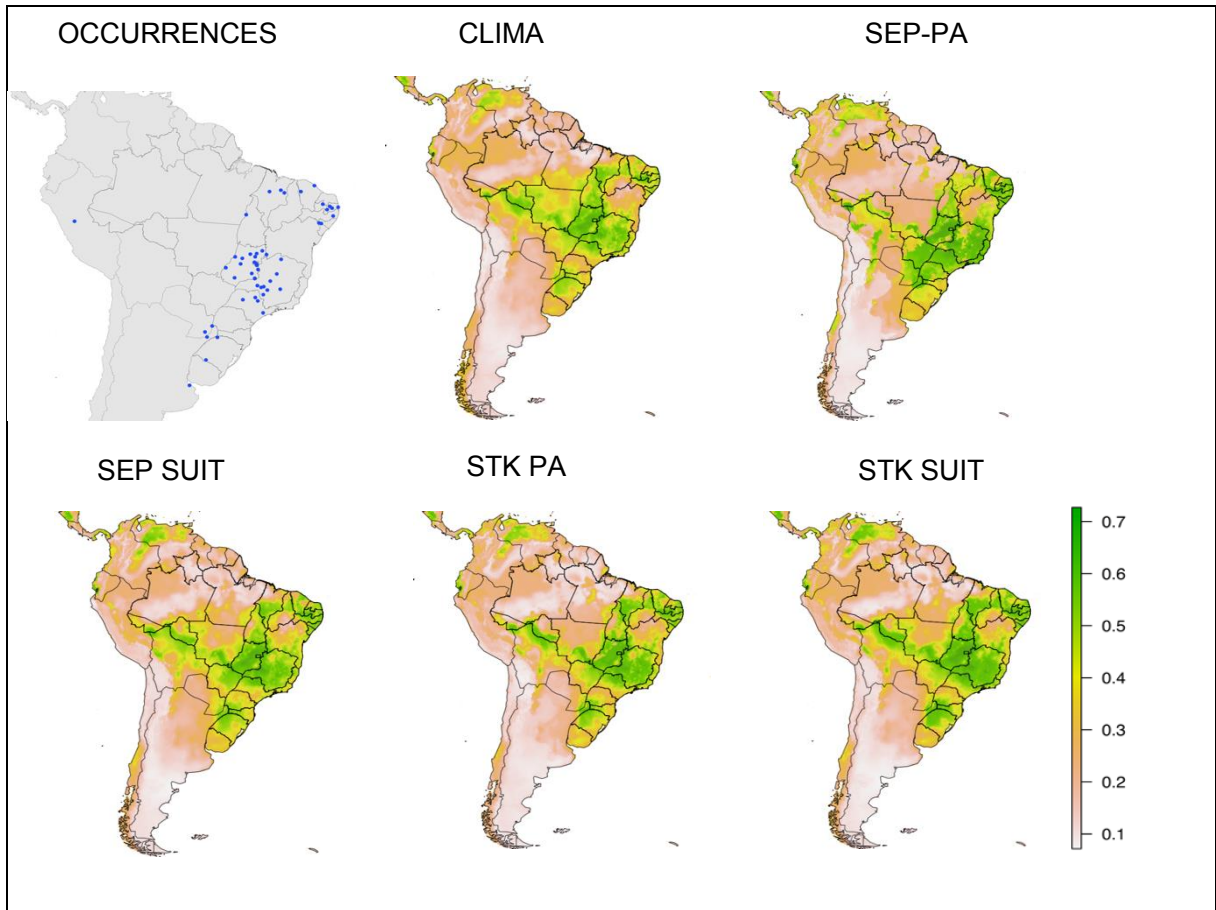


Figure 2-4 Thinned occurrences for *Lithurgus huberi* (blue dots) and ensembles of distribution range of its predictions for the current scenario in all treatments. The ensemble distributions were produced using all three methods according to each treatment in Modeling Experiment #1: CLIMA, abiotic variables only; SEP-PA, abiotic variables plus maps of presence and absence of the associated plant species; SEP-SUIT, abiotic variables plus plant species suitability; STK-PA, abiotic variables plus summed presence and absence maps of the plants; STK-SUIT, average of the suitability of the associated plants. The color scale corresponds to the suitability values for the three species in each of the current and future climate scenarios considered.

In general, the current distribution of *L. huberi* was mainly predicted to occur in the central-west, northeast and southeastern Brazilian regions (Fig. 2-4), as the predicted

distribution of its host plant species (Figs. S. 2-1 to 2-7). As expected, due to the geographical patterns of predictions for the plant species, *L. huberi* was not expected to occur in central areas of the Amazon. The only distribution that showed different results was SEP-PA, which had greater predicted area for *L. huberi* than that observed among the other treatments in modelling experiment #1.

Compared with the current prediction of *L. huberi*, the results for Bioclim show a marked reduction of the predicted area for the AOGCMs IPSL-CMSA-LR, and MIROC-ESM AOGCMs in all RCP scenarios we considered (Fig. 2-5). Compared to the current scenario, there was no significant change in the number of predicted cells among the other methods, SVM and MaxEnt in all three AOGCMs.

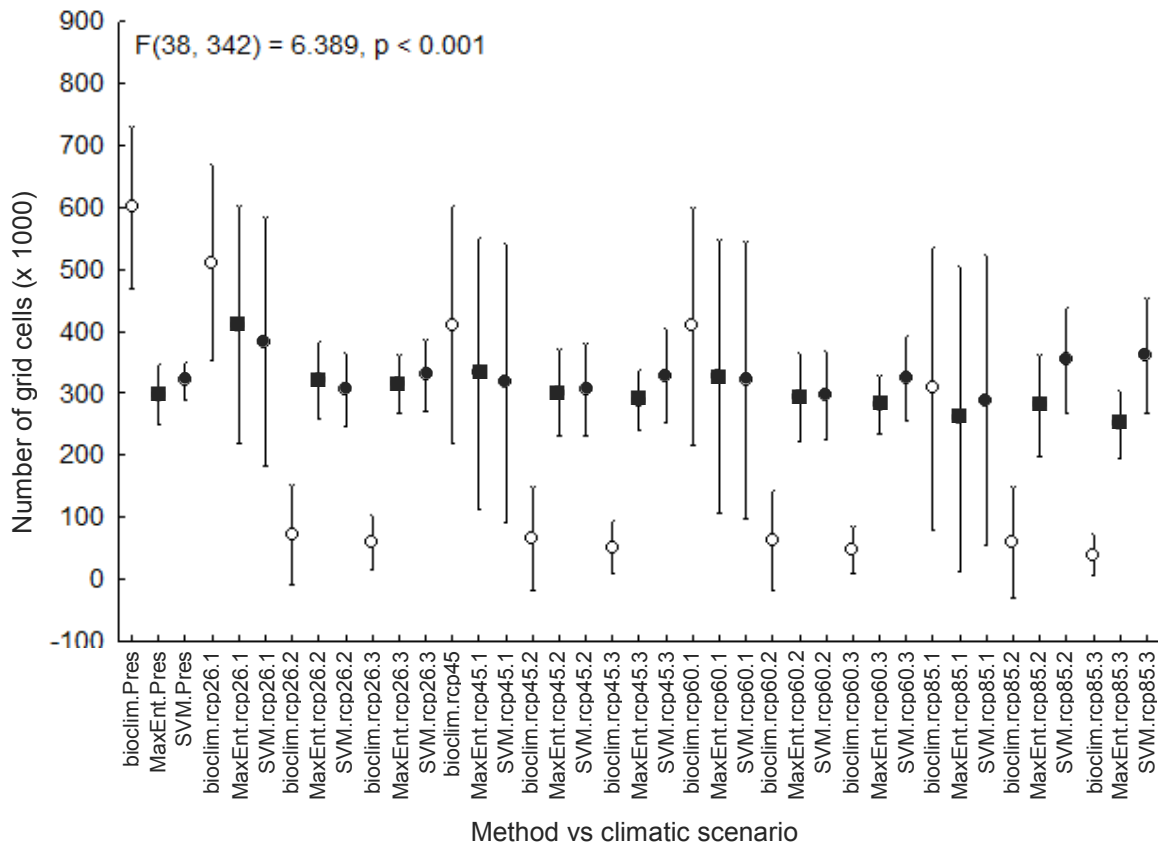


Figure 2-5 Size of the *Lithurgus huberi*'s distribution considering the predictive methods, all AOGCMs, and future scenarios (RCPs 2.6 to 8.5). The range size is represented by the number of grid cells occupied in each predictive method (x 1000) per scenario. Central values correspond to the means and the bars correspond to the 95% confidence interval. ○, ■, ● represent, respectively, the methods: Bioclim, MaxEnt, SVM. The numbering “.1”, “.2”, and “.3” represent, respectively, the following AOGCMs: CCSM4, IPSL-CMSA-LR and MIROC-ESM.

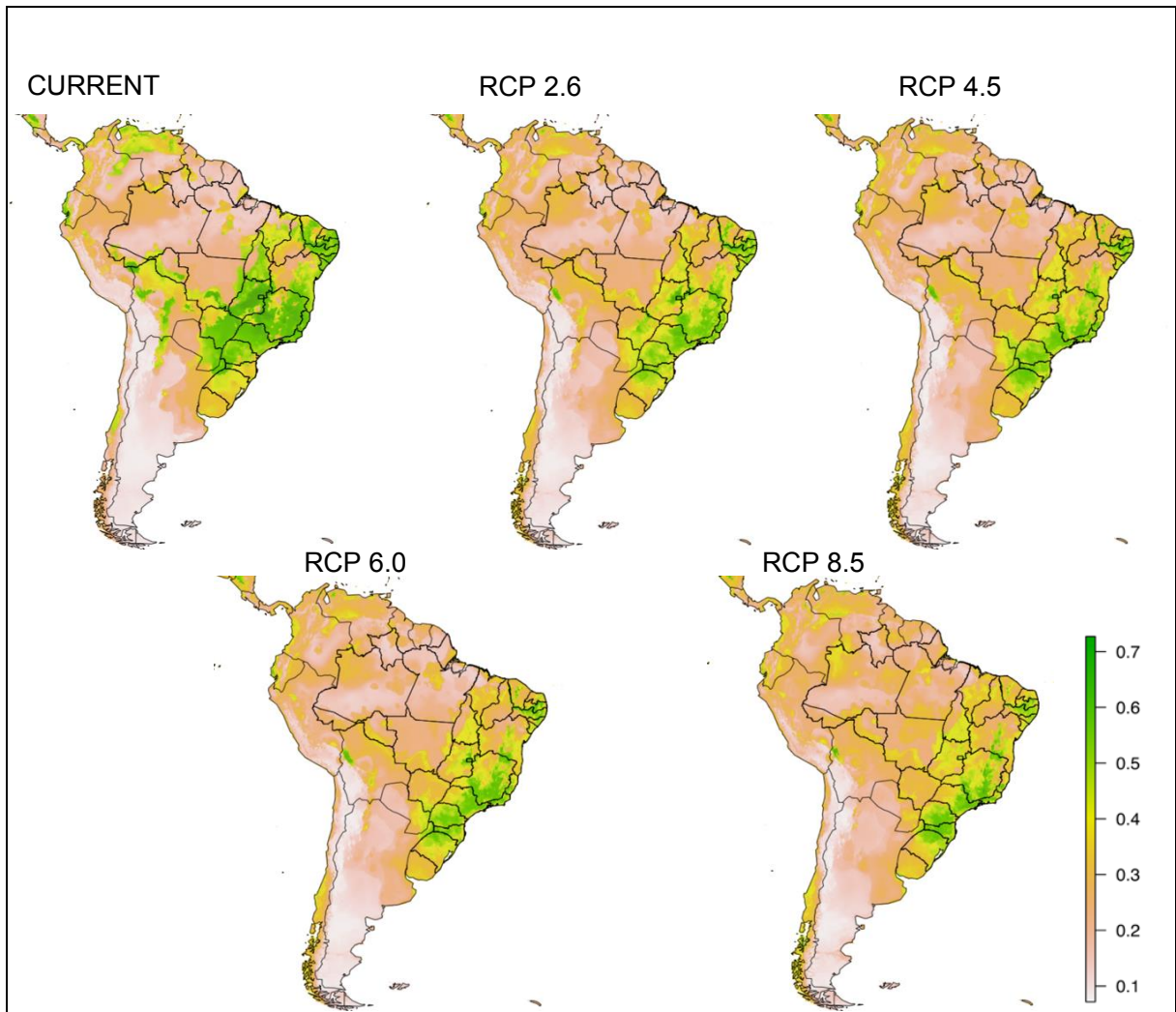


Figure 2-6 Final distribution of *Lithurgus huberi* bee for current and future scenarios (RCPs 2.6 to 8.5). The maps for the future scenarios were generated by the weighted mean of all three methods (Bioclim, MaxEnt, SVM) in all AOGCMs. The color scale corresponds to the values of suitability for the three species in each of the current and future climatic scenarios. RCP: Representative Carbon Pathway.

In the final ensembles of *L. huberi* in the current (SEP-PA) and in the four future scenarios (RCPs 2.6 to 8.5), we observed a marked reduction of suitability in all future scenarios in relation to the present, especially in the center-west region of Brazil (Fig. 2-6). The loss of future suitability is concentrated in areas of the Brazilian Savannas (central South America). If the future predictions for *L. huberi* prove to be right, climate change should isolate its populations from southern and northern South America. In addition, central areas in the distribution in the current scenario will lose suitability in the future, especially RCP8.5, both for *L. huberi* as well for all seven associated plants (Figs. S. 2-1 to 2-7).

2.4 DISCUSSION

In this study, we attempt to integrate biotic interactions in ENMs procedures to predict the future potential distribution of *L. huberi* in South America. Then, we evaluated how the inclusion of the biotic component would affect the distribution of the species bee in the future in interface of the plant species' interactions. Integrating biotic components (associated species), as additional predictor variables, has been the most used approach among the studies choosing this modelling strategy for integrating biotic interactions (Anderson, 2016). Our results show that the inclusion of the biotic component composed of the plant species where the bee searches for food improved our model. In addition, we observed that the potential distribution of *L. huberi* tends to decrease in the future, regardless of the RCP considered, but especially in RCP8.5, the most pessimistic scenario.

Bees represent a significant subset of the pollinators, accounting for 35% of global food production (Klatt et al., 2013; Klein et al., 2003; Kremen et al., 2007). Negative impacts of climate change on the pollinator-plant relationship may produce biological effects, such as: 1) competition for floral resources or nesting sites (Donovan, 1983; Rasmussen et al., 2012); 2) damaging buildings (Araújo and Rozenfeld, 2014; Rust et al., 2004); 3) the reduction in the foraging period (Settele et al., 2016); 4) alteration of pollination networks (Groom et al., 2014; Rasmussen et al., 2012); 5) transmission of pathogens or parasites (Goulson, 2003). In addition, the pollination services provided by several bee communities are well known (Garibaldi et al., 2013; Kremen et al., 2007; Winfree et al., 2007) and interactions between native and non-native bees until they are beneficial in some cases (Greenleaf and Kremen, 2006; Silva et al., 2017). Moreover, exotic bees can have positive impacts through pollination (Groom et al., 2014), increasing resilience to human disturbances (Downing and Liu, 2012) and/or climate change (Martins et al., 2015; Silva et al., 2018). Nevertheless, for very aggressive species such as *Apis mellifera* L., 1758 (Apidae: Apinae: Meliponini), recent research has shown that native species may be negatively affected, since *A. mellifera* is able to monopolize and reduce the amount of food resources available to other species (Cane and Tepedino, 2017; Santos et al., 2012). Despite these efforts, it is still unclear the role of climate change in the behavior of exotic bee species and future studies are needed to assess the invading potential of different species of bees reported as invasive in the world (Russo, 2016).

Usually, the spatial distribution of a species is determined by the intersection of the biotic, abiotic and migratory elements available to the species, according to the BAM diagram (Soberón, 2007; Soberón and Peterson, 2005). However, biotic interactions are generally not considered in macroeconomic analyzes as effective variables in determining the distribution of the modeled species because, presumably, they exert only local effects. This is in contrast to the effects of abiotic variables, which may be factors responsible for determining the spatial distribution at broader scales (Giannini et al., 2013b; Hortal et al., 2010; Soberón et al., 2007). Nevertheless, the omission of interactions in the ENMs does not necessarily imply that they do not play a role in the determination of wide-scale distribution (Anderson, 2016; Hortal et al., 2010; Meier et al., 2010). Given these concerns and criticisms of the real effects of biotic variables at large scales (Guisan and Rahbek, 2011; Wisz et al., 2013), several studies have improved the ability to predict species distribution after inclusion of the biotic component, considering different types of biotic variables and different biological scenarios in their modeling procedures (Anderson, 2016; Araújo and Luoto, 2007; Godoy et al., 2018; Meier et al., 2010; Staniczenko et al., 2017; Wisz et al., 2013). Our results indicate that the biotic variables we used (e.g. the predicted suitability of the associated plant species) are not completely independent from the abiotic variables considered in our modeling procedures, since they partially improve the ability in all predictive methods to determine the modeled distribution of *L. huberi*. Nonetheless, for one method in the selected treatment, it showed some improvement in relation to the other methods and treatments

In our case, given the dependence of insects and plants by climatic conditions (Chown and Terblanche, 2006; Hutchinson, 1957), such variables would be the main factors responsible for both the known and modeled distributions of *L. huberi* and its associated species. In addition, since the bee seems to be oligoletic to the pollen of these plant species, the observed occurrences we obtained may be a result of the intersection of the biotic and abiotic components regulating their niches (Soberón, 2007; Soberón and Peterson, 2005). Thus, although the use of the of the associated plant species' predictions to determine the potential distribution of *L. huberi* may produce a more concise distribution, perhaps this does not necessarily improve the predictive ability of the predictive methods. At least for *L. huberi* and its host plant species, our results are

in agreement with the widely held theory that climate is one of the key determinants of species distribution over a wide scale (Hortal et al., 2010; Pearson and Dawson, 2003).

Models trained using both native and exotic occurrences for the focus species may produce better predictions of future expansion, in areas not yet occupied by the more accurate exotic species (Broennimann and Guisan, 2008). Still, this may not be the best strategy, considering that exotic species may undergo niche shifting in new areas, tending to occupy regions that are climatically different from those where they occur naturally (Blois et al., 2013; Broennimann et al., 2007). Studies following this strategy have found conflicting results, both with observation of niche shifting (Atwater et al., 2018) and niche conservatism (Petitpierre et al., 2012), in particular for plant species. In contrast, invasive insects display rates of niche expansion higher than other taxonomic groups (Hill et al., 2017), with the exception perhaps of reptiles (Li et al., 2014). Therefore, the use of different sets of taxonomic groups, altogether with the biotic variables, may be a better strategy. Considering that there are an expressive number of species of exotic bees already established (Russo, 2016), it would be crucial to test what is happening to the exotic bees species.

Considering our results for the future, our predictions showed that *L. huberi* will retract its distribution range in all four RCPs, although such retraction was most marked in RCP8.5. In other studies, exotic species have shown to be resilient to pessimistic climate change scenarios (Filz and Schmitt, 2015; Kerr et al., 2015; Schweiger et al., 2012, 2010; Silva et al., 2018). According to our models of range distribution, *L. huberi*'s suitable area in the current scenario very concentrated in the South America center-west regions, will be greatly reduced and will move southwards (especially southeastward). Many studies have shown the vulnerability of species to the limits of their distributions, especially in relation to climate change (Parmesan, 2006). Since, climate is the main factor determining the limits of species distributions, It may reduce the persistence of marginal populations (Hoffmann and Blows, 1994), thus, limiting the ability of this bee species to adapt to potential climate change scenarios.

The use of additional floral resources not considered in our biotic predictors could have significant effects in determining the distribution of *L. huberi*. Thus, given their alleged relationships with Malvaceae species in their original distribution, additional studies of the natural and ecological history of this species, throughout its South American occurrence range, may be required to determine whether this bee also depends

on such pollen sources in its invaded area. In the future, if individuals of *L. huberi* were observed collecting pollen from other plant species not considered here, it would be ideal to re-evaluate the methods we used, also including these new biotic interactions as biotic variables determining their distribution in South America. Additionally, the use of plant species used by *L. huberi* as a nesting substrate, e.g. *Euphorbia carinatum*, *Euphorbia pulcherrima* (Euphorbiaceae), *Spathodea campanulata* (Bignoniaceae) and *Eucalyptus* spp. (Myrtaceae; Camillo et al., 1994) could be also considered. Specifically, *Eucalyptus* spp. is nowadays widely planted in Brazil to obtain wood and coal, and may be particularly important for the distribution of *L. huberi* (Silva et al., 2014).

