Regional features of geography, such as size or distance, are expected to shape how lineages disperse, go extinct, and speciate. Yet this fundamental link between geographical context and evolutionary consequence has not been fully incorporated into phylogenetic models of biogeography. We designed a model that allows variation in regional features (size, distance, insularity, and oceanic separation) to inform rates of biogeographic change. Our approach uses a Bayesian hierarchical modeling framework to transform regional values of quantitative and categorical features into evolutionary rates. We also make use of a parametric range split score to quantify range cohesion for widespread species, thereby allowing geographical barriers to initiate “range-splitting” speciation events. Applying our approach to Anolis lizards, a species-rich neotropical radiation, we found that distance between regions, especially over water, decreases dispersal rates and increases between-region speciation rates. For distances less than ~470 km over land, anoles tended to disperse faster than they speciate between regions. Over oceans, the equivalent maximum range cohesion distance fell to ~160 km. Our results suggest that the historical biogeography of founder event speciation may be productively studied when the same barriers that inhibit dispersal also promote speciation between regions.

How do species diversify, disperse, and go extinct? These processes and the geographical forces that shape them (size, distance, insularity, and oceanic separation) are inherently connected to the biogeographic histories of lineages. Few clades have complete fossil records, so historical biogeography is often studied using phylogenetic event-based models to reconstruct the geographical past for living species. The two most widely used models for biogeographic inference are the Dispersal–Extinction–Cladogenesis (DEC) and the Geographic State Speciation Extinction (GeoSSE) models. Both approaches use phylogenetic stochastic processes to infer how species evolve among discrete regions through dispersal, regional extinction, and cladogenesis events. One important way in which they differ, however, is that GeoSSE allows species range configurations to influence speciation and extinction rates, whereas DEC does not. Even though biogeographers generally consider GeoSSE to be mechanistically superior to DEC, the computational and statistical performance of GeoSSE is understood to scale poorly for biogeographical systems with more than two regions. For example, the standard GeoSSE model is extremely difficult to quantify.
parameter rich, requiring 7 free parameters for two regions, 120 parameters for five regions, and 9,420 parameters for nine regions (SI Appendix).

For this study, we developed a feature-informed GeoSSE model (FIG) that allows regional features, such as size or distance, to inform biogeographic rates of dispersal, extinction, and speciation. Rather than treating all possible event rates as freely estimated parameters, FIG, instead, models functional relationships between regional features and biogeographic rates, using 12 parameters regardless of how many regions are used. To illustrate the utility of FIG, we modeled a neotropical radiation of 379 lizard species (Anolis), whose conspicuous mainland–island distribution has been the subject of intense study (19–22). We tested whether, and how, four features (regional size, distance, insularity, and oceanic barrier presence) measured across nine biogeographic regions jointly shaped the processes of dispersal, extinction, within-region speciation, and between-region speciation for Anolis lizards. We found that, while region size and insularity had no detectable effect on Anolis biogeography, long distances, particularly over oceans, did. With these measurements in mind, and in light of an ongoing debate in the biogeographical literature (16, 17), we propose that founder event speciation may be modeled productively by using barriers and distance to align how dispersal and between-region speciation operate in space.

Model

FIG models biogeographic rates in terms of the local regional features that species encounter as they evolve (Fig. 1 and Materials and Methods). Species and their ranges (sets of inhabited discrete regions) stochastically change through four distinct processes: dispersal, (local and global) extinction, within-region speciation, and between-region speciation (Fig. 1A) (15). Event rates for each process may vary in response to multiple regional features; for example, within-region speciation rates might be highest in regions that are simultaneously large and continental (Fig. 1B), or