In this study, we modeled the distribution of the seven host plants, recorded in the literature as associated with *L. huberi* and used them as biotic components to determine its potential distribution in South America, both in the current and in the future climatic scenarios. Although the inclusion of model host distributions has partially improved the ability of predictive methods to predict *L. huberi* distribution, similar studies with other host plants, as well as with other biological contexts, should be considered so biotic variables could be properly evaluated in ENMs procedures. In general, we believe that new methodologies for the inclusion of biotic variables are essential for the advancement and improvement of ENM in the future, further enhancing their use in making practical conservation decisions.

2.5 SUPPORTING INFORMATION

FIGURE S. 2-1 THINNED OCCURRENCES FOR *IPOMOEA ASARIFOLIA* (RED DOTS) AND ENSEMBLES OF DISTRIBUTION RANGE OF ITS PREDICTIONS FOR THE CURRENT AND FUTURE SCENARIOS (RCPS 2.6 TO 8.5). THE MAPS FOR THE FUTURE SCENARIOS WERE GENERATED BY THE WEIGHTED MEAN OF ALL THREE METHODS (BIOCLIM, MAXENT, SVM) IN ALL AOGCMS. THE COLOR SCALE CORRESPONDS TO THE VALUES OF SUITABILITY FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATIC SCENARIOS. RCP: REPRESENTATIVE CARBON PATHWAY.....52

FIGURE S. 2-2 THINNED OCCURRENCES *IPOMOEA BAHIENSIS* OCCURRENCES (RED DOTS) AND ENSEMBLES OF DISTRIBUTION RANGE OF ITS PREDICTIONS FOR THE CURRENT AND FUTURE SCENARIOS (RCPS 2.6 TO 8.5). THE MAPS FOR THE FUTURE SCENARIOS WERE GENERATED BY THE WEIGHTED MEAN OF ALL THREE METHODS (BIOCLIM, MAXENT, SVM) IN ALL AOGCMS. THE COLOR SCALE CORRESPONDS TO THE VALUES OF SUITABILITY FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATIC SCENARIOS. RCP: REPRESENTATIVE CARBON PATHWAY.53

FIGURE S. 2-3 THINNED OCCURRENCES *IPOMOEA CAIRICA* OCCURRENCES (RED DOTS) AND ENSEMBLES OF DISTRIBUTION RANGE OF ITS PREDICTIONS FOR THE CURRENT AND FUTURE SCENARIOS (RCPS 2.6 TO 8.5). THE MAPS FOR THE FUTURE SCENARIOS WERE GENERATED BY THE WEIGHTED MEAN OF ALL THREE METHODS (BIOCLIM, MAXENT, SVM) IN ALL AOGCMS. THE COLOR SCALE CORRESPONDS TO THE VALUES OF SUITABILITY FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATIC SCENARIOS. RCP: REPRESENTATIVE CARBON PATHWAY.54

FIGURE S. 2-4 THINNED OCCURRENCES *IPOMOEA INDICA* OCCURRENCES (RED DOTS) AND ENSEMBLES OF DISTRIBUTION RANGE OF ITS PREDICTIONS FOR THE CURRENT AND FUTURE SCENARIOS (RCPS 2.6 TO 8.5). THE MAPS FOR THE FUTURE SCENARIOS WERE GENERATED BY THE WEIGHTED MEAN OF ALL THREE METHODS (BIOCLIM, MAXENT, SVM) IN ALL AOGCMS. THE COLOR SCALE CORRESPONDS TO THE VALUES OF SUITABILITY FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATIC SCENARIOS. RCP: REPRESENTATIVE CARBON PATHWAY.....55

FIGURE S. 2-5 THINNED OCCURRENCES *IPOMOEA NIL* OCCURRENCES (RED DOTS) AND ENSEMBLES OF DISTRIBUTION RANGE OF ITS PREDICTIONS FOR THE CURRENT AND FUTURE SCENARIOS (RCPS 2.6 TO 8.5). THE MAPS FOR THE FUTURE SCENARIOS WERE GENERATED BY THE WEIGHTED MEAN OF ALL THREE METHODS (BIOCLIM, MAXENT, SVM) IN ALL AOGCMS. THE COLOR SCALE CORRESPONDS TO THE VALUES OF SUITABILITY FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATIC SCENARIOS. RCP: REPRESENTATIVE CARBON PATHWAY.....56

FIGURE S. 2-6 THINNED OCCURRENCES *IPOMOEA PURPUREA* OCCURRENCES (RED DOTS) AND ENSEMBLES OF DISTRIBUTION RANGE OF ITS PREDICTIONS FOR THE CURRENT AND FUTURE SCENARIOS (RCPS 2.6 TO 8.5). THE MAPS FOR THE FUTURE SCENARIOS WERE GENERATED BY THE WEIGHTED MEAN OF ALL THREE METHODS (BIOCLIM, MAXENT, SVM) IN ALL AOGCMS. THE COLOR SCALE CORRESPONDS TO THE VALUES OF SUITABILITY FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATIC SCENARIOS. RCP: REPRESENTATIVE CARBON PATHWAY.57

FIGURE S. 2-7 THINNED OCCURRENCES *MERREMIA AEGYPTIA* OCCURRENCES (RED DOTS) AND ENSEMBLES OF DISTRIBUTION RANGE OF ITS PREDICTIONS FOR THE CURRENT AND FUTURE SCENARIOS (RCPS 2.6 TO 8.5). THE MAPS FOR THE FUTURE SCENARIOS WERE GENERATED BY THE WEIGHTED MEAN OF ALL THREE METHODS (BIOCLIM, MAXENT, SVM) IN ALL AOGCMS. THE COLOR SCALE CORRESPONDS TO THE VALUES OF SUITABILITY FOR THE THREE SPECIES IN EACH OF THE CURRENT AND FUTURE CLIMATIC SCENARIOS. RCP: REPRESENTATIVE CARBON PATHWAY.58

2.6 REFERENCES

Aiello-Lammens, M. E., Boria, R. A., Radosavljevic, A., Vilela, B., & Anderson, R. P. (2015). spThin: An R package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography*, 38(5), 541–545. <https://doi.org/10.1111/ecog.01132>

Allouche, O., Tsoar, A., & Kadmon, R. (2006). Assessing the accuracy of species distribution models: Prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology*, 43(6), 1223–1232. <https://doi.org/10.1111/j.1365-2664.2006.01214.x>

- Anderson, R. P. (2016). When and how should biotic interactions be considered in models of species niches and distributions? *Journal of Biogeography*, 104–110. <https://doi.org/10.1111/jbi.12825>
- Araújo, M. B., & Luoto, M. (2007). The importance of biotic interactions for modelling species distributions under climate change. *Global Ecology and Biogeography*, 16(6), 743–753. <https://doi.org/10.1111/j.1466-8238.2007.00359.x>
- Araújo, M. B., & Peterson, A. T. (2012). Uses and misuses of bioclimatic envelope modeling. *Ecology*, 93(7), 1527–1539. <https://doi.org/10.1890/07-1861.1>
- Araújo, M. B., & Rozenfeld, A. (2014). The geographic scaling of biotic interactions. *Ecography*, 37(5), 406–415. <https://doi.org/10.1111/j.1600-0587.2013.00643.x>
- Atwater, D. Z., Ervine, C., & Barney, J. N. (2018). Climatic niche shifts are common in introduced plants. *Nature Ecology and Evolution*, 2(1), 34–43. <https://doi.org/10.1038/s41559-017-0396-z>
- Barry, S., & Elith, J. (2006). Error and uncertainty in habitat models. *Journal of Applied Ecology*, 43, 413–423.
- Blois, J. L., Zarnetzke, P. L., Fitzpatrick, M. C., & Finnegan, S. (2013). Climate Change and the Past, Present, and Future of Biotic Interactions. *Science*, 341(2013), 499–504. <https://doi.org/10.1126/science.1237184>
- Booth, T. H., Nix, H. A., Busby, J. R., & Hutchinson, M. F. (2014). Bioclim: The first species distribution modelling package, its early applications and relevance to most current MaxEnt studies. *Diversity and Distributions*, 20(1), 1–9. <https://doi.org/10.1111/ddi.12144>
- Broennimann, O., & Guisan, A. (2008). Predicting current and future biological invasions: Both native and invaded ranges matter. *Biology Letters*, 4(5), 585–589. <https://doi.org/10.1098/rsbl.2008.0254>
- Broennimann, O., Treier, U. A., Müller-Schärer, H., Thuiller, W., Peterson, A. T., & Guisan, A. (2007). Evidence of climatic niche shift during biological invasion. *Ecology Letters*, 10(8), 701–709. <https://doi.org/10.1111/j.1461-0248.2007.01060.x>
- Camillo, E., Garófalo, C. A., Campos, M. J. O., & Serrano, J. C. (1983). Preliminary notes on the biology of *Lithurgus huberi* (Hymenoptera, Megachilidae). *Revista Brasileira de Biologia*.
- Camillo, E., Garófalo, C. A., & Serrano, J. C. (1994). Nesting activities and nest reuse of *Lithurge huberi* (Hymenoptera, Megachilidae). *Revista Brasileira de Biologia*.
- Cane, J. H., & Tepedino, V. J. (2017). Gauging the Effect of Honey Bee Pollen Collection on Native Bee Communities James. *Conservation Letters*, 10, 205–210. <https://doi.org/10.1111/conl.12263>
- Cattell, R. B. (1966). The scree test for the numbers of factors. *Multivariate Behavioral Research*, 1(August), 245–276. <https://doi.org/10.1207/s15327906mbr0102>
- Chown, S. L., & Terblanche, J. S. (2006). Physiological diversity in insects: ecology and evolutionary contexts. *Advances in Insect Physiology*, 33(06), 50–152.
- Development Core Team, R. (2018). R: A language and environment for statistical computing. Vienna: R Foundation for Statistical Computing.
- Dillon, M. E., Wang, G., & Huey, R. B. (2010). Global metabolic impacts of recent climate

- warming. *Nature*, 467(7316), 704–706. <https://doi.org/10.1038/nature09407>
- Distefano, C., Zhu, M., & Mîndrilă, D. (2009). Understanding and using factor scores: Considerations for the applied researcher. *Practical Assessment, Research & Evaluation*, 14(20), 1–11. <https://doi.org/10.1.1.460.8553>
- Donovan, B. J. (1983). Occurrence of the Australian bee *Hyleoides concinna* (Hymenoptera: Colletidae) in New Zealand. *New Zealand Journal of Zoology*, 10(4), 345–347. <https://doi.org/10.1080/03014223.1983.10423929>
- Downing, J. L., & Liu, H. (2012). Friend or foe? Impacts of the introduced tropical oil bee *Centris nitida* on a threatened and specialized native mutualism in Southern Florida. *Biological Invasions*, 14(10), 2175–2185. <https://doi.org/10.1007/s10530-012-0223-z>
- Elith, J., Graham, C. H., Anderson, R. P., Dudik, M., Ferrier, S., Guisan, A., ... Zimmermann, N. E. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, 29(2), 129–151. <https://doi.org/10.1111/j.2006.0906-7590.04596.x>
- Filz, K. J., & Schmitt, T. (2015). Niche overlap and host specificity in parasitic *Maculinea* butterflies (Lepidoptera: Lycaenidae) as a measure for potential extinction risks under climate change. *Organisms Diversity and Evolution*, 15(3), 555–565. <https://doi.org/10.1007/s13127-015-0210-1>
- Garibaldi, L. A., Steffan-Dewenter, I., Winfree, R., Aizen, M. A., Bommarco, R., Cunningham, S. A., ... Klein, A. M. (2013). Wild pollinators enhance fruit set of crops regardless of honey bee abundance. *Science*, (339), 1608–1611. <https://doi.org/10.1126/science.1235809>
- Giannini, T. C., Pinto, C. E., Acosta, A. L., Taniguchi, M., Saraiva, A. M., & Alves-dos-Santos, I. (2013). Interactions at large spatial scale: The case of *Centris* bees and floral oil producing plants in South America. *Ecological Modelling*, 258, 74–81. <https://doi.org/10.1016/j.ecolmodel.2013.02.032>
- Godoy, O., Bartomeus, I., Rohr, R. P., & Saavedra, S. (2018). Towards the Integration of Niche and Network Theories, 33(4), 287–300.
- Golicher, D., Ford, A., & Cayuela, L. (2012). Pseudo-absences, pseudo-models and pseudo-niches: pitfalls of model selection based on the area under the curve. *International Journal of Geographical Information Science*, 26(11), 2049–2063.
- Goulson, D. (2003). Effects of Introduced Bees on Native Ecosystems. *Annual Review of Ecology, Evolution, and Systematics*, 34(1), 1–26. <https://doi.org/10.1146/annurev.ecolsys.34.011802.132355>
- Greenleaf, S. S., & Kremen, C. (2006). Wild bees enhance honey bees' pollination of hybrid sunflower. *Proceedings of the National Academy of Sciences*, 103(37), 13890–13895. <https://doi.org/10.1073/pnas.0600929103>
- Groom, S. V. C., Hayes, S. E., Ngo, H. T., Stevens, M. I., & Schwarz, M. P. (2014). Recipe for disruption: Multiple recent arrivals of megachilid bees in Pacific archipelagos. *Journal of Insect Conservation*, 18(4), 613–622. <https://doi.org/10.1007/s10841-014-9665-1>
- Guisan, A., & Rahbek, C. (2011). SESAM - a new framework integrating macroecological and species distribution models for predicting spatio-temporal patterns of species assemblages. *Journal of Biogeography*, 38(8), 1433–1444. <https://doi.org/10.1111/j.1365-2699.2011.02550.x>
- Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., & Jarvis, A. (2005). Very high

- resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, 25, 1965–1978.
- Hijmans, R. J., Phillips, S., & Leathwi, J. (2017). *dismo: Species Distribution Modeling*. Retrieved from <https://cran.r-project.org/package=dismo>
- Hill, M. P., Gallardo, B., & Terblanche, J. S. (2017). A global assessment of climatic niche shifts and human influence in insect invasions. *Global Ecology and Biogeography*, 26(6), 679–689. <https://doi.org/10.1111/geb.12578>
- Hirzel, A. H., Le Lay, G., Helfer, V., Randin, C., & Guisan, A. (2006). Evaluating the ability of habitat suitability models to predict species presences. *Ecological Modelling*, 199(2), 142–152. <https://doi.org/10.1016/j.ecolmodel.2006.05.017>
- Hoffmann, A. A., & Blows, M. W. (1994). Rigorous Validation of Isolating Blocks for Flows and Their Conley Indices. *Trends in Ecology & Evolution*, 9, 223–227.
- Hortal, J., Roura-Pascual, N., Sanders, N. J., & Rahbek, C. (2010). Understanding (insect) species distributions across spatial scales. *Ecography*, 33(1), 51–53. <https://doi.org/10.1111/j.1600-0587.2009.06428.x>
- Hughes, L. (2000). Biological consequences of global warming: is the signal already. *TREE*, 15(2), 56–61.
- Hutchinson, G. E. (1957). Concluding remarks. *Cold Spring Harbor Symposia on Quantitative Biology*, 22, 415–427. <https://doi.org/10.1101/SQB.1957.022.01.039>
- Jiménez-Valverde, A., Peterson, A. T., Soberón, J., Overton, J. M., Aragón, P., Lobo, J. M., ... Lobo, J. M. (2011). Use of niche models in invasive species risk assessments. *Biological Invasions*, 13(12), 2785–2797. <https://doi.org/10.1007/s10530-011-9963-4>
- Karatzoglou, A., Smola, A., Hornik, K., & Zeileis, A. (2004). kernlab: An S4 Package for Kernel Methods in R. *Journal of Statistical Software*, 11(9), 1–20. Retrieved from <http://www.jstatsoft.org/v11/i09/>
- Kerr, J. T., Pindar, A., Galpern, P., Packer, L., Potts, S. G., Roberts, S. M., ... Pantoja, A. (2015). Climate change impacts on bumblebees converge across continents. *Science*, 349(6244), 1–14. <https://doi.org/10.1126/science.aaa7031>
- Klatt, B. K., Holzschuh, A., Westphal, C., Clough, Y., Smit, I., Pawelzik, E., & Tschardtke, T. (2013). Bee pollination improves crop quality, shelf life and commercial value. *Proceedings of the Royal Society B: Biological Sciences*, 281(1775). <https://doi.org/10.1098/rspb.2013.2440>
- Klein, A. M., Steffan-Dewenter, I., & Tschardtke, T. (2003). Fruit set of highland coffee increases with the diversity of pollinating bees. *Proceedings of the Royal Society B: Biological Sciences*, 270(1518), 955–961. <https://doi.org/10.1098/rspb.2002.2306>
- Kremen, C., Williams, N. M., Aizen, M. A., Gemmill-Herren, B., LeBuhn, G., Minckley, R., ... Ricketts, T. H. (2007). Pollination and other ecosystem services produced by mobile organisms: A conceptual framework for the effects of land-use change. *Ecology Letters*, 10(4), 299–314. <https://doi.org/10.1111/j.1461-0248.2007.01018.x>
- Lawley, D. N., & Maxwell, A. E. (1962). Factor analysis as a statistical method. *Wiley for the Royal Statistical Society*, 12(3), 209–229.
- Li, Y., Liu, X., Li, X., Petitpierre, B., & Guisan, A. (2014). Residence time, expansion toward the equator in the invaded range and native range size matter to climatic niche shifts in

- non-native species. *Global Ecology and Biogeography*, 23(10), 1094–1104. <https://doi.org/10.1111/geb.12191>
- Liu, C., Berry, P. M., Dawson, T. P., & Pearson, R. G. (2005). Selecting thresholds of occurrence in the prediction of species distributions. *Ecography*, 28(3), 385–393. <https://doi.org/10.1111/j.0906-7590.2005.03957.x>
- Liu, C., White, M., & Newell, G. (2011). Measuring and comparing the accuracy of species distribution models with presence-absence data. *Ecography*, 34, 232–243.
- Lobo, J. M. (2016). The use of occurrence data to predict the effects of climate change on insects. *Current Opinion in Insect Science*, 17, 62–68. <https://doi.org/10.1016/j.cois.2016.07.003>
- Lobo, J. M., & Tognelli, M. F. (2011). Exploring the effects of quantity and location of pseudo-absences and sampling biases on the performance of distribution models with limited point occurrence data. *Journal for Nature Conservation*, 19(1), 1–7. <https://doi.org/10.1016/j.jnc.2010.03.002>
- Lockwood, J. L., Cassey, P., & Blackburn, T. M. (2009). The more you introduce the more you get: The role of colonization pressure and propagule pressure in invasion ecology. *Diversity and Distributions*, 15(5), 904–910.
- Lucas, A. (2018). amap: Another Multidimensional Analysis Package.
- Martins, A. C., Silva, D. P., De Marco, P., & Melo, G. A. R. (2015). Species conservation under future climate change: the case of *Bombus bellicosus*, a potentially threatened South American bumblebee species. *Journal of Insect Conservation*, 19(1), 33–43. <https://doi.org/10.1007/s10841-014-9740-7>
- McGuffie, K., & Henderson-Sellers, A. (2014). *A Climate Modelling Primer*. Oxford: John Wiley & Sons.
- Meier, E. S., Kienast, F., Pearman, P. B., Svenning, J. C., Thuiller, W., Araújo, M. B., ... Zimmermann, N. E. (2010). Biotic and abiotic variables show little redundancy in explaining tree species distributions. *Ecography*, 33(6), 1038–1048. <https://doi.org/10.1111/j.1600-0587.2010.06229.x>
- Michener, C. D. (1965). A classification of the bees of the Australian and South Pacific regions. *Bulletin of the American Museum of Natural History*, 130, 1–362.
- Michener, C. D. (2007). *The Bees of The World*. The Johns Hopkins University Press.
- Nix, H. (1986). A biogeographic analysis of Australian elapid snakes. In Longmore, R., Ed., *Atlas of Elapid Snakes of Australia. Australian Flora and Fauna Series No. 7* (pp. 4–15). Canberra: Australian Government Publishing Service.
- Parmesan, C. (2006). Ecological and evolutionary responses to recent climate change. *Annual Review of Ecology and Systematics*, 37(1), 637–669. <https://doi.org/10.1146/annurev.ecolsys.37.091305.110100>
- Parmesan, C., & Yohe, G. (2003). A globally coherent fingerprint of climate change impacts across natural systems. *Nature*, 421, 37. <https://doi.org/10.1038/nature01286>
- Pearson, R. G., & Dawson, T. P. (2003). Predicting the impacts of climate change on the distribution of species : are bioclimate envelope models useful ?, 361–371.
- Pearson, R. G., Raxworthy, C. J., Nakamura, M., & Townsend Peterson, A. (2007). Predicting species distributions from small numbers of occurrence records: A test case using cryptic