![Fig. 1. Regional features, biogeographic events and rates, and example predictions for the FIG model. (A) Species may inhabit regions with suitable habitat (green) that are separated by barriers, such as arid zones (brown) or ocean (blue) (Top). Inhabitable regions have measurable quantitative and categorical features (Middle Left) that are transformed into evolutionary rates (Middle Right). Dispersal rates and between-region speciation rates are potentially informed by distance and the separation of land/water between regions. Extinction and within-region speciation rates are potentially informed by region size and type (continental vs. insular). FIG generates biogeographic range data (region presence/absence) conditional on its feature-informed rates and a time-calibrated phylogeny (Bottom). (B and C) Example FIG parameters (Materials and Methods) induce opposite responses in biogeographic rates to the same regional features. (B) Region size and region type (solid or dashed line) determine the within-region speciation rate (yellow) and extinction rate (red) for each region. (C) Distance and barrier type (solid or dashed line) determine the dispersal rate (blue) for any pair of regions and the between-region speciation rate (purple) for any range undergoing a “split.” Note that the same regional feature may have different and asymmetrical effects on different biogeographic rates, depending on the model parameter values. Refer to Materials and Methods and SI Appendix, Table S1 for definitions and interpretations of FIG model parameters.](https://doi.org/10.1073/pnas.2116948119)
dispersal rates might be lowest between regions separated by long distances and major bodies of water (Fig. 1C). Even though FIG is primarily designed to infer whether such relationships are supported by the data—and, if so, what the signs and strengths of those relationships are—it can also generate ancestral range estimates and stochastic mappings (SI Appendix).

As a model, FIG defines four sets of relative rate factors that may influence region-specific rates of dispersal ($m_d$), extinction ($m_e$), within-region speciation ($m_w$), and between-region speciation ($m_b$). For this study, we assume that extinction and within-region speciation rate factors are informed by region sizes (square kilometers) and region types (insular [islands and/or archipelagoes] or continental), while dispersal and between-region speciation are informed by distances (kilometers) and barrier types (over water or land), and that all regional features held constant over time (Discussion). Exact rate factor values are determined by four categorical scaler parameters ($\sigma_d$, $\sigma_e$, $\sigma_w$, $\sigma_b$) that rescale the relative sizes of insular regions or over water distances, and four feature exponent parameters ($\phi_d$, $\phi_e$, $\phi_w$, $\phi_b$) that control the sign and scale for how the rescaled regional features relate to different evolutionary rates (Materials and Methods).

In practice, absolute event rates are computed as the product of a scaling base rate ($\rho_d$, $\rho_e$, $\rho_w$, $\rho_b$) and the relative rate factor that is directly ($m_d$, $m_e$, $m_w$) or indirectly ($m_b$ through the range split score function, $f_b$) informed by the designated regional features (Materials and Methods). Following the event types of Geoesse (15), species disperse from region $i$ into $j$ at rate $r_d(i, j) = \rho_d \times m_d(i, j)$. Local extinction of a species in region $i$ proceeds at rate $r_e(i) = \rho_e \times m_e(i)$; if a species goes extinct in its final region, that lineage goes globally extinct and no longer diversifies or disperses. Within-region speciation produces a new species in the ancestral region $i$ at rate $r_w(i) = \rho_w \times m_w(i)$. Lastly, between-region speciation “splits” (bipartitions) a widespread species range into two daughter lineages with ranges $i$ and $j$ at rate $r_b(i, j) = \rho_b \times f_b(s, t; m_b)$.

This formulation allows FIG to detect and quantify correlational relationships between regional features and evolutionary rates when provided a fixed time-calibrated phylogeny, species range data, and measurements of regional features. For example, if FIG estimates $\sigma_d = 3$ and $\phi_d = -1$, dispersal rates are assumed to have an inverse log-linear relationship to distance, with overwater distances effectively treated as 3 times as far as equivalent distances over land (Materials and Methods). FIG also permits regional features to have no effect on evolutionary rates. For instance, distance would have no effect on dispersal if $\phi_d = 0$, and distances over land and water would have equivalent effects on dispersal rates if $\sigma_d = 1$; FIG defines analogous relationships between other regional features and evolutionary rates. To detect which features have effects on evolutionary rates, we used Bayesian reversible-jump Markov chain Monte Carlo (RJMCMC) (23) to turn the effects for the eight feature exponent and categorical scaler parameters “on” ($\phi_d \neq 0$ or $\sigma_d \neq 1$) and “off” ($\phi_d = 0$ or $\sigma_d = 1$), where $P_0$ represents the marginal posterior probability that the parameter, $\theta$, is “on.” We consider $P_0 > 0.95$ as support for a direct or indirect relationship between the relevant regional feature and biogeographic process.