- geckos in Madagascar. *Journal of Biogeography*, 34(1), 102–117. <https://doi.org/10.1111/j.1365-2699.2006.01594.x>
- Pecl, G. T., Araújo, M. B., Bell, J. D., Blanchard, J., Bonebrake, T. C., Chen, I. C., ... Williams, S. E. (2017). Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science*, 355(6332). <https://doi.org/10.1126/science.aai9214>
- Peterson, A. T., & Soberón, J. (2012). Species distribution modeling and ecological niche modeling: Getting the Concepts Right. *Natureza e Conservacao*, 10(2), 102–107. <https://doi.org/10.4322/natcon.2012.019>
- Peterson, A. T., Soberón, J., Pearson, R., Anderson, R. P., Martínez-Meyer, E., Nakamura, M., & Araújo, M. B. (2011). *Ecological niches and geographic distributions*. *Ecological niches and geographic distributions* (Vol. 94).
- Petitpierre, B., Kueffer, C., Broennimann, O., Randin, C., Daehler, C., & Guisan, A. (2012). Climatic niche shifts are rare among terrestrial plant invaders. *Science*, 335(6074), 1344–1348. <https://doi.org/10.1126/science.1215933>
- Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *International Journal of Global Environmental Issues*, (190), 231–259. <https://doi.org/10.1016/j.ecolmodel.2005.03.026>
- Phillips, S. J., & Dudík, M. (2008). Modeling of species distribution with Maxent: new extensions and a comprehensive evaluation. *Ecography*, 31(December 2007), 161–175. <https://doi.org/10.1111/j.2007.0906-7590.05203.x>
- Pick, R. A., & Schindwein, C. (2011). Pollen partitioning of three species of Convolvulaceae among oligolectic bees in the Caatinga of Brazil. *Plant Systematics and Evolution*, 293(1–4), 147–159.
- Plate, T., & Heiberger, R. (2016). abind: Combine Multidimensional Arrays. Retrieved from <https://cran.r-project.org/package=abind>
- Rasmussen, C., Carrion, A. L., Castro-Urgal, R., Chamorro, S., Gonzalez, V. H., Griswold, T. L., ... Traveset, A. (2012). *Megachile timberlakei* Cockerell (Hymenoptera: Megachilidae): Yet another adventive bee species to the Galápagos Archipelago. *The Pan-Pacific Entomologist*, 88(1), 98–102. <https://doi.org/10.3956/2012-04.1>
- Revelle, W. (2018). psych: Procedures for Personality and Psychological Research. Illinois, USA: Northwestern University. Retrieved from <https://cran.r-project.org/package=psych>
- Richardson, D. M., Pyšek, P., Rejmánek, M., Barbour, M. G., Dane Panetta, F., & West, C. J. (2000). Naturalization and invasion of alien plants: Concepts and definitions. *Diversity and Distributions*, 6(2), 93–107. <https://doi.org/10.1046/j.1472-4642.2000.00083.x>
- Rocchini, D., Hortal, J., Lengyel, S., Lobo, J. M., Jiménez-Valverde, A., Ricotta, C., ... Chiarucci, A. (2011). Accounting for uncertainty when mapping species distributions: The need for maps of ignorance. *Progress in Physical Geography*, 35(2), 211–226.
- Russo, L. (2016). Positive and negative impacts of non-native bee species around the world. *Insects*, 7(4). <https://doi.org/10.3390/insects7040069>
- Rust, R. W., Cambon, G., Grossa, J.-P. T., & Vaissière, B. E. (2004). Nesting Biology Lithurgus and Foraging Ecology of the Wood-boring chrysurus (Hymenoptera : Megachilidae). *Journal of the Kansas Entomological Society*, 77(3), 269–279.
- Santos, G. M. de M., Aguiar, C. M. L., Genini, J., Martins, C. F., Zanella, F. C. V., & Mello, M.

- A. R. (2012). Invasive Africanized honeybees change the structure of native pollination networks in Brazil. *Biological Invasions*, *14*(11), 2369–2378. <https://doi.org/10.1007/s10530-012-0235-8>
- Schölkopf, B., Platt, J. C., Shawe-Taylor, J., Smola, A. J., & Williamson, R. C. (2001). Estimating the support of a high-dimensional distribution. *Neural Computation*, *13*(7), 1443–1471. <https://doi.org/10.1162/089976601750264965>
- Schweiger, O., Biesmeijer, J. C., Bommarco, R., Hickler, T., Hulme, P. E., Klotz, S., ... Settele, J. (2010). Multiple stressors on biotic interactions: How climate change and alien species interact to affect pollination. *Biological Reviews*, *85*(4), 777–795. <https://doi.org/10.1111/j.1469-185X.2010.00125.x>
- Schweiger, O., Heikkinen, R. K., Harpke, A., Hickler, T., Klotz, S., Kudrna, O., ... Settele, J. (2012). Increasing range mismatching of interacting species under global change is related to their ecological characteristics. *Global Ecology and Biogeography*, *21*(1), 88–99. <https://doi.org/10.1111/j.1466-8238.2010.00607.x>
- Schweiger, O., Settele, J., Kudrna, O., Klotz, S., & Kuhn, I. (2008). Climate change can cause spatial mismatch of trophically interacting species. *Ecology*, *89*(12), 3472–3479. <https://doi.org/10.1890/07-1748.1>
- Settele, J., Bishop, J., & Potts, S. G. (2016). Climate change impacts on pollination. *Nature Plants*, *2*(July), 16092.
- Shcheglovitova, M., & Anderson, R. P. (2013). Estimating optimal complexity for ecological niche models: A jackknife approach for species with small sample sizes. *Ecological Modelling*, *269*, 9–17. <https://doi.org/10.1016/j.ecolmodel.2013.08.011>
- Silva, D. P., Dew, R. M., Vilela, B., Stevens, M. I., & Schwarz, M. P. (2018). No deaths in the desert: predicted responses of an arid-adapted bee and its two nesting trees suggest resilience in the face of warming climates. *Insect Conservation and Diversity*. <https://doi.org/10.1111/icad.12318>
- Silva, D. P., Gonzalez, V. H., Melo, G. A. R., Lucia, M., Alvarez, L. J., & De Marco, P. (2014). Seeking the flowers for the bees: Integrating biotic interactions into niche models to assess the distribution of the exotic bee species *Lithurgus huberi* in South America. *Ecological Modelling*, *273*, 200–209. <https://doi.org/10.1016/j.ecolmodel.2013.11.016>
- Silva, D. P., Groom, S. V. C., da Silva, C. R. B., Stevens, M. I., & Schwarz, M. P. (2017). Potential pollination maintenance by an exotic allodapine bee under climate change scenarios in the Indo-Pacific region. *Journal of Applied Entomology*, *141*(1–2), 122–132. <https://doi.org/10.1111/jen.12337>
- Snelling, R. R. (1983). The North American species of the bee genus *Lithurge* (Hymenoptera: Megachilidae). *Contributed Science, Los Angeles County Museum of Natural History*, *343*, 1–11.
- Soberón, J. (2007). Grinnellian and Eltonian niches and geographic distributions of species. *Ecology Letters*, *10*(12), 1115–1123. <https://doi.org/10.1111/j.1461-0248.2007.01107.x>
- Soberón, J. (2010). Niche and area of distribution modeling: A population ecology perspective. *Ecography*, *33*(1), 159–167. <https://doi.org/10.1111/j.1600-0587.2009.06074.x>
- Soberón, J., Jiménez, R., Golubov, J., & Koleff, P. (2007). Assessing completeness of biodiversity databases at different spatial scales. *Ecography*, *30*(1), 152–160. <https://doi.org/10.1111/j.2006.0906-7590.04627.x>

- Soberón, J., & Peterson, A. T. (2005). Interpretation of models of fundamental ecological niches and species' distributional areas. *Biodiversity Informatics*, 2, 1–10.
- Staniczenko, P. P. A., Sivasubramaniam, P., Suttle, K. B., & Pearson, R. G. (2017). Linking macroecology and community ecology: refining predictions of species distributions using biotic interaction networks. *Ecology Letters*, 20(6), 693–707. <https://doi.org/10.1111/ele.12770>
- Stocker, T. F., Qin, D., Plattner, G.-K., Alexander, L. V., Allen, S. K., Bindoff, N. L., ... Xie, S.-P. (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, NY, USA.: Cambridge University.
- Tax, D. M. J., & Duin, R. P. W. (2004). Support vector data description. *Machine Learning*, 54(1), 45–66. Retrieved from <http://www.springerlink.com/index/JL3N42J6067703N2.pdf>
- Thomas, C. D., Cameron, A., Green, R. E., Bakkenes, M., Beaumont, L. J., Collingham, Y. C., ... Williams, S. E. (2004). Extinction risk from climate change. *Nature(London)*, 427(6970), 145–148. <https://doi.org/10.1038/nature02121>
- Thuiller, W., Richardson, D. M., & Midgley, G. F. (2007). Will Climate Change Promote Alien Plant Invasions? *Biological Invasions*, 193, 197–211. https://doi.org/10.1007/978-3-540-36920-2_12
- Travis, J. M. J., Delgado, M., Bocedi, G., Baguette, M., Barton, K., Bonte, D., ... Bullock, J. M. (2013). Dispersal and species' responses to climate change. *Oikos*, 122, 1532–1540. <https://doi.org/10.1111/j.1600-0706.2013.00399.x>
- Tylianakis, J. M., & Binzer, A. (2014). Effects of global environmental changes on parasitoid-host food webs and biological control. *Biological Control*, 75, 77–86. <https://doi.org/10.1016/j.biocontrol.2013.10.003>
- VanDerWal, J., Shoo, L. P., Graham, C., & Williams, S. E. (2009). Selecting pseudo-absence data for presence-only distribution modeling: How far should you stray from what you know? *Ecological Modelling*, 220(4), 589–594. <https://doi.org/10.1016/j.ecolmodel.2008.11.010>
- Varela, S., Lima-Ribeiro, M. S., & Terribile, L. C. (2015). A short guide to the climatic variables of the last glacial maximum for biogeographers. *PLoS ONE*, 10(6), 1–15. <https://doi.org/10.1371/journal.pone.0129037>
- Visser, M. E., & Both, C. (2005). Shifts in phenology due to global climate change : the need for a yardstick. *Proceedings of the Royal Society B*, 272(November), 2561–2569.
- Visser, M. E., Both, C., & Lambrechts, M. M. (2004). Global Climate Change Leads to Mistimed Avian Reproduction. *Advances in Ecological Research*, 35, 89–110. [https://doi.org/10.1016/S0065-2504\(04\)35005-1](https://doi.org/10.1016/S0065-2504(04)35005-1)
- Winfree, R., Williams, N. M., Dushoff, J., & Kremen, C. (2007). Native bees provide insurance against ongoing honey bee losses. *Ecology Letters*, 10(11), 1105–1113. <https://doi.org/10.1111/j.1461-0248.2007.01110.x>
- Wisz, M. S., Pottier, J., Kissling, W. D., Pellissier, L., Lenoir, J., Damgaard, C. F., ... Svenning, J. C. (2013). The role of biotic interactions in shaping distributions and realised assemblages of species: Implications for species distribution modelling. *Biological Reviews*, 88(1), 15–30. <https://doi.org/10.1111/j.1469-185X.2012.00235.x>

2.7 SUPPLEMENTARY MATERIALS

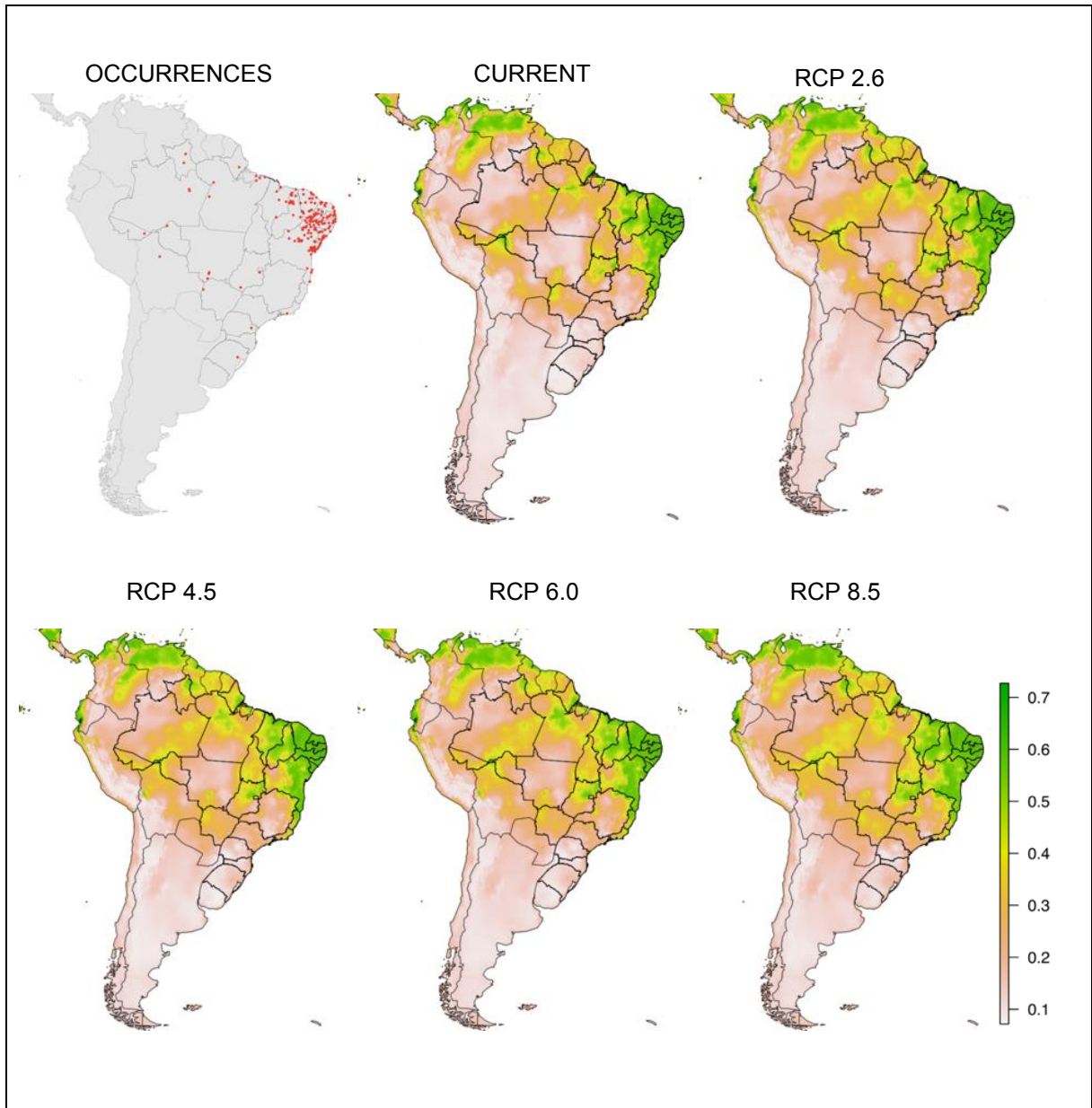


Figure S. 2-1 Thinned occurrences for *Ipomoea asarifolia* (red dots) and ensembles of distribution range of its predictions for the current and future scenarios (RCPs 2.6 to 8.5). The maps for the future scenarios were generated by the weighted mean of all three methods (Bioclim, MaxEnt, SVM) in all AOGCMs. The color scale corresponds to the values of suitability for the three species in each of the current and future climatic scenarios. RCP: Representative Carbon Pathway.

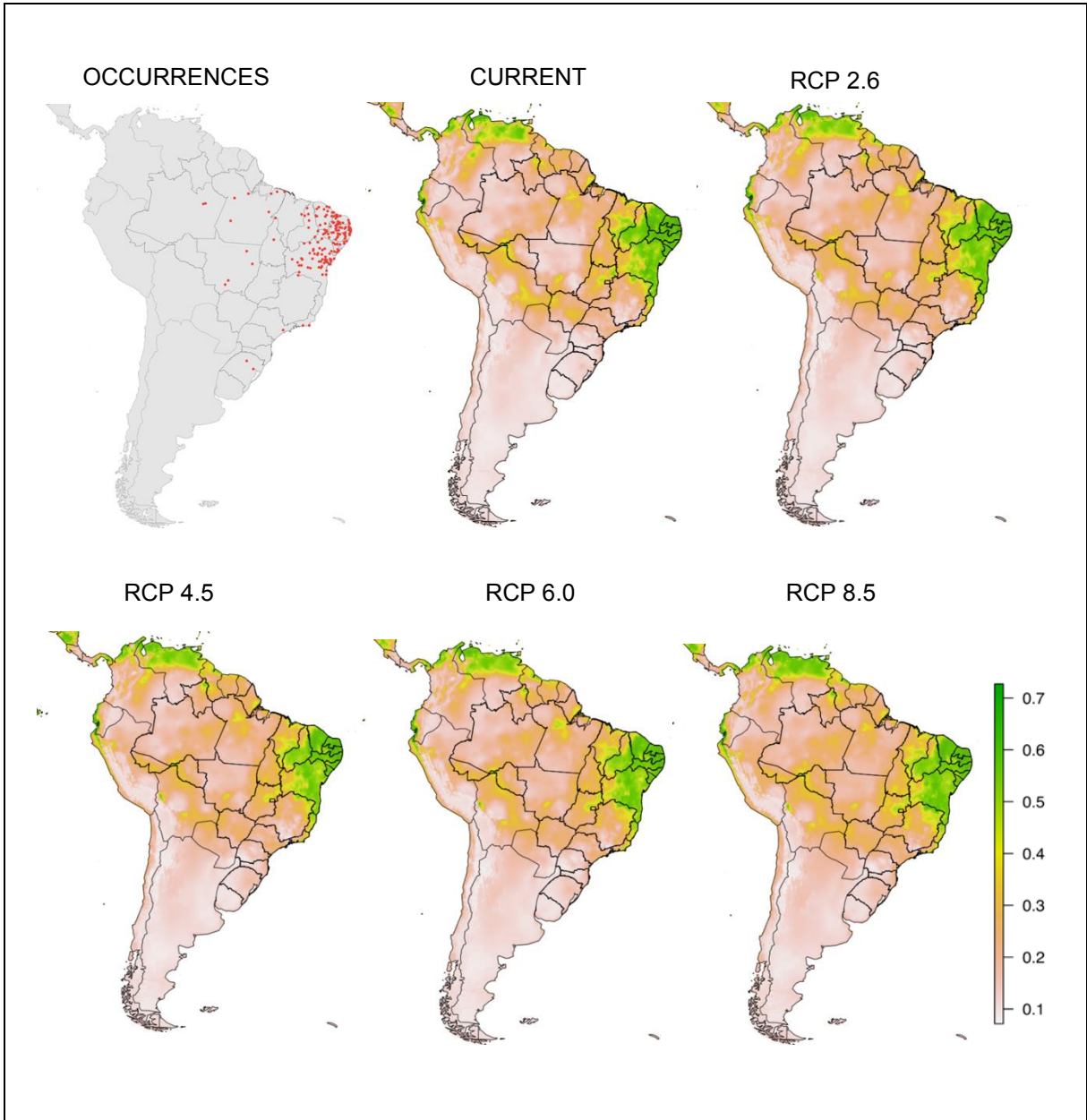


Figure S. 2-2 Thinned occurrences *Ipomoea bahiensis* occurrences (red dots) and ensembles of distribution range of its predictions for the current and future scenarios (RCPs 2.6 to 8.5). The maps for the future scenarios were generated by the weighted mean of all three methods (Bioclim, MaxEnt, SVM) in all AOGCMs. The color scale corresponds to the values of suitability for the three species in each of the current and future climatic scenarios. RCP: Representative Carbon Pathway.

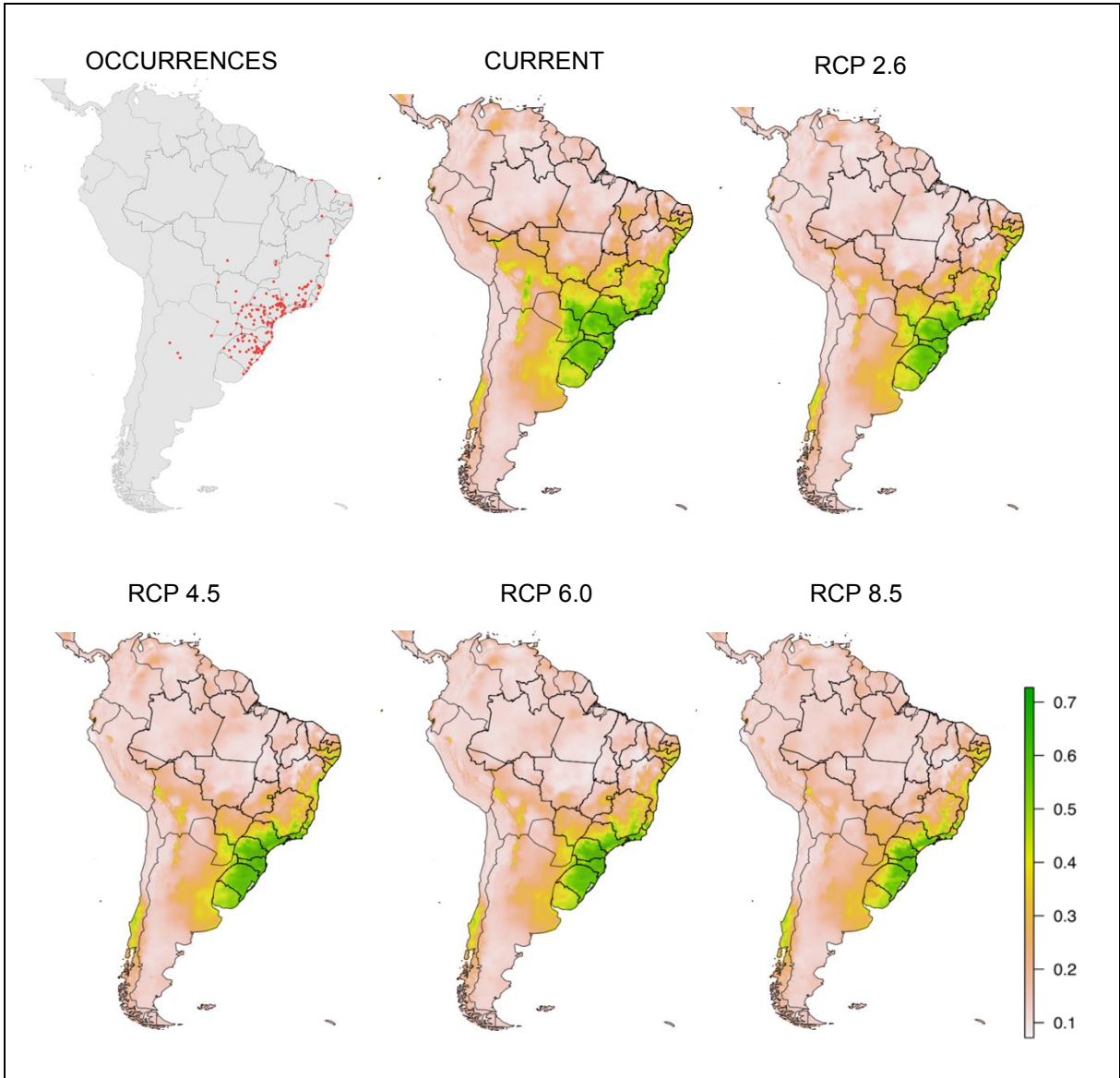


Figure S. 2-3 Thinned occurrences *Ipomoea cairica* occurrences (red dots) and ensembles of distribution range of its predictions for the current and future scenarios (RCPs 2.6 to 8.5). The maps for the future scenarios were generated by the weighted mean of all three methods (Bioclim, MaxEnt, SVM) in all AOGCMs. The color scale corresponds to the values of suitability for the three species in each of the current and future climatic scenarios. RCP: Representative Carbon Pathway.

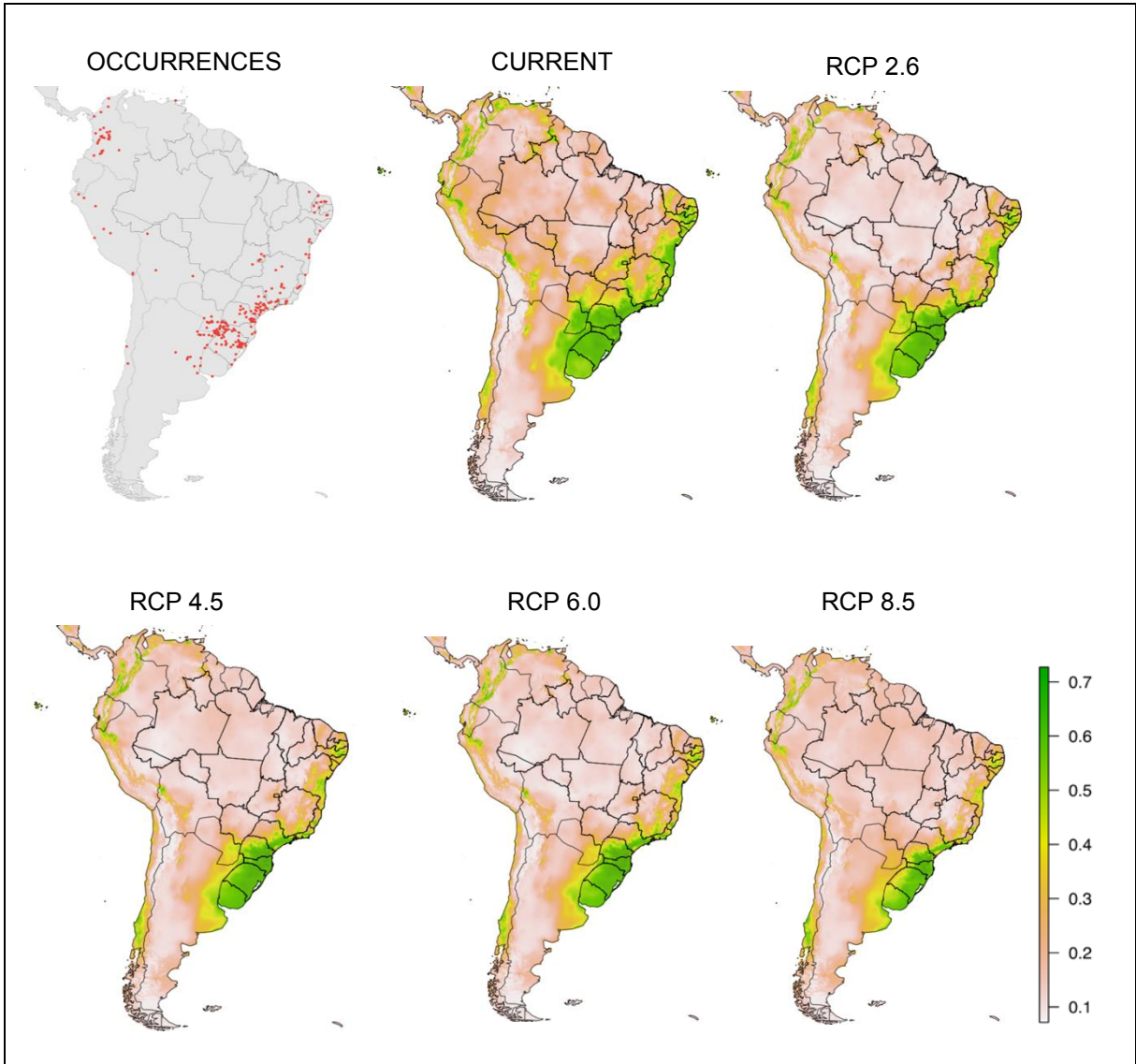


Figure S. 2-4 Thinned occurrences *Ipomoea indica* occurrences (red dots) and ensembles of distribution range of its predictions for the current and future scenarios (RCPs 2.6 to 8.5). The maps for the future scenarios were generated by the weighted mean of all three methods (Bioclim, MaxEnt, SVM) in all AOGCMs. The color scale corresponds to the values of suitability for the three species in each of the current and future climatic scenarios. RCP: Representative Carbon Pathway.

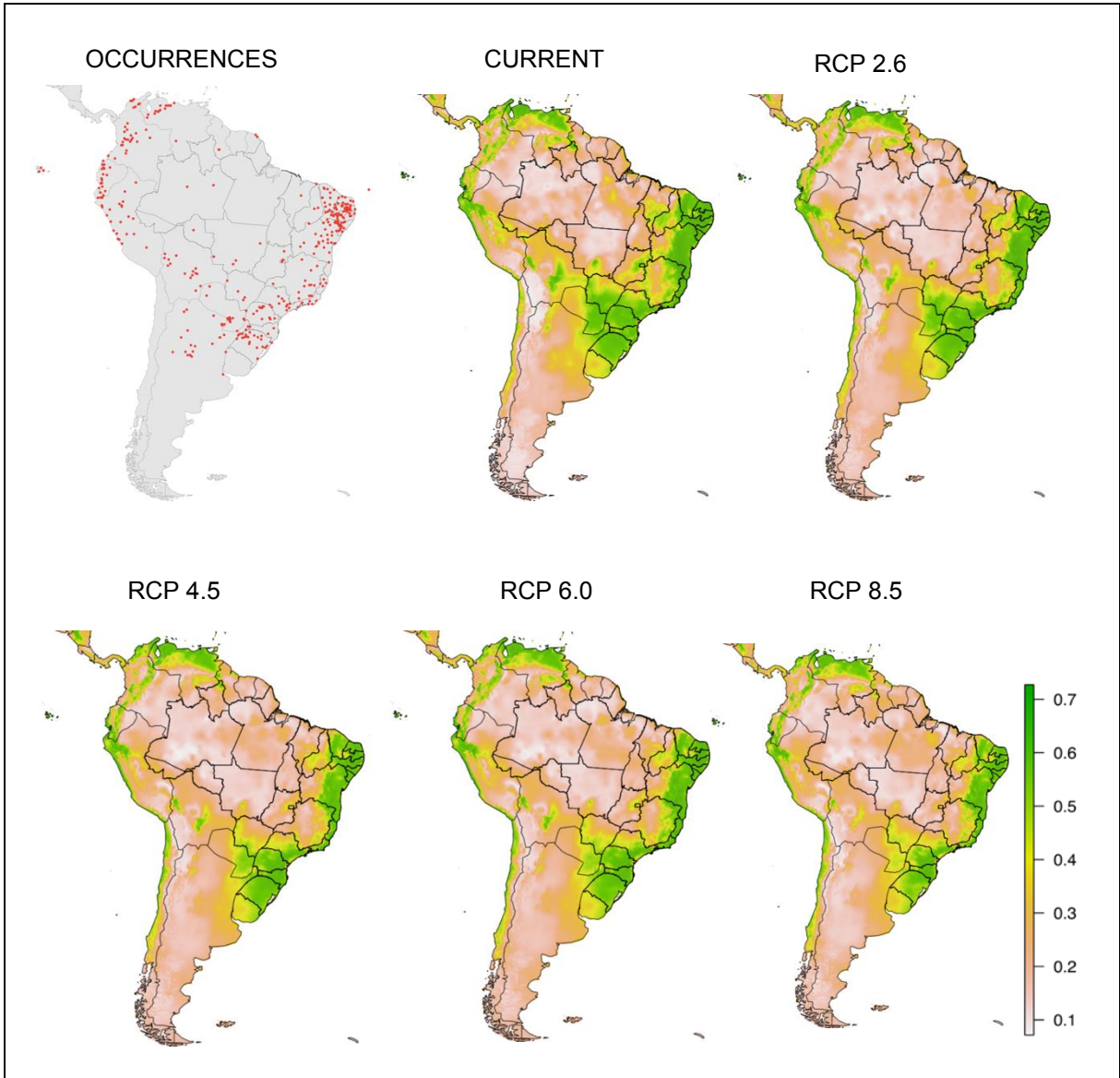


Figure S. 2-5 Thinned occurrences *Ipomoea nil* occurrences (red dots) and ensembles of distribution range of its predictions for the current and future scenarios (RCPs 2.6 to 8.5). The maps for the future scenarios were generated by the weighted mean of all three methods (Bioclim, MaxEnt, SVM) in all AOGCMs. The color scale corresponds to the values of suitability for the three species in each of the current and future climatic scenarios. RCP: Representative Carbon Pathway.

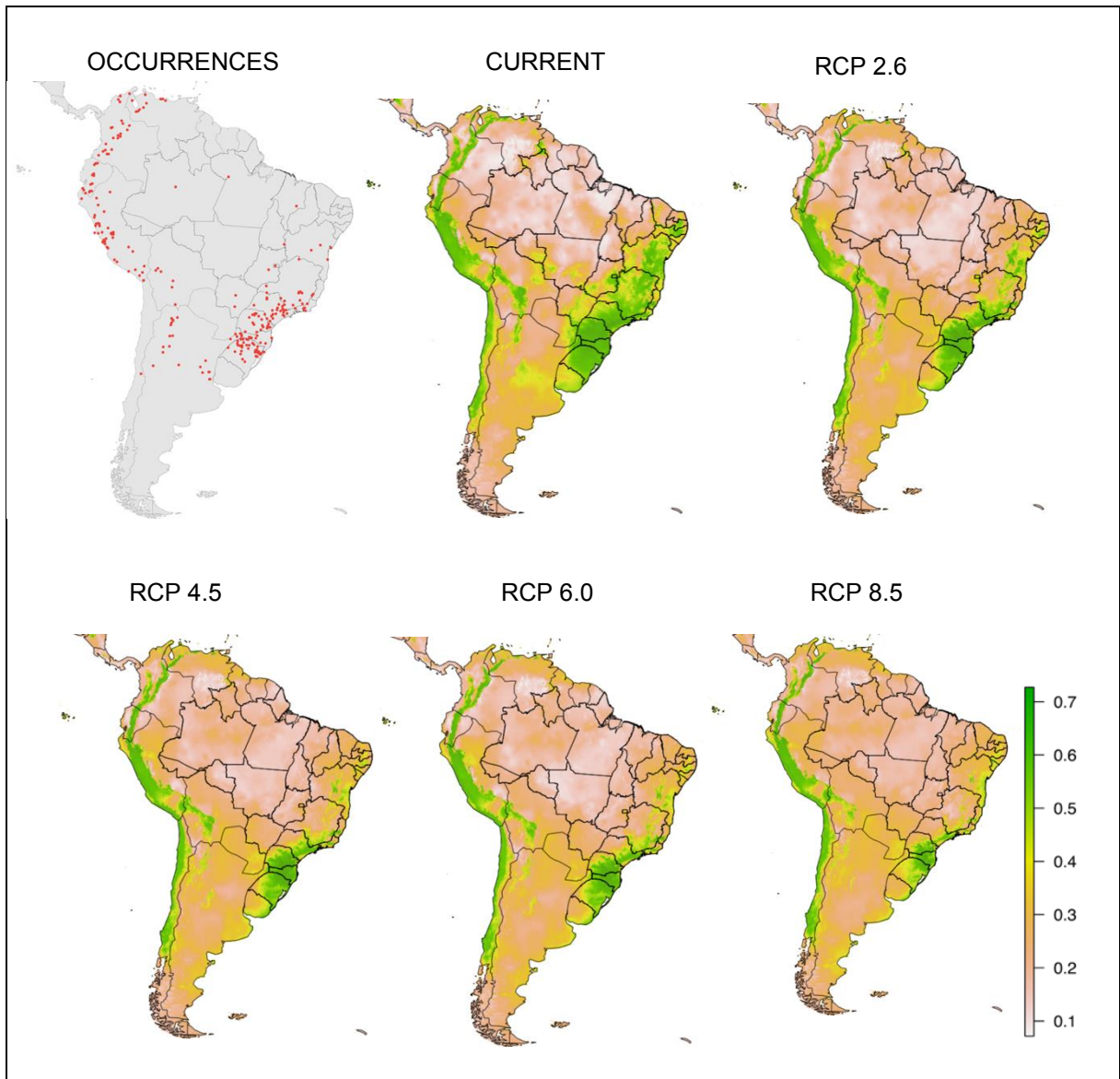


Figure S. 2-6 Thinned occurrences *Ipomoea purpurea* occurrences (red dots) and ensembles of distribution range of its predictions for the current and future scenarios (RCPs 2.6 to 8.5). The maps for the future scenarios were generated by the weighted mean of all three methods (Bioclim, MaxEnt, SVM) in all AOGCMs. The color scale corresponds to the values of suitability for the three species in each of the current and future climatic scenarios. RCP: Representative Carbon Pathway.

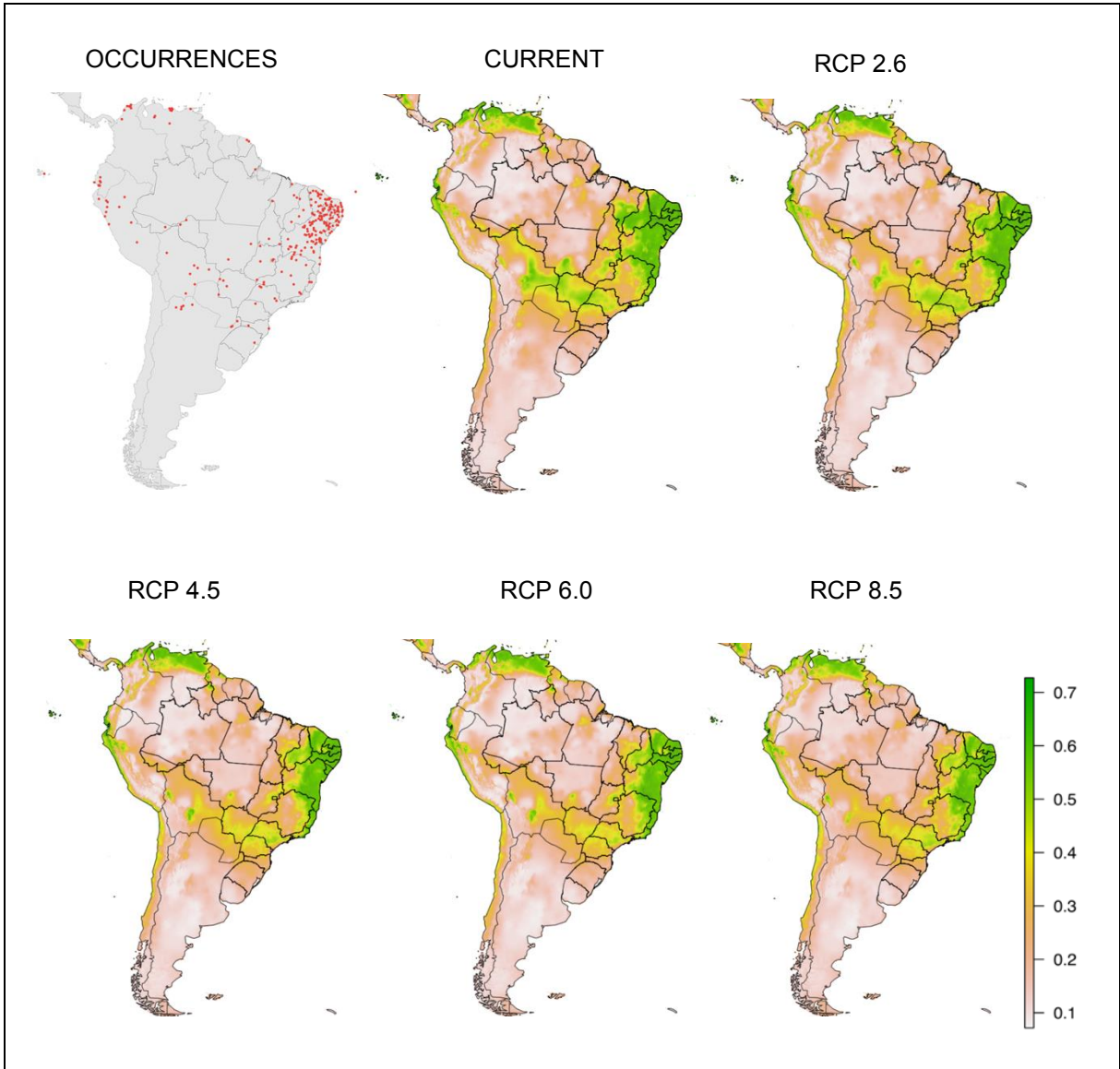


Figure S. 2-7 Thinned occurrences *Merremia aegyptia* occurrences (red dots) and ensembles of distribution range of its predictions for the current and future scenarios (RCPs 2.6 to 8.5). The maps for the future scenarios were generated by the weighted mean of all three methods (Bioclim, MaxEnt, SVM) in all AOGCMs. The color scale corresponds to the values of suitability for the three species in each of the current and future climatic scenarios. RCP: Representative Carbon Pathway.