Results

Power Analysis. We measured how reliably FIG detected the effect of regional features on evolutionary rates using simulated data. To do so, we simulated 200 datasets with random effect strengths for the feature exponent ($\phi_d$, $\phi_e$, $\phi_w$, $\phi_b$) and categorical scaler ($\sigma_d$, $\sigma_e$, $\sigma_w$, $\sigma_b$) parameters, and random tree sizes (from 20 to 250 tips), and then fitted FIG to each of those datasets using RJMCMC (Materials and Methods). The effect of regional features on evolutionary rates was detected most reliably (i.e., when the reversible-jump model probability is $>0.95$; Materials and Methods) when tree sizes were large and/or when parameter effect strengths were strong (Fig. 2). FIG reliably detected the effect of quantitative features (region size and distance) on evolutionary rates through the feature exponent parameters ($\phi_d$) under a wider range of conditions than it detected effect of categorical features (insularity and barrier presence) on rates through the categorical scaler parameter ($\sigma_d$). In this, it is because the effect of a categorical scaler ($\sigma_d$) is throttled when its matching feature exponent ($\phi_d$) has a weak effect (Materials and Methods). Nonetheless, for trees with $\geq$100 tips, the effect of distance on dispersal and the effect of region size on speciation could be detected when their corresponding feature exponents were only moderate in strength ($\phi_d < -1$ and $\phi_d > 1$, respectively). Trees with 175 or more tips and/or higher effect strengths were generally needed to reliably detect relationships between distance and between-region speciation ($\phi_d > 2$) or between region size and extinction rates ($\phi_d < -2$), possibly because these two evolutionary event types expose lineages to an increased risk of global extinction (i.e., data erasure) through range size reduction. In general, large trees with more than 175 tips and strong effects were necessary to infer the effect of categorical features on evolutionary rates. Barriers could be detected when they effectively doubled distances between regions for dispersal ($\sigma_d > 2$) and, less frequently, for between-region speciation ($\sigma_d > 2$). Only rarely could FIG detect the effect of insularity on within-region speciation ($\sigma_d < 1/3$) or extinction ($\sigma_d < 1/3$) rates. Last of all, FIG almost never detected effects between regional features and evolutionary rates when the parameter effect strength was low (i.e., when $\phi_p \approx 0$ or $\sigma_p \approx 1$), indicating that FIG has a low false discovery rate.

Anolis Biogeography. We applied FIG to model the biogeography of Anolis lizards across nine neotropical regions (five continental, four insular; Fig. 3A, Materials and Methods, and SI Appendix). Roughly half (49%) of extant anoles inhabit one continental region, 43% inhabit one insular region, and the remaining 8% of species in ref. 21 are widespread among continental regions (Fig. 3B; see SI Appendix for caveats). Notably, four continental regions (B, C, D, E) and two insular regions (F, H) of vastly different sizes ($10^5$ km$^2$ to $10^7$ km$^2$) each possess similar numbers of species (35 to 50 spp.). Biogeographic rates for multiregion processes ($m_d$ and $m_b$), but not single-region processes ($m_e$ and $m_w$), varied substantially among regions. Dispersal ($m_d$; Fig. 3C, edges) favored movement between adjacent continental regions. Similar in pattern, but opposite in manner, rates of between-region speciation were elevated for widespread ranges that involved insular regions and/or the most-distant continental regions ($m_e$; Fig. 3D, edges). Extinction rates ($m_e$; Fig. 3C, nodes) were nearly identical, regardless of region size or island status, except that the posterior mean rate for Amazonia (region E) was higher than average. Within-region speciation rates ($m_w$; Fig. 3D, nodes) were also relatively constant across regions.