**O IMPACTO DAS MUDANÇAS CLIMÁTICAS NA DISTRIBUIÇÃO
DE ABELHAS NATIVAS DA REGIÃO NEOTROPICAL**

Periódico a ser submetido:

Agriculture, Ecosystems & Environment

CLIMATE CHANGE WILL CONTRACT THE DISTRIBUTION RANGE OF NEOTROPICAL CARPENTER BEES

ABSTRACT

Native bees are important providers of pollination services, directly impacting global food production. There is cumulative evidence of their decline. Climate change is one of the possible drivers of the decline of these pollinators. However, there is a lack of studies the effects of climate change in future distribution of native bees from the genus *Xylocopa* Latreile, 1802 (Apidae: Xylocopinae: Xylocopini) and its occupation of protected areas (PA). *Xylocopa* are the main pollinators from several plant families, among them, one of great commercial interest, the passion fruit (*Passiflora*, Passifloraceae). Our main objective here was to predict areas of present and future potential distribution of three species: *Xylocopa abbreviata* Hurd & Moure (1963), *Xylocopa Truxali* Hurd & Moure (1963) and *Xylocopa vestita* Hurd & Moure (1963). We also estimated the proportion of the predicted area of each species occurring within PAs, comparing the current climate scenario with four future scenarios. We used all climate models of the four representative concentration pathways (RCP). To reduce uncertainty in our results, we selected three models of each RCP by means of cluster analysis. Our evaluation index was a statistical test based on the True Presence Rate estimated by each method. Our results show that these bees will suffer reduction in their potential distribution range due to global climate change, particularly in areas of central-west Brazil. Since we also found significant reduction of suitable PAs, conservation politics should be considered for these species.

Keywords: Xylocopini, Pollinators, Protected Areas, Ecological Services.

3.1 INTRODUCTION

The impacts of climate change on ecological systems are expected to be significant and to produce biological changes in (1) phenological relationships between species (Ovalle-Rivera et al., 2015; Schweiger et al., 2012), (2) interspecific ecological interactions (Araújo and Rozenfeld, 2014; Tylianakis and Binzer, 2014) and (3) the geographic distributions of species (Parmesan, 2006). Since climate is the primary control of species distribution and ecological processes, climate change can lead to the breakdown of interspecific associations among them (Pecl et al., 2017). The decline of pollinators around the world has become a major conservation concern (Ghazoul, 2005; Hegland et al., 2009; Potts et al., 2010; Steffan-Dewenter et al., 2005; Winfree et al., 2009). Thus, understanding how they can respond to future climate change may show us how ecosystem services will be affected by this climate changes, with potential consequences for economic activity involved in pollination (Aizen and Harder, 2009), ecosystems dynamics (Potts et al., 2010), as well for human well-being (Potts et al., 2016).

Bees correspond to a very important group of pollinators with economic relevance (Costanza et al., 2014; Kremen et al., 2007). To understand and anticipate potential species substitutions in species communities, changes in their distributions have been studied in detail (Fitzpatrick et al., 2007; Giannini et al., 2012; Memmott et al., 2004). Agricultural intensification and intense pesticide use were claimed to be the main causes for the decline of bees in Europe and North America (e.g. Fitzpatrick et al., 2007; Goulson, 2003). Otherwise, studies in the Neotropical region suggest that the main drivers of pollinator decline are deforestation (Nemésio et al., 2016) associated with global climate change (Giannini et al., 2012; Martins et al., 2015).

Ecological Niche Modeling (ENM; also known as Potential Distribution Models - but see Peterson and Soberón, 2012) constitute a common approach in the literature both to assess the establishment of exotic species (Jiménez-Valverde et al., 2011), as well to assess the impact of climate change on its distribution (Araújo and Peterson, 2012). Other studies have tried to predict how various species of bees will respond to future scenarios of climate change. Ten species of Brazilian bees under different scenarios of future warming showed range contractions in face of the potential effects of climate change (Giannini et al. 2012). Future distributions were also modeled for the rare bee species *Euglossa marianae* Nemésio (2011), which occupies highly fragmented

habitats in eastern Brazil (Nemésio et al., 2016). In another study, four *Xylocopa* species along with one of their main floral features, passion fruit, showed a change in their predicted distribution, with greater effects on more tropical habitats (Giannini et al., 2013b).

The genera *Xylocopa* Latreile, 1802 (Apidae: Xylocopinae: Xylocopini) encompasses about 700 species widely distributed between New and Old worlds (Hurd and Moure, 1963; Michener, 2007), with ~50 Brazilian species described (Hurd, 1978). This genus has the highest diversity of species in the tropical and subtropical regions with 31 subgenera described, with 11 of the New World and 19 in the Old World (Michener, 2007). *Xylocopa* bees are also popularly known as “carpenter bees” due to their habit of building nests in dead trees’ thin branches and/or hollow stems (Hurd and Moure, 1963). According to climate conditions, carpenter bees could be uni-, bi- or polivoltine (Watmough, 1974). The females of *Xylocopa* bees dehydrate the nectar they obtain from flowers, increasing the concentration of sugar, and consequently, improving the nutrition to their nestlings, allowing them to occupy a territory for a longer time (Wittmann and Scholz, 1989). Information on plant relationships indicates that *Xylocopa* species are poliletic (Gerling et al., 1983; Hurd, 1978). Important sources of pollen for *Xylocopas* are plants with flowers that have porous anthers such as passion fruit (*Passiflora*, Passifloraceae), *Solanum* (Solanaceae), *Cassia*, *Senna*, and *Chamaecrista* (Caesalpinaceae, Melastomataceae), whose pollen grains are collected by vibration and sonication (Buchmann, 1983; Van Der Pul, 1954).

The carpenter bees are the main pollinators of plants of great commercial interest, among them, one of strong dependency of these pollinators, regards the pollination of the passion fruit (*Passiflora*, Passifloraceae) (Garcia and Hoc, 1997; Roubik, 1995; Sazima and Sazima, 1989; Souza et al., 2004). The pollinator species richness (Yamamoto et al., 2012), abundance (Camillo, 2003) and frequency of visitation (Benevides et al., 2009) have been proved to increase the fruit set in passion fruit orchards. Although passion fruit flowers may be manually pollinated, natural pollination is cost free and increases the quality and quantity of fruits, providing higher income and giving value to this commodity (Junqueira and Augusto, 2017). Thus, the conservation of passion fruit natural pollinator should be encouraged.

Considering this context, our main objective was to evaluate the effects of global climate change on the future distribution of three species of native carpenter bees of the

Brazilian Cerrado, *Xylocopa abbreviata* Hurd & Moure (1963), *Xylocopa Truxali* Hurd & Moure (1963) e *Xylocopa vestita* Hurd & Moure (1963). We used several methods of ENM to predict areas of potential occurrence of these species. Finally, we also estimated the proportion of the predicted area of each species occurring within environmental protection units, comparing the current climate scenario with four scenarios of future atmospheric carbon emissions (RCPs 2.6 to 8.5), from the most optimistic to the most pessimistic ones, for the year 2070.

3.2 METHODS

3.2.1 Occurrence data

We obtained the geographic distribution data for the three bee species in three ways: 1) in the entomological collections of the *Universidade Federal do Paraná* and the *Universidade Federal de Minas Gerais*; 2) field sampling; 3) literature review (Hurd and Moure, 1963; Zanella and Silva, 2010). The total database consisted of 36 occurrences of *X. abbreviata*, 15 occurrences of *X. truxali* as well as 9 occurrences of *X. vestita* (Fig 3-1).

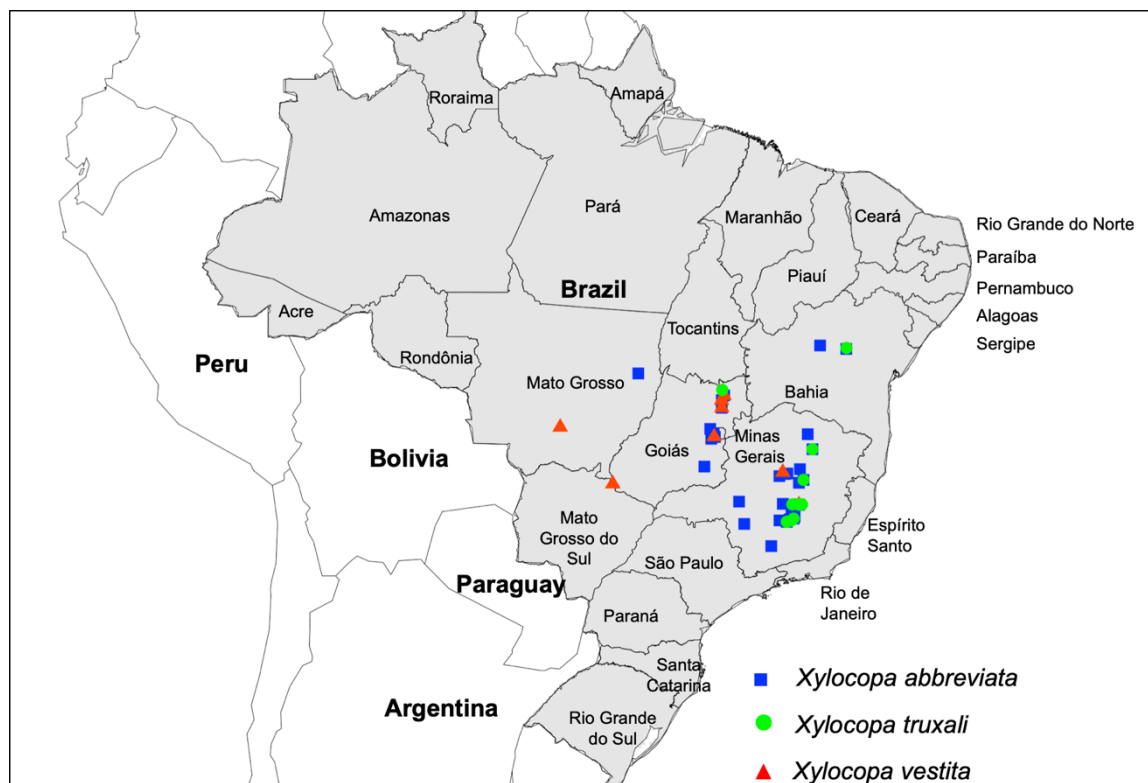


Figure 3-1 Total occurrence data for the modeled bees *Xylocopa abbreviata*, *Xylocopa truxali*, and *Xylocopa vestita*, including all sources composing the database. The names of the Brazilian states cited along the text are shown in the figure.

3.2.2 Selecting environmental variables and processing occurrences

We encoded all the processes of preparation and selection of variables, processing of occurrences and operationalization of the predictive methods, in open source language R (Development Core Team, 2018). We delimited the extension of the grid cells of the predictor variables to South America. All variables were in the resolution of 2.5 arcmin (cells with $\sim 4 \text{ km}^2$ on the equator). We collected all 19 climatic variables (abiotic component), both for current period (interpolations of observed data, representative of 1960-1990) and for each of the 11 Atmospheric Oceanic Global Circulation Models (AGOCMs hereon) common at all four IPCC's Representative Concentration Pathways (RCP hereon) (RCP2.6, RCP4.5, RCP6.0 e RCP8.5), with projections for 2070 (average interpolations for 2061-2080). Such variables are freely available in the online database WorldClim (www.worldclim.org; Hijmans et al., 2005). Since modelling with all climatic variables may produce overfitted models (Jiménez-Valverde et al., 2011), we selected our predictor variables using an Exploratory Factor Analysis (EFA hereon) with VARIMAX axis rotation type.

The EFA is a method commonly used in the social sciences to identify the factors (structure or axes) that highlights the correlation of each raw variable with each one of these factors (Distefano et al., 2009; Lawley and Maxwell, 1962). (Distefano et al., 2009; Lawley and Maxwell, 1962). We defined the number of factors in the EFA graphically, by performing a scree test (Cattell, 1966) and analyzing the resulting plot generated via the function `fa.parallel` from the *psych* package (Revelle, 2018). This test showed us that only five factors, that reached observed eigenvalues higher than a random expectation, were needed as environmental predictors for South America. Each one of these factors provide a specific loading value, ranging from -1 to 1, for each variable, where 1 represents the maximum correlation value to the factor (Cattell, 1966; Distefano et al., 2009). Starting from our initial set of 19 abiotic variables for the present scenario, we selected the variables with the highest loading value to represent each one of the five EFA axes (Tab. 3-1). Therefore, our set of abiotic components was composed by: Mean Diurnal Range (Bio02); Isothermality (Bio03); Mean Temperature of Warmest Quarter (Bio10); Precipitation of Driest Month (Bio14); Precipitation of Wettest Quarter (Bio16).

Table 3-1 Results of the Exploratory Factor Analysis, with VARIMAX axis rotation, among the 19 WorldClim variables. Bold values represent loading greater than 0.8. Variables in bold represent those that we maintained in our study.

VARIABLES	COD.	FACTORS				
		1	2	3	4	5
Annual Mean Temperature	bio01	0.914	0.042	0.315	0.223	-0.103
Mean Diurnal Range	bio02	-0.121	-0.358	-0.238	-0.194	0.865
Isothermality	bio03	0.312	0.109	0.842	0.278	-0.008
Temperature Seasonality	bio04	-0.294	-0.014	-0.856	-0.376	0.177
Max Temperature of Warmest Month	bio05	0.982	-0.040	-0.058	0.115	0.101
Min Temperature of Coldest Month	bio06	0.782	0.124	0.451	0.279	-0.299
Temperature Annual Range	bio07	-0.223	-0.220	-0.720	-0.302	0.536
Mean Temperature of Wettest Quarter	bio08	0.920	0.045	0.193	0.141	0.024
Mean Temperature of Driest Quarter	bio09	0.777	0.039	0.420	0.275	-0.247
Mean Temperature of Warmest Quarter	bio10	0.985	0.051	0.046	0.130	-0.071
Mean Temperature of Coldest Quarter	bio11	0.821	0.041	0.474	0.281	-0.137
Annual Precipitation	bio12	0.280	0.527	0.303	0.720	-0.129
Precipitation of Wettest Month	bio13	0.351	0.190	0.342	0.835	-0.127
Precipitation of Driest Month	bio14	-0.010	0.956	0.142	0.209	-0.106
Precipitation Seasonality	bio15	0.039	-0.686	0.222	0.032	0.282
Precipitation of Wettest Quarter	bio16	0.349	0.207	0.340	0.837	-0.119
Precipitation of Driest Quarter	bio17	0.009	0.946	0.150	0.250	-0.120
Precipitation of Warmest Quarter	bio18	0.136	0.548	0.181	0.415	0.138
Precipitation of Coldest Quarter	bio19	0.153	0.430	0.185	0.551	-0.297

Usually, the climatic variables derived for future scenarios and widely used in ENMs studies are generated by the production of several AOGCMs by independent research organizations. Broadly speaking, these models are mathematical representations of physical processes operating in the atmosphere, ocean, cryosphere,

and on the earth's surface (Stocker et al., 2013). Each AOGCM has its peculiarities, since each one uses a unique set of equations to simulate the climatic dynamics. Thus, differences in the initial configuration and in the algorithms that generate this model inevitably lead to different environmental predictions (McGuffie and Henderson-Sellers, 2014). In contrast to the current scenario, where we modeled the species with only one AOGCM available in Worldclim, for the future scenarios, we used several AOGCMs available for the four RCPs available in WorldClim. To reduce the repeatability between models that are similar and that may increase the uncertainty of the predictions (Varela et al., 2015), we used a hierarchical clustering analysis (HCA hereon) to select the appropriate AOGCMs along all four RCPs.

To maintain the models' comparability, we initially selected only the 11 AOGCMs common to the four RCPs. Then, we built four initial arrays, one for each RCP, with the 19 variables of the 11 AOGCMs, using the *abind* function from the package *abind* (Plate and Heiberger, 2016). We classified the models into groups using the correlation between their predictions. Finally, we used the *hcluster* function from the package *amap* (Lucas, 2018) to proceed with our HCA, ordering the similarities among the predictions of the models based on the correlation between the predictions in the AOGCMs among the same variables. We set the maximum number of clusters to four. Finally, we analyzed all AOGCM from the four resulting dendrograms following the criteria of 1) be in only one of the four groups of the individual cluster and 2) be present in all four dendrograms referring to each RCP. Hence, we selected the AOGCMs CCSM4, IPSL-CMSA-LR and MIROC-ESM in all RCPs as our future variable sets, to represent the future distribution of our modeled species (Fig. 3-2).

To avoid potential effects of spatial autocorrelation between the occurrences of the eight species (one bee and seven host plants) (Fig. 3-3A), we used the *spThin* package (Aiello-Lammens et al., 2015) to eliminate occurrences that were very close to each other (Fig. 3-3B). We only kept the occurrences that were at a minimum distance of 20 km from each. After the geographic space filtering process, the total of spatially unique occurrences remaining for each species was 27 occurrences for *X. abbreviata*, 8 occurrences for *X. truxali*, and 8 occurrences for *X. vestita*.

We divided the occurrences of all species into 10 training-test subsets, where in each of these subsets, 70% of the occurrence records randomly composed the replication training groups, while the remaining 30% were assigned to the testing subsets (Fig 3-3

C). We used the same subsets in the same order in all our modelling runs for all climatic scenarios considered here.

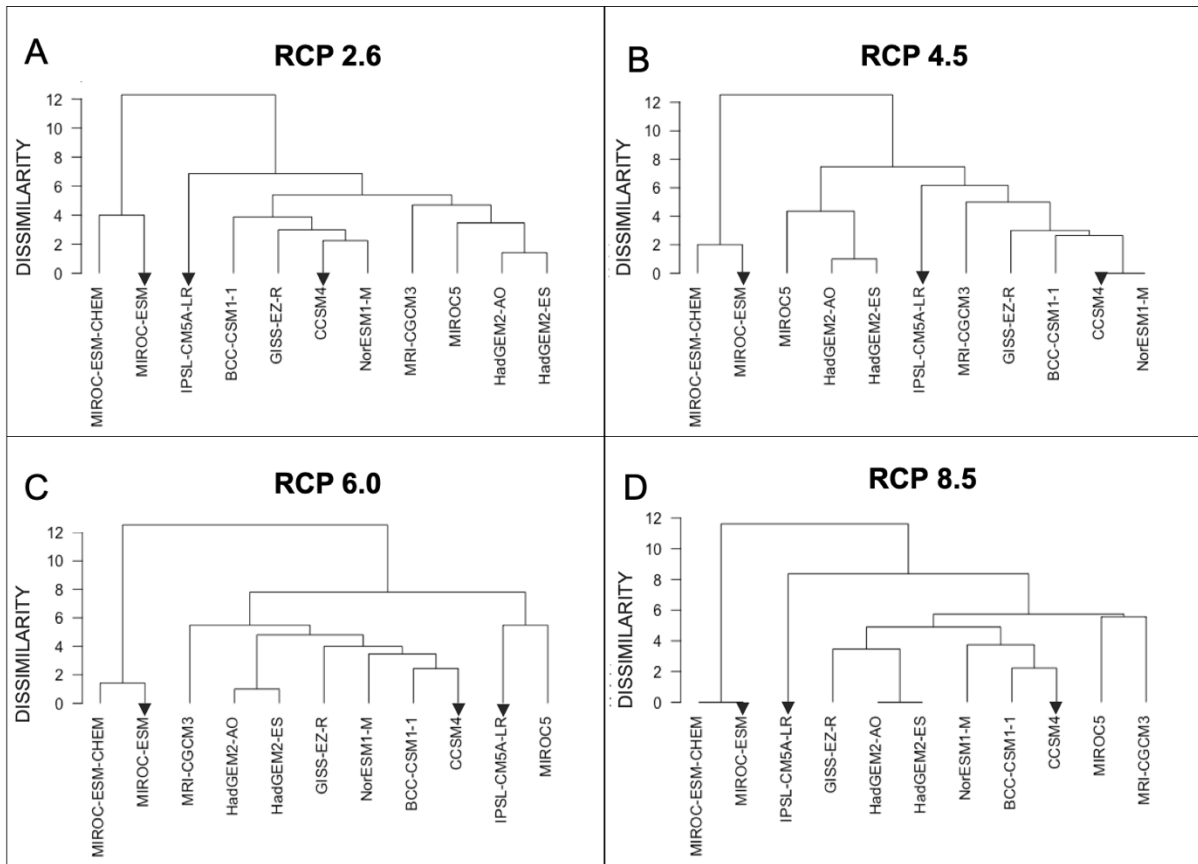


Figure 3-2 Hierarchical clustering of the 11 AOGCMs according to the correlation between all 19 climatic variables for the future scenarios in A) RCP 2.6, B) RCP 4.5, C) RCP 6.0, and D) RCP 8.5. ▼ indicates the selected AOGCMs in all scenarios: CCSM4, IPSL-CMSA-LR and MIROC-ESM. RCP: Representative Carbon Pathway.

3.2.3 Modelling procedures and evaluation

Given the predictive methods' individual bias and the uncertainty nature of the ENM, different predictive methods may result in different patterns of distribution of the modeled species (Barry and Elith, 2006; Rocchini et al., 2011). Thus, we predicted the three carpenter bees potential distribution through four different predictive methods (Fig 3-3 D): 1) BIOCLIM (Booth et al., 2014; Nix, 1986), implemented via bioclim function from *dismo* package (Hijmans et al., 2017); 2) Maximum Entropy (MaxEnt; Phillips et al., 2006; Phillips and Dudík, 2008), using the MaxEnt function from *dismo* package, loaded in the MaxEnt program installation; 3) *Support Vector Machines* (SVM; Schölkopf et al., 2001; Tax and Duin, 2004), modeled by the *ksvm* function from *kernelab*

package (Karatzoglou et al., 2004); 4) Gower distance (Gower, 1971), implemented via the domain function from the *dismo* package.

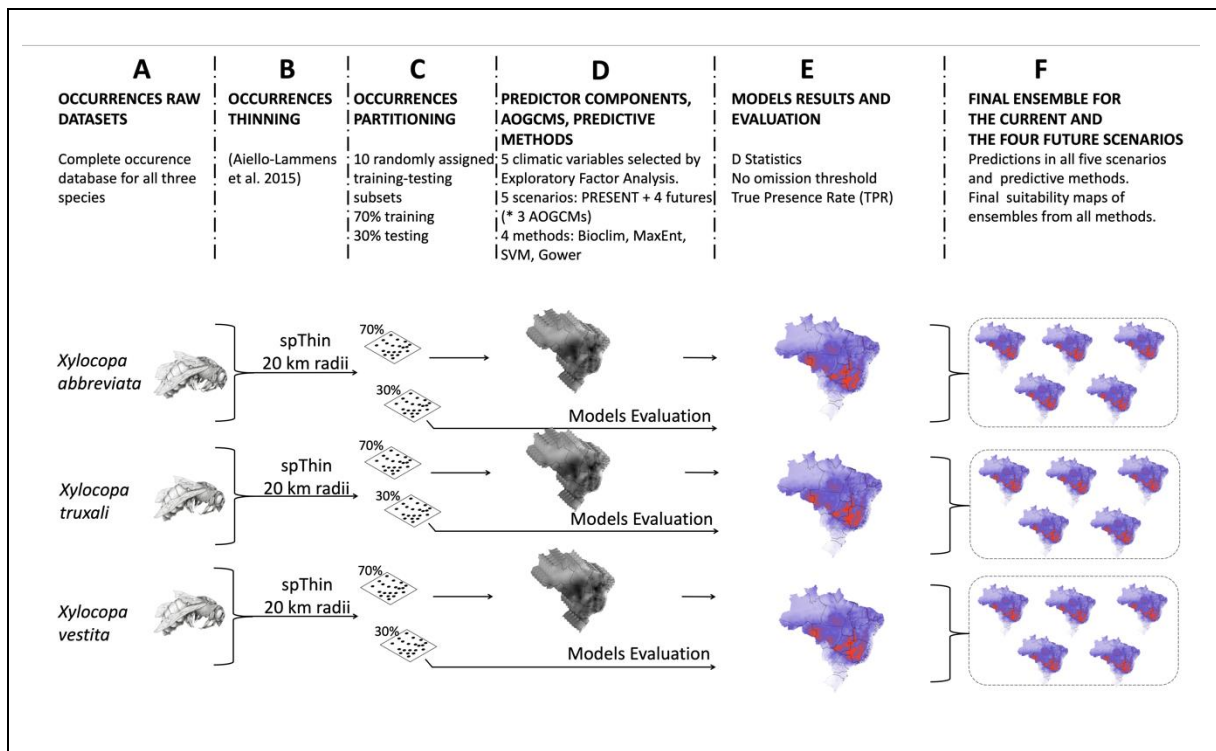


Figure 3-3 Summary of the modeling procedures. (A) Occurrences datasets. (B) Filtering of occurrences in the geographic space. (C) Partitioning occurrences in test training subsets. (D) Models parameterization and general modeling procedures. (E) Predictions evaluation. (F) Ensembles of all predictions produced by all methods by scenario.

One way of evaluating the predictions, commonly used by ecologists, is through metrics associated with pseudo-absences, where absence data are generated to fill the lack of knowledge regarding real absences. In this type of evaluation, after the determination of the predictions by means of some threshold that makes the balance between the errors of omission and commission (e.g. the ROC threshold; Liu et al., 2011, 2005), the predictions are evaluated by a metric compatible with pseudo-absences (e.g. true skill statistic; TSS; Allouche et al., 2006). This type of evaluation may represent conceptually flawed analysis given the unreal nature of pseudo-absence data (Golicher et al., 2012; Hirzel et al., 2006; Lobo, 2016; VanDerWal et al., 2009). Moreover, different scales applied in the creation of distribution maps using pseudo-absences may generate divergent final results depending on the proximity to the occurrences of the known species (Lobo and Tognelli, 2011; VanDerWal et al., 2009).

Thus, to avoid these potential setbacks, we grounded our modelling procedures in using presence only methods. The statistical test we adopted here, D , was adapted from Pearson et al., 2007, defined simply as

$$D = TPR * (1 - pi)$$

Where, TPR refers to the True Presence Rate (TPR), and pi refers to the proportion of the area predicted as presence for the species.

Here, we only changed the logic of weighting success binarily (hit/miss), described by Pearson *et al.* (2007), for a rate of success in percentage, i.e. ranging from 0 to 1. Models that predict the entire area of study as the presence of the species are trivial, as they also predict all occurrence points as true (Golicher et al., 2012; Pearson et al., 2007). This metric was used as the weight of the weighted average used for ensemble the predictions from all predictive methods (Fig. 3-3 E). Thus, low values of D indicate models of low predictive ability and assume a negligible weight in the ensemble, since they are reflected directly in the final weighted suitability. Otherwise, models with high predictive ability would be those that predict a relatively small area as the presence of the species and, even so, they predict the known occurrences of the target species. These models with higher D values contribute with greater importance for the final ensemble (Hirzel et al., 2006; Pearson et al., 2007; Peterson et al., 2011; Shcheglovitova and Anderson, 2013).

We ensemble the 10 prediction replicates, both for the current as well for all four future scenarios, into a single map for each scenario, via a weighted average with all predictions made from each predictive method. We repeated this process in all modeling experiments for *X. abbreviata*, *X. truxali*, and *X. vestita* which were modeled in the all climate scenarios modeled (one for the current scenario and four RCPs for the future scenarios) (Fig. 3-3 F).

Considering all ensembles of the four future scenarios, we used a consensus method to produce the final future distribution of all the three species. We calculated the no-omission threshold from the ensemble of the current scenario. Then, we delimited each of the four future models with values above such threshold to produce a final mean distribution of the species for the future. We used the final sets of each climatic scenario (present and future) and the no-omission threshold to assess the amount of predicted proportion of the distribution range of the three carpenter bees that is covered by protected areas. To do this, we obtained shapefiles of protected areas (PAs hereon) in

South America from Protected Planet (<https://www.protectedplanet.net/>), the online Interface of the World Database on Protected Areas (WDPA). To carry out this analysis, we consider only the strict reserves, those of categories I to IV of the IUCN, in both shapefiles. The shapefiles we obtained were rasterized, considering the grid cell sizes we used in our modelling procedures, in all climatic scenarios used. All R scripts written for our modelling procedures are available at <https://github.com/miltonmta/xylocopas>

3.3 RESULTS

The predicted distributions of the three modeled species showed good D values, considering all methods (Tab 3-2). Overall, in the current scenario, the Brazilian central-west and western regions, were always predicted to be suitable for the occurrence of all these bees, but there were suitable patches predicted in western Bolivia for *X. abbreviata* and *X. truxali*. The resulting distribution of the three species for the future scenarios showed a clear trend, despite the intrinsic differences of the methods considered (AOGCMS and the emission scenarios): the appropriate climatic conditions observed in the present will retreat to the South, in all climatic scenarios (Fig. 3-4). It is also possible to note a significant loss of suitable areas in the central region of South America, for the three species considered here. The most restricted distribution was the consensus of RCP 8.5 for three bee species. (Fig.3-4). According to these combinations, the three species may occupy Brazilian areas ranging from Southward Minas Gerais and Northeastward of São Paulo. To a lesser extent, *X. abbreviata* and *X. truxali* may occupy isolated regions in the central-western region of Bolivia (Fig. 3-5).

Table 3-2 Results obtained for each method by predicting the current potential distribution of *Xylocopa abbreviata*, *Xylocopa vestita* and *Xylocopa truxali*, modeled with WorldClim interpolations of observed data, representative of 1960-1990.

METHOD	D (average \pm Standard Deviation)		
	<i>X. abbreviata</i>	<i>X. vestita</i>	<i>X. truxali</i>
Bioclim	0.489 \pm 0.426	0.397 \pm 0.314	0.296 \pm 0.345
MaxEnt	0.797 \pm 0.085	0.448 \pm 0.249	0.574 \pm 0.184
SVM	0.838 \pm 0.097	0.582 \pm 0.200	0.609 \pm 0.266
Gower	0.702 \pm 0.102	0.683 \pm 0.249	0.727 \pm 0.347
All Methods	0.707 \pm 0.258	0.552 \pm 0.324	0.552 \pm 0.324

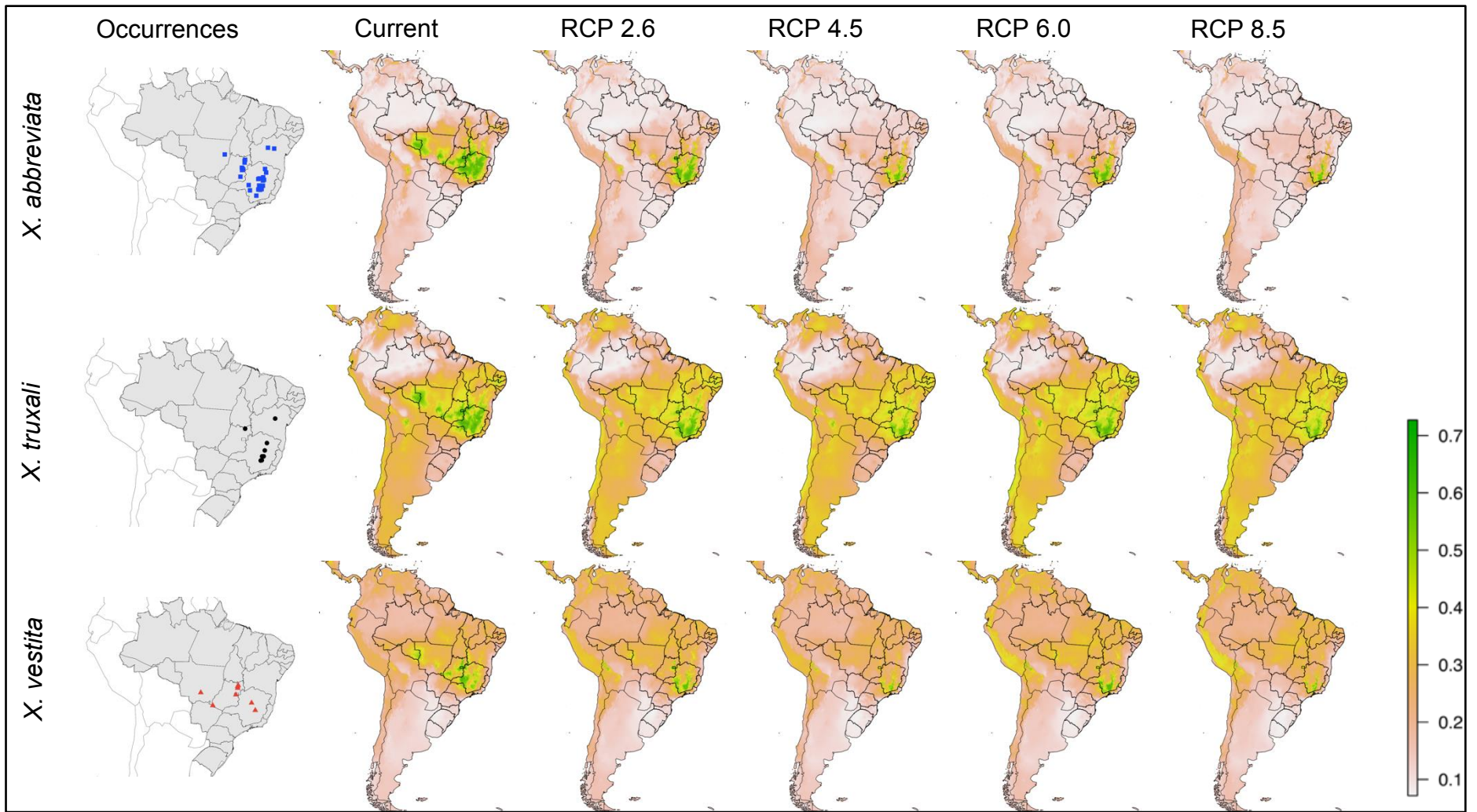


Figure 3-4 Occurrences and distribution predictions for *Xylocopa abbreviata*, *Xylocopa truxali*, and *Xylocopa vestita*. The color scale corresponds to the suitability values for the three species in each of the current and future climate scenarios (RCPs 2.6 to 8.5) considered. The maps for the current scenario were generated by the weighted mean of all predictive methods. The maps for the for the future scenarios were generated by the weighted mean of all four predictive methods (Bioclim, Gower, MaxEnt, SVM) in all AOGCMs. RCP: Representative Carbon Pathway.

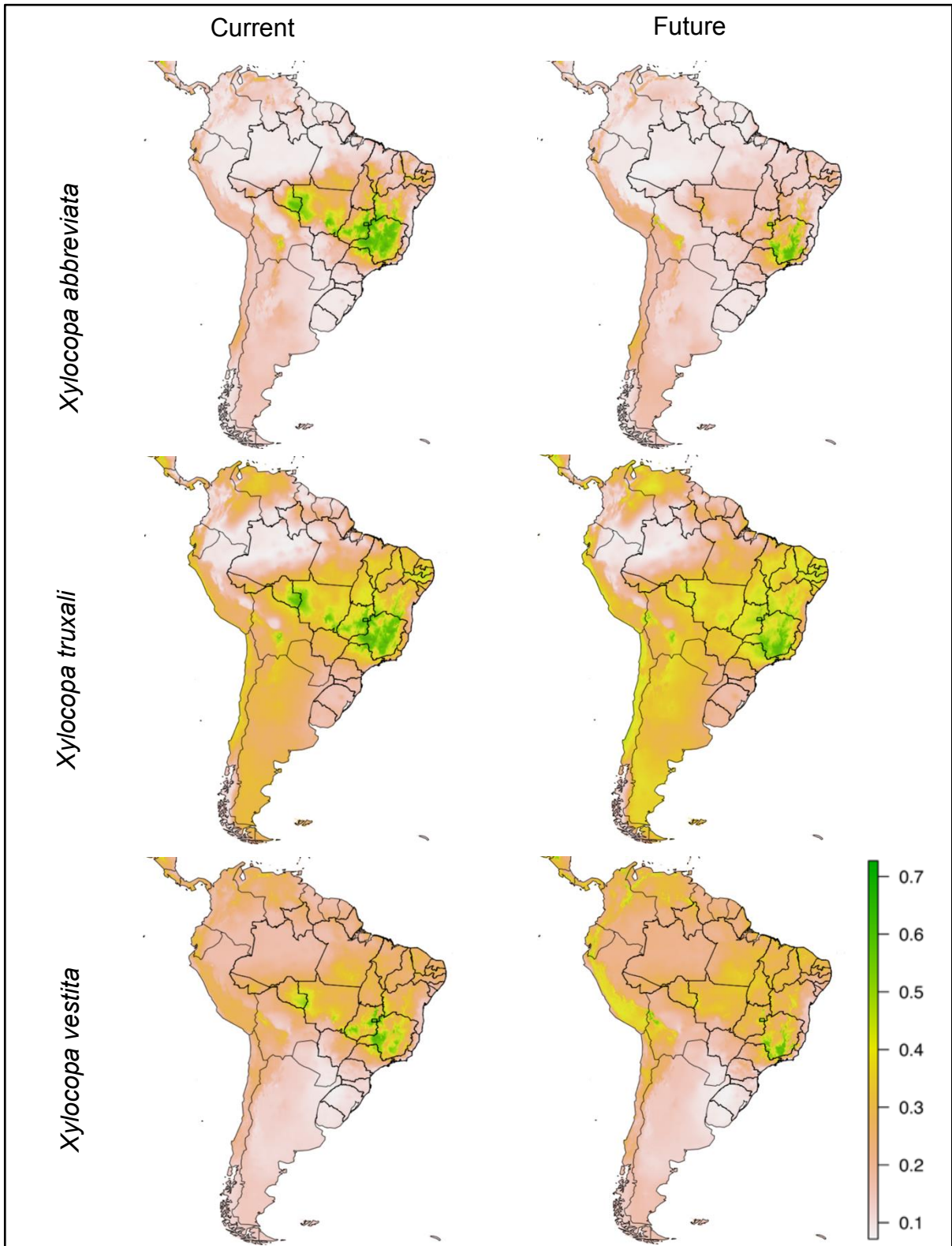


Figure 3-5 Comparison of current and ensemble future predictions for *Xylocopa abbreviata*, *Xylocopa truxali*, and *Xylocopa vestita*. The maps for the future were generated by the average suitability of the four RCP scenarios, for each species. The color scale corresponds to the suitability values for the three species in each of the current and future climate scenarios considered.

Overall, the amount of PAs for all species will decrease in the future in comparison to the current scenario (Tab. 3-3). Even though, for some species it seems that the PA percentage increases in the future, since the overall distribution range area for the species decreases, the absolute protected range areas in the will also decrease. Additionally, for all three species, the amount of range in the future was at least 75% smaller in comparison to their range size found in the current scenario. For example, only 17.07% of *X. abbreviata*'s current predicted range (78,404 grid cells) were predicted in the future (13,379 grid cells), accounting for 83.93% of range loss. Moreover, suitability loss within protected areas utmost relevant, for instance *X. abbreviata*'s will lose 88.94% of its current projected areas. This very same trend was observed for *X. truxali* (~9% of the areas predicted in the current scenario were suitable in the future and ~70% of protected areas loss) and *X. vestita* (only ~1% of the areas predicted in the current scenario were suitable in the future and ~90% of protected areas loss).