Between-region speciation rates were much higher than dispersal rates for all pairs of regions that were separated by the Caribbean (Fig. 3E). Among continental regions, however, dispersal often met or even exceeded the rate of between-region
Fig. 2. Hypothesis testing power for Fig. 3. Panels show the posterior model probabilities that RJMCMC correctly detects the effect of region size increasing within-region speciation rates ($\phi_w > 0$; A) or decreasing extinction rates ($\phi_w < 0$; B), the effect of distance increasing between-region speciation rates ($\phi_d > 0$; C) or decreasing dispersal rates ($\phi_d < 0$; D), the effect of insularity increasing the impact of region size on within-region speciation rates ($\phi_e < 1$; E) or extinction rates ($\phi_e < 1$; F), and the effect of water increasing the impact of distance on between-region speciation rates ($\phi_w > 1$; G) or dispersal rates ($\phi_w > 1$; H). Each estimate (point) gives the posterior probability (y axis) of correctly detecting an effect and its sign relative to the effect strength (x axis) and tree size (20 to 49 species, yellow; 50 to 99 species, red; 100 to 174 species, green; 175 to 250 species, blue). Estimates above a black dashed line correctly detected the simulated effect, with a probability of >0.95. Logistic regression curves summarize the distribution of effect strengths and detection probabilities for each parameter and tree size category. Shaded regions indicate regression confidence intervals.

speciation. Geographical distance was strongly associated with decreased dispersal rates (posterior median and 95% highest posterior density interval [HPD], $\phi_d = -1.03 [-1.27, -0.80]$) and increased between-region speciation rates ($\phi_e = 1.77 [0.85, 2.83]$; Table 1). For regions separated by ocean, those distances were effectively tripled for between-region speciation rates ($\sigma_d = 3.34 [1.45, 5.76]$) and dispersal ($\sigma_d = 3.45 [1.70, 5.69]$; Table 1) when compared to equivalent distances over land. In other words, water presents a formidable barrier to movement in anole lizards, both in terms of range expansion and in the maintenance of range cohesion.

Linear models predicted that dispersal outpaced speciation when distances over land were shorter than 279 [156, 472] km and shorter than 97 [46, 164] km over water (Fig. 3F and Materials and Methods). Validating this maximum range cohesion distance (MRCD) estimate against other aspects of our study, we found that 6 out of 20 possible ordered pairs of continental regions (BA, BC, CD, CE, DC, DE; Fig. 3F) had distances below the upper limit of 472 km, which defines a set of adjacent regions occupied by extant widespread continental anoles (Fig. 3B). No insular region pairs fell below the analogous over-water MRCD threshold of 164 km.

Within regions, speciation occurred more often than extinction (Fig. 3G). An RJMCMC analysis could not determine a positive or negative relationship between region size and extinction rates ($P_{\phi_e} = 0.47$) or speciation rates ($P_{\phi_e} = 0.20$; Table 1). Because of this, linear models do not predict a narrow window of region sizes in which Anolis extinction rates exceed speciation rates within regions (Fig. 3H).

Phylogenetic uncertainty had no major effect on our parameter estimates (SI Appendix, Fig. S3). Combined posterior estimates for 15 sampled phylogenies from the original Poe et al. (21) output deviated little from our primary estimates that we obtained using the maximum clade credibility tree (Table 1 and SI Appendix, Fig. S3). Combined reversible jump probabilities across posterior tree samples also favored relationships for distance and water with dispersal ($\phi_w \approx 1$, $\phi_e \approx 1$) and between-region speciation ($P_{\phi_w} = 0.98$, $P_{\phi_e} = 0.96$), and not for regional features with extinction ($P_{\phi_e} = 0.53$, $P_{\phi_e} = 0.50$) or within-region speciation ($P_{\phi_w} = 0.19$, $P_{\phi_e} = 0.50$).

Discussion

Geographical distances were simultaneously related to decreased dispersal rates and increased between-region speciation rates in Anolis (Table 1). When we assume that dispersal rates represent how easily species move between regions, our estimates suggest that Anolis ranges lose cohesion and tend to split beyond ~500 km for continental species (Table 1). Only continental pairs of regions fell below this threshold, and these are precisely the regions that are, today, inhabited by widespread anoles (Fig. 3B and F). Water is a more formidable barrier to movement in Anolis, as insular regions were effectively 3 times farther apart than continental regions when relating distance to dispersal and between-region speciation (Table 1). The shortest distance among insular regions (an average of 266 km from the Bahamas [II] into Cuba [G]) was still greater than the oceanic MRCD of about 160 km. Numerous phylogeographic studies in Anolis similarly found that intraspecific genetic divergence often met or surpassed typical levels of interspecific divergence ($F_{ST} > 0.3$) (24) when anole populations were separated by hundreds of kilometers over land and, in some cases, just tens of kilometers over water (Dataset S1).

The brown anole (Anolis sagrei), which is naturally found in both Cuba and the Bahamas, provides plausible support for a single species spanning multiple insular regions. Recent work, however, points to surprisingly deep divergences (2.8 Ma to 4.1 Ma) between the A. sagrei ordinatus subspecies in the Bahamas and its closest relatives in Cuba (25). Even within-island divergence in Cuba is steep for A. sagrei (25), and for other island anoles, like Anolis distichus from Hispaniola, which has suggested the need for taxonomic revision (e.g., ref. 26). Separate exploratory analyses that recoded the Poe et al. (21) range for A. sagrei to include the occurrence of the A. sagrei ordinatus
Fig. 3. Inferred relationships between regional features and biogeographic rates in Anolis. (A) Five continental (purple) and four insular (blue) regions drawn in proportion. (B) Counts of geographical ranges (sets of inhabited regions) among extant species. Counts and percentages for continental endemics (left), insular endemics (center), and widespread continental (right) species are listed above the histogram. (C and D) Relative regional rate estimates are displayed as networks. Thicker widths for node borders correspond to larger rates of extinction (C) or within-region speciation (D). Thicker widths for edges correspond to larger rates of dispersal (C) or between-region speciation (D); dispersal features are averaged across each source–destination pair. (E) Rates of dispersal (x axis) versus between-region speciation (y axis) for all pairs of two continental regions (purple) and all pairs that involve any insular regions (blue). (F) Ratios of between-region speciation over dispersal rates (y axis) plotted against distance (x axis). The vertical dashed lines approximate the maximum distance where \( r_d \geq r_b \) over land (purple) and over water (blue). (G) Rates of extinction (x axis) versus within-region speciation (y axis) for all continental regions (purple) and insular regions (blue). (H) Ratios of within-region speciation over extinction rates (y axis) plotted against size (x axis). For E–H, rates are plotted as posterior means (points) and their 95% highest posterior densities (segments). Dotted lines indicate rate ratios of 1:1 (black) and 5:1 or 1:5 (gray).
phenotypic uncertainty may in

tion and between-region speciation. Because the effect of a cate-
nies with as few as 50 taxa may be suf-
hypotheses to assess the impact of phylogenetic uncertainty (e.g., for fossils) (32). We imagine that modeling historical features of paleogeography is not always necessary to accurately estimate biogeographic parameters (35). While we do not expect that modeling Caribbean paleogeography would change our findings that distance and water act as barriers for Anolis movement, it is possible that fluctuations in island sizes over time detectably influenced within-region speciation and extinction rates.