Table 3-3 Distribution range size (in grid cells) in both present and future ensemble distributions (all scenarios) and percentage of distribution range and protected areas loss in both present and future scenarios for *Xylocopa abbreviata*, *Xylocopa truxali*, and *Xylocopa vestita*. The numbers within brackets in the columns regarding the percentage of protected distribution range for each species refer to the raw amount of grid cells predicted within protected areas.

Species	Current range	Future range	Range loss	Current protected range	Future protected range	Protected range loss
<i>X. abbreviata</i>	78404	13379	82.93%	2369	362	88.94%
<i>X. truxali</i>	26170	2396	90.84%	571	179	68.65%
<i>X. vestita</i>	10397	114	98.90%	273	18	93.30%

Considering the current and consensual future (average off all four RCPs by each species) potential distributions obtained with all different predictive methods, *X. abbreviata*, *X. truxali*, and *X. vestita* are expected to occur in some of the available South American protected areas (Fig. 3-6). Nonetheless, Brazilian southeastern protected areas may provide better refuges than northwestern ones, which is set to lose most of the current suitable overlapping.

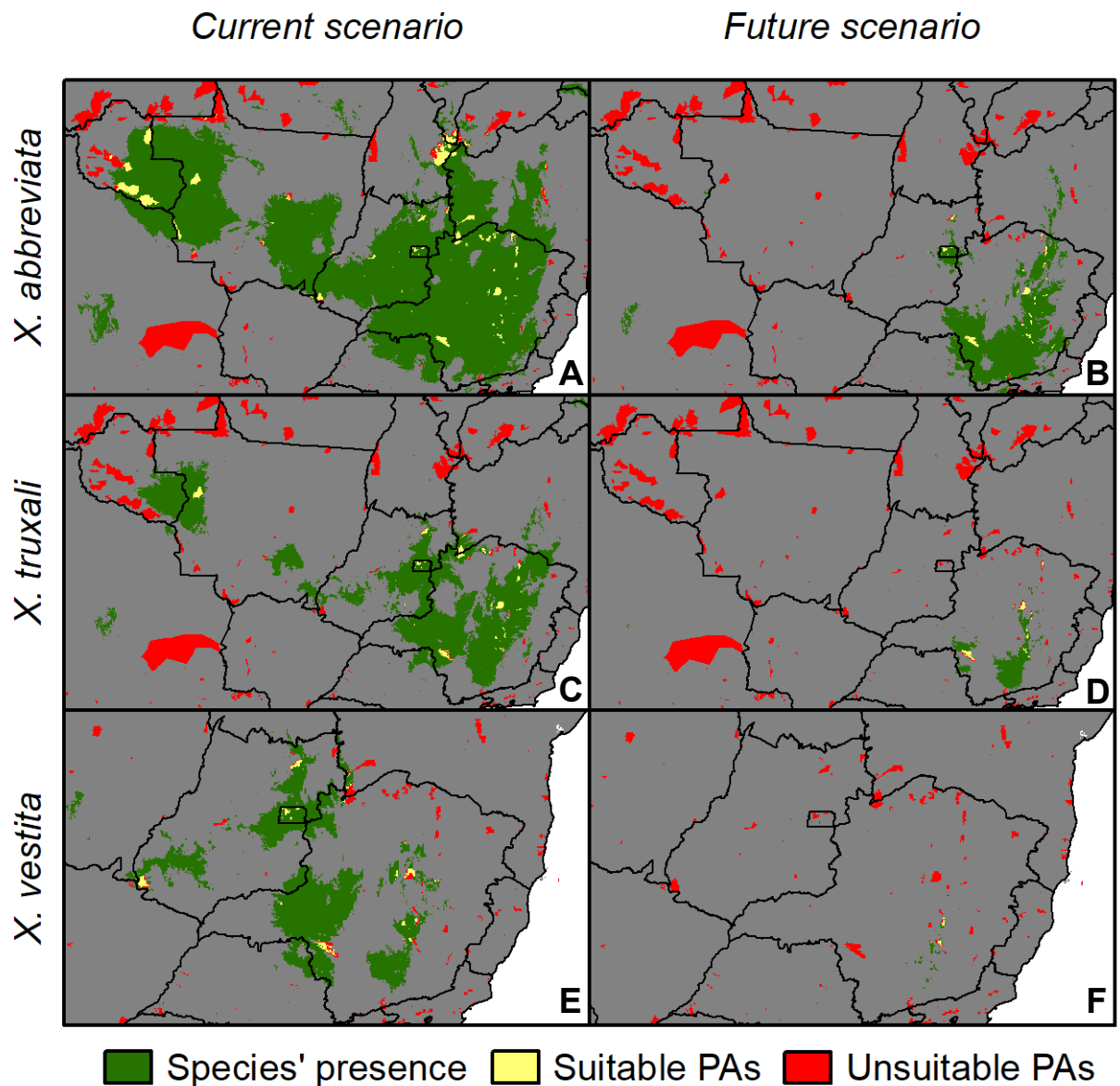


Figure 3-6 Current and future distribution ranges for *Xylocopa abbreviata* (A and B), *Xylocopa truxali* (C and D), and *Xylocopa vestita* (E and F) overlapped with Brazilian's strict use protected areas network (IUCN's classes I to IV). The three maps for the future scenario represent the consensual distribution all maps obtained from the ensembles of each Representative Concentration Pathway. Green polygons refer to the suitable area above the threshold no-omission obtain from the present ensemble by each species. Yellow polygons refer to Brazilian's protected areas overlapping with the species' predicted range. Red polygons refer to the protected areas not suitable for the species..

3.4 DISCUSSION

Here, we produced the first prediction of range distribution for the carpenter bees *X. abbreviata*, *X. truxali*, and *X. vestita*, under both current and future scenarios with different levels of predicted climate changes, from the most optimistic to the most pessimistic one, but also intermediary scenarios for 2070. Furthermore, we estimated the amount of their ranges that are and will be potentially protected considering the current network of the strict use conservation units in South America. In addition, we observed that the potential range of the species is expected to shift southeastwards in response to the potential climate changes around the year 2070.

Our results show that these carpenter bees may suffer a significant reduction in their distribution areas due to climatic changes, particularly in areas of the Midwest. We report high loss levels of both suitable areas and environmental protected areas specifically. For instance, *X. vestita* will potentially lose, respectively, ~98% and ~90% of its range into the next 50 years. This result is consistent with the findings of a previous study that investigated the overall impact of climate change on pollination services in Brazilian native species. Based on two different climate scenarios for the years of 2050 and 2080, Giannini et al. (2012) showed a reduction of the total of suitable areas for nine out of ten species of Brazilian native bees. Nonetheless, this result was the opposite for more generalist species (Silva et al., 2015), exotic species (Silva et al., 2017), or even species from more xeric regions in Australia (Silva et al., 2018).

Besides Giannini et al. (2012), we have knowledge of only six previous studies that analyzed future climate change scenarios for Brazilian bees (Giannini et al., 2017a, 2017b, 2013a; Martins et al., 2015; Nemésio et al., 2016; Silva et al., 2015), and only one of them modeled the distribution of *Xylocopa* species. For one of the species evaluated in Giannini et al. (2013), there was a potential loss of about 90% of the area of occupation predicted for it in the next 40 years. On the same direction, Martins et al. (2015) showed that the distribution of the Neotropical bee *Bombus bellicosus* Smith, 1879 should move to southwards to climatically more favorable areas in the South American continent. The only case of range expansion in the future scenarios was shown by Silva et al. (2015), where the orchid bee *Eulaema nigrata* Lepelletier (1841) is expected to increase its future range, especially in deforested man-related areas. The rare orchid-bee, *Euglossa marianae* Nemésio (2011), which occupies highly fragmented habitats in eastern Brazil, is expected to be resistant to climate change, still the

fragmentation of its natural habitats may prevent its long-term survival in and increase its risk of extinction (Nemésio et al., 2016). In another study, Giannini *et al.* (2017a) detected a possible suitability change for populations of the stingless bee, *Melipona subnitida* Ducke (1910), towards the edges of its current distribution range in the future, with consequent disconnections with the central core of its current distribution. Such future change threatens the dispersion ability and the gene flow among populations of this species and puts it at risk of future extinction. Finally, the most recent study showed the negative impacts of climate change on agricultural production of crop plants due to the reduction of important pollinating bee species (Giannini et al., 2017b).

Understanding a species' ecological and biological requirements, may improve the chances of its future conservation. Regrettably, basic ecological information regarding many of interspecific interactions the modeled carpenter bees (and other Neotropical insects in general) remain unknown (the so called Eltonian shortfall; Cardoso et al., 2011; Hortal et al., 2015), and the possibility that these bees change their future ranges implies that the interactions they maintain with plant species will be kept or they may develop new interactions with other plant species. The eventual loss of interactions the species currently maintains with plant species in the Brazilian Cerrado savanna is also likely. In this scenario, while these bees' ranges contracts southeastwards, the plants they interact with may dislocate elsewhere, disrupting their interaction, both phenologically (Memmott et al., 2007) and/or geographically (Parmesan and Yohe, 2003; Schweiger et al., 2012, 2008).

The use of ENMs to endorse decision makers regarding species conservation in the future climate change scenarios is not a negligible task, primarily due to the resulting potential distributions are impossible to be truly validated at the field (Araújo et al., 2005), since the future is yet to come. Additionally, the AOGMs we used may be underestimated and the climate change effects may be even worse than previously expected (Fischer et al., 2018; Steffen et al., 2018) and the results we obtain, consequently, wrong. Nonetheless, ENMs are still one of the best alternatives to discuss species conservation under future climate change (Guisan et al., 2013; Hannah et al., 2007). The current network of PAs distributed in South America, especially those in Brazil's southeastern portion, could be able to protect small non-related portions of the modeled carpenter bees under both the current and the future climate change scenarios. Regardless, the presence of the modeled species within a PA in the current scenario does

not quite mean they will be protected in the future. The current effectiveness of a PA in protecting these carpenter bees (and other bee species as well) may vary, especially because such areas were, generally, created without any ecological criteria (Asaad et al., 2017). In addition, when we consider the future climate change scenarios, the current network of protected areas will not be enough to protect species (Hannah et al., 2007). Considering this situation, future implementation of new PAs need to be based on ecological theories rather than only on the subjective criteria, such as scenic beauty or political interests (Asaad et al., 2017; Hannah et al., 2007).

The need for countries around the world to assess the impacts of climate change on pollination of economically farmed species and their potential effects on food security was discussed by the World Summit on Food Security (FAO, 2009). Food security involves physical, social, and economic access to food at all times for all people (FAO, 2009), in order to meet their food needs and preferences. Thus, climate change can significantly affect food security by altering crop growth and yield (Costanza et al., 2014), impact on crop prices, cause land abandonment, migration, and urbanization (Yu et al., 2012). This is particularly significant as the pollination services provided by native bees are important for maintaining the diversity of natural ecosystems as well as for agriculture and food production (Costanza et al., 2014).

Globally, climate change is expected to cause a 14% per capita decline in cereal production by 2030 (Funk and Brown, 2009). It is expected that Brazilian crop production may be affected by climate change, but the development and the use of proper agricultural technology could drive productivity positively, despite the effects of the worst climate change effects projected for some crops, as soybean (Caetano et al., 2018). The projected total loss in Brazilian production estimated by 2070 ranges from 2 to 5 billion dollars (Pinto et al., 2008). Therefore, it is important to outline strategies aiming to reduce pollinators population declines (Giannini et al., 2017a) and, simultaneously, improve crop productivity by promoting better income for farmers and helping to minimize the additional losses of natural areas for agriculture (Costanza et al., 2014; Pecl et al., 2017). Henceforth, continuous efforts to elucidate how pollinators species will be distributed in the future, foremost increasing the area and representativeness of PAs, is highly recommended to assure the continuity of ecological function and Humanity well-being in times to come. In this direction, our results are even utmost alarming, considering the current Brazilian policies of weakening federal environmental

organs and signaling disregarding Global Climate Change policies, ignoring the direct impacts of pollination decline on Brazil's largest economic activity and the Brazilian greatest current commodity: agriculture.

3.5 REFERENCES

- Aiello-Lammens, M. E., Boria, R. A., Radosavljevic, A., Vilela, B., & Anderson, R. P. (2015). spThin: An R package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography*, *38*(5), 541–545. <https://doi.org/10.1111/ecog.01132>
- Aizen, M. A., & Harder, L. D. (2009). The Global Stock of Domesticated Honey Bees Is Growing Slower Than Agricultural Demand for Pollination. *Current Biology*, *19*(19), 915–918.
- Allouche, O., Tsoar, A., & Kadmon, R. (2006). Assessing the accuracy of species distribution models: Prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology*, *43*(6), 1223–1232. <https://doi.org/10.1111/j.1365-2664.2006.01214.x>
- Araújo, M. B., Pearson, R. G., Thuiller, W., & Erhard, M. (2005). Validation of species-climate impact models under climate change. *Global Change Biology*, *11*(9), 1504–1513. <https://doi.org/10.1111/j.1365-2486.2005.01000.x>
- Araújo, M. B., & Peterson, A. T. (2012). Uses and misuses of bioclimatic envelope modeling. *Ecology*, *93*(7), 1527–1539. <https://doi.org/10.1890/07-1861.1>
- Araújo, M. B., & Rozenfeld, A. (2014). The geographic scaling of biotic interactions. *Ecography*, *37*(5), 406–415. <https://doi.org/10.1111/j.1600-0587.2013.00643.x>
- Asaad, I., Lundquist, C. J., Erdmann, M. V., & Costello, M. J. (2017). Ecological criteria to identify areas for biodiversity conservation. *Biological Conservation*, *213*, 309–316. <https://doi.org/10.1016/j.biocon.2016.10.007>
- Barry, S., & Elith, J. (2006). Error and uncertainty in habitat models. *Journal of Applied Ecology*, *43*, 413–423.
- Benevides, C. R., Gaglianone, M. C., & Hoffmann, M. (2009). Visitantes florais do maracujá-amarelo (*Passiflora edulis* f. *flavicarpa* Deg. Passifloraceae) em áreas de cultivo com diferentes proximidades a fragmentos florestais na região Norte Fluminense, RJ. *Revista Brasileira de Entomologia*, *53*(3), 415–421. <https://doi.org/10.1590/S0085-56262009000300016>
- Booth, T. H., Nix, H. A., Busby, J. R., & Hutchinson, M. F. (2014). Bioclim: The first species distribution modelling package, its early applications and relevance to most current MaxEnt studies. *Diversity and Distributions*, *20*(1), 1–9. <https://doi.org/10.1111/ddi.12144>
- Buchmann, S. L. (1983). Buzz pollination in angiosperms. In C. E. JONES & R. J. LITTLE (Eds.), *Handbook of experimental pollination biology* (pp. 73–117). New York, Van Nostrand Reinhold, 558 p.
- Caetano, J. M., Tessarolo, G., De Oliveira, G., da Silva e Souza, K., Felizola Diniz-Filho, J. A., & Nabout, J. C. (2018). Geographical patterns in climate and agricultural technology drive soybean productivity in Brazil. *PLoS ONE*, *13*(1), 1–16. <https://doi.org/10.1371/journal.pone.0191273>

- Camillo, E. (2003). *Polinização de maracujá*. Ribeirão Preto: Holos.
- Cardoso, P., Erwin, T. L., Borges, P. A. V., & New, T. R. (2011). The seven impediments in invertebrate conservation and how to overcome them. *Biological Conservation*, *144*(11), 2647–2655. <https://doi.org/10.1016/j.biocon.2011.07.024>
- Cattell, R. B. (1966). The scree test for the numbers of factors. *Multivariate Behavioral Research*, *1*(August), 245–276. <https://doi.org/10.1207/s15327906mbr0102>
- Costanza, R., de Groot, R., Sutton, P., van der Ploeg, S., Anderson, S. J., Kubiszewski, I., ... Turner, R. K. (2014). Changes in the global value of ecosystem services. *Global Environmental Change*, *26*(1), 152–158. <https://doi.org/10.1016/j.gloenvcha.2014.04.002>
- Development Core Team, R. (2018). R: A language and environment for statistical computing. Viena: R Foundation for Statistical Computing.
- Distefano, C., Zhu, M., & Mîndrilă, D. (2009). Understanding and using factor scores: Considerations for the applied researcher. *Practical Assessment, Research & Evaluation*, *14*(20), 1–11. <https://doi.org/10.1.1.460.8553>
- FAO. (2009). FAO—Food and Agriculture Organization of the United Nations. In *Declaration of the World Summit on Food Security*. Rome.
- Fischer, H., Meissner, K. J., Mix, A. C., Abram, N. J., Austermann, J., Brovkin, V., ... Zhou, L. (2018). Palaeoclimate constraints on the impact of 2 °c anthropogenic warming and beyond. *Nature Geoscience*, *11*(7), 474–485. <https://doi.org/10.1038/s41561-018-0146-0>
- Fitzpatrick, Ú., Murray, T. E., Paxton, R. J., Breen, J., Cotton, D., Santorum, V., & Brown, M. J. F. (2007). Rarity and decline in bumblebees - A test of causes and correlates in the Irish fauna. *Biological Conservation*, *136*(2), 185–194. <https://doi.org/10.1016/j.biocon.2006.11.012>
- Funk, C. C., & Brown, M. E. (2009). Declining global per capita agricultural production and warming oceans threaten food security. *Food Security*, *1*(3), 271–289. <https://doi.org/10.1007/s12571-009-0026-y>
- Garcia, M. T. A., & Hoc, P. S. (1997). Floral biology and reproductive system of *Passiflora caerulea* (Passifloraceae). *Beitrage Zur Biologie Der Pflanzen*, *71*, 1–21.
- Gerling, D., Hurd, P. D., & Hefetz, A. (1983). Comparative behavioral biology of two Middle East species of carpenter bees (*Xylocopa Latreille*) (Hymenoptera: Apoidea). *Smithsonian Contributions to Zoology*, *369*, 1–33.
- Ghazoul, J. (2005). Buzziness as usual? Questioning the global pollination crisis. *Trends in Ecology and Evolution*, *20*(7), 367–373. <https://doi.org/10.1016/j.tree.2005.04.026>
- Giannini, T. C., Acosta, A. L., Garófalo, C. A., Saraiva, A. M., Alves-dos-Santos, I., & Imperatriz-Fonseca, V. L. (2012). Pollination services at risk: Bee habitats will decrease owing to climate change in Brazil. *Ecological Modelling*, *244*, 127–131.
- Giannini, T. C., Acosta, A. L., Silva, C. I. da, de Oliveira, P. E. A. M., Imperatriz-Fonseca, V. L., & Saraiva, A. M. (2013). Identifying the areas to preserve passion fruit pollination service in Brazilian Tropical Savannas under climate change. *Agriculture, Ecosystems and Environment*, *171*(June), 39–46. <https://doi.org/10.1016/j.agee.2013.03.003>
- Giannini, T. C., Costa, W. F., Cordeiro, G. D., Imperatriz-Fonseca, V. L., Saraiva, A. M., Biesmeijer, J., & Garibaldi, L. A. (2017). Projected climate change threatens pollinators and crop production in Brazil. *PloS One*, *12*(8), e0182274.