Furthermore, the Anolis parameter estimates that we derived from a maximum clade credibility tree (Table 1 and Fig. 3) were highly congruent with those derived from 15 posterior tree samples (SI Appendix, Fig. S1). Biogeographers should suspect that phylogenetic uncertainty may influence FIG estimates in other clades, particularly for those phylogenies with few taxa, weak clade support, and/or highly uncertain node ages. At present, we suggest combining posterior estimates across phylogenetic hypotheses to assess the impact of phylogenetic uncertainty (SI Appendix). The ideal solution, however, will be to jointly estimate phylogeny and biogeography under FIG. Joint estimation not only is the correct statistical approach for handling phylogenetic uncertainty (29), it also creates opportunities for biogeography to inform phylogenetic divergence times (30, 31) and taxon placement (e.g., for fossils) (32).

We emphasize that the four regional features we selected (size, distance, insularity, and barrier presence) are likely only indirect drivers of biogeographic diversification (33, 34). Size, distance, and other factors may be strongly correlated with a host of more direct drivers, including ecological complexity, topographical complexity, climatological stability, and region age—drivers that are generally more difficult to measure and model. Such factors are likely key to uncovering what forces govern adaptive radiation. For instance, Amazonia is a two orders of magnitude larger than Hispaniola but contains fewer than half as many species. In this case, direct measurements of ecological and geographical complexity may predict differences between insular and continental anoles better than size alone. We also note that our analysis used modern-day features to model biogeographic diversification. Previous research suggests that modeling historical features of paleogeography is not always necessary to accurately estimate biogeographic parameters (35). While we do not expect that modeling Caribbean paleogeography would change our findings that distance and water act as barriers for Anolis movement, it is possible that fluctuations in island sizes over time detectably influenced within-region speciation and extinction rates.

Moreover, this line of inquiry reveals one purpose for the model design of FIG: It allows biologists to study a wide range of first-order biogeographic hypotheses concerning how regional features are related to evolutionary dynamics for different clades and regions (12). It also establishes a framework to test second-order hypotheses, such as whether biogeographic tendencies are correlated with the phylogenetic distributions of traits. For example, does the tendency for species ranges to spread or split correlate with dispersal mode (36), physiology (37, 38), reproductive system (39), ploidy level (40), or ecology (41)?

The feature-informed rates of FIG also mitigate concerns raised by biogeographers (13, 15, 16, 18, 42), that GeoSSSE-type models are doomed to be overparameterized when applied to systems involving more than two or three regions. When available, additional regional features can readily be incorporated into the construction of the parameterized geography functions \(f_i \) (SI Appendix). Independent of the number of regions, each additional feature would require at least one additional model parameter, and its explanatory power could be assessed using RJMCMC for Bayesian model selection.

Range split scores (Materials and Methods) are central to the model’s efficiency, as they allow a small number of parameters

![Table 1. Posterior estimates for analysis of Anolis lizards](https://doi.org/10.1073/pnas.2116948119)