<https://doi.org/10.1371/journal.pone.0182274>

- Giannini, T. C., Maia-Silva, C., Acosta, A. L., Jaffé, R., Carvalho, A. T., Martins, C. F., ... Imperatriz-Fonseca, V. L. (2017). Protecting a managed bee pollinator against climate change: strategies for an area with extreme climatic conditions and socioeconomic vulnerability. *Apidologie*, 48(6), 784–794. <https://doi.org/10.1007/s13592-017-0523-5>
- Giannini, T. C., Pinto, C. E., Acosta, A. L., Taniguchi, M., Saraiva, A. M., & Alves-dos-Santos, I. (2013). Interactions at large spatial scale: The case of Centris bees and floral oil producing plants in South America. *Ecological Modelling*, 258, 74–81. <https://doi.org/10.1016/j.ecolmodel.2013.02.032>
- Golicher, D., Ford, A., & Cayuela, L. (2012). Pseudo-absences, pseudo-models and pseudo-niches : pitfalls of model selection based on the area under the curve. *International Journal of Geographical Information Science*, 26(11), 2049–2063.
- Goulson, D. (2003). Effects of Introduced Bees on Native Ecosystems. *Annual Review of Ecology, Evolution, and Systematics*, 34(1), 1–26. <https://doi.org/10.1146/annurev.ecolsys.34.011802.132355>
- Guisan, A., Tingley, R., Baumgartner, J. B., Naujokaitis-Lewis, I., Sutcliffe, P. R., Tulloch, A. I. T., ... Buckley, Y. M. (2013). Predicting species distributions for conservation decisions. *Ecology Letters*, 16(12), 1424–1435. <https://doi.org/10.1111/ele.12189>
- Hannah, L., Midgley, G. F., Anelman, S., Araujo, M. B., Hughes, G., Martinez-Meyer, E., ... Williams, P. J. (2007). Protected area needs in a changing climate. *Frontiers in Ecology and the Environment*, 5(3), 131–138. [https://doi.org/10.1890/1540-9295\(2007\)5\[131:PANIAC\]2.0.CO;2](https://doi.org/10.1890/1540-9295(2007)5[131:PANIAC]2.0.CO;2)
- Hegland, S. J., Nielsen, A., Lázaro, A., Bjercknes, A. L., & Totland, Ø. (2009). How does climate warming affect plant-pollinator interactions? *Ecology Letters*, 12(2), 184–195. <https://doi.org/10.1111/j.1461-0248.2008.01269.x>
- Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., & Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, 25, 1965–1978.
- Hijmans, R. J., Phillips, S., & Leathwi, J. (2017). dismo: Species Distribution Modeling. Retrieved from <https://cran.r-project.org/package=dismo>
- Hirzel, A. H., Le Lay, G., Helfer, V., Randin, C., & Guisan, A. (2006). Evaluating the ability of habitat suitability models to predict species presences. *Ecological Modelling*, 199(2), 142–152. <https://doi.org/10.1016/j.ecolmodel.2006.05.017>
- Hortal, J., de Bello, F., Diniz-Filho, J. A. F., Lewinsohn, T. M., Lobo, J. M., & Ladle, R. J. (2015). Seven Shortfalls that Beset Large-Scale Knowledge of Biodiversity. *Annual Review of Ecology, Evolution, and Systematics*, 46(1), 523–549. <https://doi.org/10.1146/annurev-ecolsys-112414-054400>
- Hurd, P. D. (1978). *An annotated catalog of the carpenter bees (genus Xylocopa Latr.) of the Western Hemisphere (Hymenoptera, Anthophoridae)*. Washington Smithsonian Institution.
- Hurd, P. D., & Moure, J. S. (1963). A classification of the large carpenter bees (Xylocopini) (Hymenoptera: Apoidea). *University of California Publications in Entomology*, 29, 1–365.
- Jiménez-Valverde, A., Peterson, A. T., Soberón, J., Overton, J. M., Aragón, P., Lobo, J. M., ... Lobo, J. M. (2011). Use of niche models in invasive species risk assessments. *Biological*

- Invasions*, 13(12), 2785–2797. <https://doi.org/10.1007/s10530-011-9963-4>
- Junqueira, C. N., & Augusto, S. C. (2017). Bigger and sweeter passion fruits: effect of pollinator enhancement on fruit production and quality. *Apidologie*, 48(2), 131–140. <https://doi.org/10.1007/s13592-016-0458-2>
- Karatzoglou, A., Smola, A., Hornik, K., & Zeileis, A. (2004). kernlab: An S4 Package for Kernel Methods in R. *Journal of Statistical Software*, 11(9), 1–20. Retrieved from <http://www.jstatsoft.org/v11/i09/>
- Kremen, C., Williams, N. M., Aizen, M. A., Gemmill-Herren, B., LeBuhn, G., Minckley, R., ... Ricketts, T. H. (2007). Pollination and other ecosystem services produced by mobile organisms: A conceptual framework for the effects of land-use change. *Ecology Letters*, 10(4), 299–314. <https://doi.org/10.1111/j.1461-0248.2007.01018.x>
- Lawley, D. N., & Maxwell, A. E. (1962). Factor analysis as a statistical method. *Wiley for the Royal Statistical Society*, 12(3), 209–229.
- Liu, C., Berry, P. M., Dawson, T. P., & Pearson, R. G. (2005). Selecting thresholds of occurrence in the prediction of species distributions. *Ecography*, 28(3), 385–393. <https://doi.org/10.1111/j.0906-7590.2005.03957.x>
- Liu, C., White, M., & Newell, G. (2011). Measuring and comparing the accuracy of species distribution models with presence-absence data. *Ecography*, 34, 232–243.
- Lobo, J. M. (2016). The use of occurrence data to predict the effects of climate change on insects. *Current Opinion in Insect Science*, 17, 62–68. <https://doi.org/10.1016/j.cois.2016.07.003>
- Lobo, J. M., & Tognelli, M. F. (2011). Exploring the effects of quantity and location of pseudo-absences and sampling biases on the performance of distribution models with limited point occurrence data. *Journal for Nature Conservation*, 19(1), 1–7. <https://doi.org/10.1016/j.jnc.2010.03.002>
- Lucas, A. (2018). amap: Another Multidimensional Analysis Package.
- Martins, A. C., Silva, D. P., De Marco, P., & Melo, G. A. R. (2015). Species conservation under future climate change: the case of *Bombus bellicosus*, a potentially threatened South American bumblebee species. *Journal of Insect Conservation*, 19(1), 33–43. <https://doi.org/10.1007/s10841-014-9740-7>
- McGuffie, K., & Henderson-Sellers, A. (2014). *A Climate Modelling Primer*. Oxford: John Wiley & Sons.
- Memmott, J., Craze, P. G., Waser, N. M., & Price, M. V. (2007). Global warming and the disruption of plant-pollinator interactions. *Ecology Letters*, 10(8), 710–717. <https://doi.org/10.1111/j.1461-0248.2007.01061.x>
- Memmott, J., Waser, N. M., & Price, M. V. (2004). Tolerance of pollination networks to species extinctions. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 271(1557), 2605–2611. <https://doi.org/10.1098/rspb.2004.2909>
- Michener, C. D. (2007). *The Bees of The World*. The Johns Hopkins University Press.
- Nemésio, A., Silva, D. P., Nabout, J. C., & Varela, S. (2016). Effects of climate change and habitat loss on a forest-dependent bee species in a tropical fragmented landscape. *Insect Conservation and Diversity*, 9(2), 149–160. <https://doi.org/10.1111/icad.12154>
- Nix, H. (1986). A biogeographic analysis of Australian elapid snakes. In Longmore, R., Ed.,

- Atlas of Elapid Snakes of Australia. Australian Flora and Fauna Series No. 7* (pp. 4–15). Canberra: Australian Government Publishing Service.
- Ovalle-Rivera, O., Läderach, P., Bunn, C., Obersteiner, M., & Schroth, G. (2015). Projected shifts in *Coffea arabica* suitability among major global producing regions due to climate change. *PLoS ONE*, *10*(4). <https://doi.org/10.1371/journal.pone.0124155>
- Parmesan, C. (2006). Ecological and evolutionary responses to recent climate change. *Annual Review of Ecology and Systematics*, *37*(1), 637–669. <https://doi.org/10.1146/annurev.ecolsys.37.091305.110100>
- Parmesan, C., & Yohe, G. (2003). A globally coherent fingerprint of climate change impacts across natural systems. *Nature*, *421*, 37. <https://doi.org/10.1038/nature01286>
- Pearson, R. G., Raxworthy, C. J., Nakamura, M., & Townsend Peterson, A. (2007). Predicting species distributions from small numbers of occurrence records: A test case using cryptic geckos in Madagascar. *Journal of Biogeography*, *34*(1), 102–117. <https://doi.org/10.1111/j.1365-2699.2006.01594.x>
- Pecl, G. T., Araújo, M. B., Bell, J. D., Blanchard, J., Bonebrake, T. C., Chen, I. C., ... Williams, S. E. (2017). Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science*, *355*(6332). <https://doi.org/10.1126/science.aai9214>
- Peterson, A. T., & Soberón, J. (2012). Species distribution modeling and ecological niche modeling: Getting the Concepts Right. *Natureza e Conservacao*, *10*(2), 102–107. <https://doi.org/10.4322/natcon.2012.019>
- Peterson, A. T., Soberón, J., Pearson, R., Anderson, R. P., Martínez-Meyer, E., Nakamura, M., & Araújo, M. B. (2011). *Ecological niches and geographic distributions. Ecological niches and geographic distributions* (Vol. 94).
- Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *International Journal of Global Environmental Issues*, *(190)*, 231–259. <https://doi.org/10.1016/j.ecolmodel.2005.03.026>
- Phillips, S. J., & Dudík, M. (2008). Modeling of species distribution with Maxent: new extensions and a comprehensive evaluation. *Ecography*, *31*(December 2007), 161–175. <https://doi.org/10.1111/j.2007.0906-7590.05203.x>
- Pinto, H. S., Assad, E., Junior, J. Z., Evangelista, Sr., Otavian, a F., Ávila, Amh., ... Coral, G. (2008). *Aquecimento Global e a Nova Geografia da Produção Agrícola no Brasil. Embrapa*. <https://doi.org/10.1080/20464177.2005.11020183>
- Plate, T., & Heiberger, R. (2016). abind: Combine Multidimensional Arrays. Retrieved from <https://cran.r-project.org/package=abind>
- Potts, S. G., Biesmeijer, J. C., Kremen, C., Neumann, P., Schweiger, O., & Kunin, W. E. (2010). Global pollinator declines: trends, impacts and drivers. *Trends in Ecology & Evolution*, *25*(6), 345–353. <https://doi.org/10.1016/j.tree.2010.01.007>
- Potts, S. G., Imperatriz-Fonseca, V., Ngo, H. T., Aizen, M. A., Biesmeijer, J. C., Breeze, T. D., ... Vanbergen, A. J. (2016). Safeguarding pollinators and their values to human well-being. *Nature*, *540*(7632), 220–229. <https://doi.org/10.1038/nature20588>
- Revelle, W. (2018). psych: Procedures for Personality and Psychological Research. Illinois, USA: Northwestern University. Retrieved from <https://cran.r-project.org/package=psych>
- Rocchini, D., Hortal, J., Lengyel, S., Lobo, J. M., Jiménez-Valverde, A., Ricotta, C., ...

- Chiarucci, A. (2011). Accounting for uncertainty when mapping species distributions: The need for maps of ignorance. *Progress in Physical Geography*, 35(2), 211–226.
- Roubik, D. W. (1995). *Applied pollination in tropical America. Pollination of cultivated plants in the tropics. FAO Agricultural Services Bulletin* (Vol. 118).
- Sazima, I., & Sazima, M. (1989). Mamangavas e irapuás (Hymenoptera, Apoidea): Visitas, interações e consequências para polinização do maracujá (Passifloraceae). *Revista Brasileira de Entomologia*, 33, 119–134.
- Schölkopf, B., Platt, J. C., Shawe-Taylor, J., Smola, A. J., & Williamson, R. C. (2001). Estimating the support of a high-dimensional distribution. *Neural Computation*, 13(7), 1443–1471. <https://doi.org/10.1162/089976601750264965>
- Schweiger, O., Heikkinen, R. K., Harpke, A., Hickler, T., Klotz, S., Kudrna, O., ... Settele, J. (2012). Increasing range mismatching of interacting species under global change is related to their ecological characteristics. *Global Ecology and Biogeography*, 21(1), 88–99. <https://doi.org/10.1111/j.1466-8238.2010.00607.x>
- Schweiger, O., Settele, J., Kudrna, O., Klotz, S., & Kuhn, I. (2008). Climate change can cause spatial mismatch of trophically interacting species. *Ecology*, 89(12), 3472–3479. <https://doi.org/10.1890/07-1748.1>
- Shcheglovitova, M., & Anderson, R. P. (2013). Estimating optimal complexity for ecological niche models: A jackknife approach for species with small sample sizes. *Ecological Modelling*, 269, 9–17. <https://doi.org/10.1016/j.ecolmodel.2013.08.011>
- Silva, D. P., Dew, R. M., Vilela, B., Stevens, M. I., & Schwarz, M. P. (2018). No deaths in the desert: predicted responses of an arid-adapted bee and its two nesting trees suggest resilience in the face of warming climates. *Insect Conservation and Diversity*. <https://doi.org/10.1111/icad.12318>
- Silva, D. P., Groom, S. V. C., da Silva, C. R. B., Stevens, M. I., & Schwarz, M. P. (2017). Potential pollination maintenance by an exotic allodapine bee under climate change scenarios in the Indo-Pacific region. *Journal of Applied Entomology*, 141(1–2), 122–132. <https://doi.org/10.1111/jen.12337>
- Silva, D. P., Macêdo, A. C. B. A., Ascher, J. S., & De Marco, P. (2015). Range increase of a Neotropical orchid bee under future scenarios of climate change. *Journal of Insect Conservation*, 19(5), 901–910. <https://doi.org/10.1007/s10841-015-9807-0>
- Souza, M. M., Pereira, T. N. S., Viana, A. P., Pereira, M. G., Do Amaral Júnior, A. T., & Madureira, H. C. (2004). Flower receptivity and fruit characteristics associated to time of pollination in the yellow passion fruit *Passiflora edulis* Sims f. *flavicarpa* Degener (Passifloraceae). *Scientia Horticulturae*, 101(4), 373–385. <https://doi.org/10.1016/j.scienta.2003.11.020>
- Steffan-Dewenter, I., Potts, S. G., Packer, L., & Ghazoul, J. (2005). Pollinator diversity and crop pollination services are at risk [3] (multiple letters). *Trends in Ecology and Evolution*, 20(12), 651–653. <https://doi.org/10.1016/j.tree.2005.09.004>
- Steffen, W., Rockström, J., Richardson, K., Lenton, T. M., Folke, C., Liverman, D., ... Schellnhuber, H. J. (2018). Trajectories of the Earth System in the Anthropocene. *Proceedings of the National Academy of Sciences*, 115(33), 8252–8259. <https://doi.org/10.1073/pnas.1810141115>
- Stocker, T. F., Qin, D., Plattner, G.-K., Alexander, L. V., Allen, S. K., Bindoff, N. L., ... Xie,

- S.-P. (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, NY, USA.: Cambridge University.
- Tax, D. M. J., & Duin, R. P. W. (2004). Support vector data description. *Machine Learning*, 54(1), 45–66. Retrieved from <http://www.springerlink.com/index/JL3N42J6067703N2.pdf>
- Tylianakis, J. M., & Binzer, A. (2014). Effects of global environmental changes on parasitoid-host food webs and biological control. *Biological Control*, 75, 77–86. <https://doi.org/10.1016/j.biocontrol.2013.10.003>
- Van Der Pul, L. (1954). Xylocopa and flowers in the tropics. *Proceedings of the Koninklijke Nederlandse Akademie von Wetenschappen Natural Sciences*, 57, 413–423.
- VanDerWal, J., Shoo, L. P., Graham, C., & Williams, S. E. (2009). Selecting pseudo-absence data for presence-only distribution modeling: How far should you stray from what you know? *Ecological Modelling*, 220(4), 589–594. <https://doi.org/10.1016/j.ecolmodel.2008.11.010>
- Varela, S., Lima-Ribeiro, M. S., & Terribile, L. C. (2015). A short guide to the climatic variables of the last glacial maximum for biogeographers. *PLoS ONE*, 10(6), 1–15. <https://doi.org/10.1371/journal.pone.0129037>
- Watmough, R. H. (1974). Biology and behavior of carpenter bees in Southern Africa. *Journal of the Entomological Society of Southern Africa*, 37, 261–281.
- Winfrey, R., Aguilar, R., Vázquez, D. P., LeBuhn, G., & Aizen, M. A. (2009). A Meta-Analysis of Bees' Responses to Anthropogenic Disturbance, 90(8), 2068–2076.
- Wittmann, D., & Scholz, E. (1989). Nectar dehydration by male carpenter bees as preparation for mating flights. *Behavioral Ecology and Sociobiology*, 25, 387–391.
- Yamamoto, M., Da Silva, C. I., Augusto, S. C., Barbosa, A. A. A., & Oliveira, P. E. (2012). The role of bee diversity in pollination and fruit set of yellow passion fruit (*Passiflora edulis* forma *flavicarpa*, Passifloraceae) crop in Central Brazil. *Apidologie*, 43(5), 515–526. <https://doi.org/10.1007/s13592-012-0120-6>
- Yu, Q., Wu, W., Yang, P., Li, Z., Xiong, W., & Tang, H. (2012). Proposing an interdisciplinary and cross-scale framework for global change and food security researches. *Agriculture, Ecosystems and Environment*, 156, 57–71. <https://doi.org/10.1016/j.agee.2012.04.026>
- Zanella, F. C. V., & Silva, M. (2010). Uma Nova Espécie de Xylocopa (Monoxylocopa) Hurd & Moure e Novos Registros de X. abbreviata Hurd & Moure (Hymenoptera: Apidae). *SYSTEMATICS, MORPHOLOGY AND PHYSIOLOGY*, 39(1), 61–66.

CONCLUSÕES GERAIS

Os resultados do capítulo um mostraram que a inclusão do componente biótico melhorou nosso modelo para a abelha exótica no método preditivo MaxEnt, mas não para Bioclim e SVM. A modelagem de distribuição potencial de *L. huberi* no cenário presente foi mais influenciada pelo tratamento com predições isoladas de cada planta associada transpostas em mapa de presença ausência (SEP-PA), dentre os cinco tratamentos variando composições de componentes bióticos (CLIMA, SEP-PA, STK-PA, STK-SUIT, SEP-SUIT). Assim, selecionamos SEP-PA para modelar a distribuição futura de *L. huberi*. Identificamos que distribuição de áreas adequadas a *L. huberi* tende diminuir com deslocamento expressivo para o Norte das áreas atualmente ocupadas na América do Sul em todos os cenários considerados, com destaque no cenário mais pessimista (RCP 8.5), tanto para *L. huberi* quanto para as sete espécies de plantas.

Já no capítulo dois as três espécies de abelhas nativas perderam significativas áreas atualmente ocupadas, especialmente na região centro-oeste brasileira, com redução total detectada de 82.93% para *X. abbreviata*, 90.84% para *X. truxali* e 98.90% para *X. vestita*. Em reflexo disso, as áreas de proteção ambiental atualmente ocupadas também sofrerão perdas no futuro contabilizando redução de 88.94% para *X. abbreviata*, 68.65% para *X. truxali*, e 93.30% para *X. vestita*. Esses resultados são ainda mais alarmantes, considerando-se as atuais políticas brasileiras de enfraquecimento dos órgãos ambientais federais e sinalização de se desconsiderar as políticas internacionais de mitigação às Mudanças Climáticas, ignorando os impactos diretos do declínio da polinização na maior atividade econômica, e atualmente a maior comódite, do Brasil: a agricultura.

A falta de conhecimento sobre os efeitos das mudanças climáticas no comportamento de abelhas e como suas distribuições podem ser afetadas é preocupante em muitos níveis, particularmente, em impactos nas relações interespecíficas, nos serviços ecossistêmicos economicamente significantes à produção agrícola global bem como na manutenção da diversidade do Cerrado, um dos *hotspots* mundiais para conservação da biodiversidade. Portanto, esforços contínuos para elucidar como as espécies são potencialmente distribuídas, hoje e no futuro, são de extrema importância em um mundo que está sempre mudando, especialmente devido ao resultado das atividades humanas. Nós esperamos que os resultados apresentados aqui, eventualmente,

deixem fundamentos teóricos a tal propósito e que sirvam tanto aos interessados em estudar modelos de nicho com inclusão das interações Eltonianas, quanto aos conservacionistas para que possam tomar medidas mitigadoras, presentes e futuras, dos impactos ou danos decorrentes dos temas abordados em cada estudo.



**INSTITUTO
FEDERAL**

Goiano

Campus
Urutaí