| Variable          | Mean     | Lower CI   | Upper CI   | RJ prob. | Interpretation                             |
|-------------------|----------|------------|------------|----------|--------------------------------------------|
| \( \rho_d \)      | 5.12e-4  | 2.04e-4    | 8.94e-4    | –        | –                                          |
| \( \rho_x \)      | 1.50e-3  | 3.02e-7    | 3.93e-3    | –        | –                                          |
| \( \rho_y \)      | 3.45e-2  | 3.04e-2    | 3.84e-2    | –        | –                                          |
| \( \rho_b \)      | 1.37e-1  | 3.65e-2    | 2.91e-1    | –        | –                                          |
| \( \phi_d \)      | −1.03    | −1.27      | −0.80      | 1.00     | Dispersal limited by distance              |
| \( \phi_x \)      | 0.13     | −0.97      | 1.00       | 0.47     | Extinction independent of size             |
| \( \phi_y \)      | −0.07    | −0.14      | 0.01       | 0.20     | Within-region speciation independent of size |
| \( \phi_b \)      | 1.77     | 0.85       | 2.83       | 0.99     | Between-region speciation accelerated by distance |
| \( \sigma_d \)    | 3.45     | 1.70       | 5.69       | 1.00     | Dispersal limited by water                 |
| \( \sigma_x \)    | 1.07     | 0.18       | 2.45       | 0.50     | Extinction independent of insularity        |
| \( \sigma_y \)    | 0.88     | 0.22       | 1.91       | 0.50     | Within-region speciation independent of insularity |
| \( \sigma_b \)    | 3.34     | 1.45       | 5.76       | 0.99     | Between-region speciation accelerated by water |
| MRCD, over land   | 279      | 156        | 472        | –        | Measured in kilometers; see main text      |
| MRCD, over water  | 97       | 46         | 164        | –        | Measured in kilometers; see main text      |

Credible interval (CI) bounds were computed from 95% highest posterior densities. FIs that did not contain \( \phi_d \) or \( \sigma_d \) were considered significant; no significance test was applied to \( \rho_b \). Reversible jump probabilities (RJ prob.) greater than 0.05 also indicate support that \( \phi_d \) or \( \rho_d \) ≠ 1. Interpretations follow Table 2 (Materials and Methods).
to modulate the explosive number of between-region speciation rates (SI Appendix) through a biologically plausible mechanism (e.g., allopatric speciation via isolation by distance). In particular, regions separated by the weakest barriers prevent a species range from splitting (e.g., gene flow generates range cohesion) and thus generate the lowest split scores. Even trace amounts of gene flow between the most distant regions in a widespread range will marginally decrease the split score. None of this, however, implies that widespread ranges split at slower rates than species with narrower ranges, as larger ranges may split in more distinct ways, and thus have greater total rates of splitting in any way. Although we interpret the mechanism for range splitting in anoles as allopatric speciation between regions, ecological speciation with gene flow should behave similarly between regions when the feature catalyzing divergence is spatially autocorrelated (11).

Several aspects of FIG are admittedly “crude” (2) but not beyond repair. Reformulated range split scores, for instance, could depend directly on metrics of genetic differentiation (e.g., FST) rather than on its proxies, like distance. It is also possible to link phylogenetic shifts in biogeographic tempo and mode to observed (43) and hidden (18) evolutionary factors. Paleogeographic features, which may influence estimates of ancestral ranges and rates (44), can inform evolutionary rates through parameterized functions of time and space (30). In model development, first steps are necessary before taking such next steps (45, 46).

Still, even simple models can cast light upon complex issues. Few biologists would be surprised that our model inferred that anoles rarely disperse great distances or over water or that, after they do, they tend to instantaneously split into two species. This finding does, however, highlight a deeper unresolved problem in historical biogeography concerning founder event speciation. Conceptual models of the phenomenon begin with any number of colonists expanding the range of the progenitor species into a new region, with the new colonizing population having sufficiently low levels of gene flow with the progenitor population to allow rapid divergence and the fixation of genetic incompatibilities, resulting in allopatric speciation (4). This has provoked critical discussion regarding what statistical features are necessary, or can even be estimated, when modeling founder event speciation in a phylogenetic context (14–17, 47).

Here, we take a particular interest in whether founder event speciation should be modeled as one compound event (i.e., dispersal with speciation) or two sequential events (i.e., dispersal, then speciation). We conclude from our analysis of Anolis biogeography that two-event models can help refine our understanding of geophysical speciation. Dispersal and between-region speciation are both oriented around a common factor, namely, the movement of individuals (and genes) across distances and barriers, and our biogeographic models should somehow recognize their shared spatial basis. Widespread ranges comprising adjacent regions, where gene flow is uninhibited, are expected to be more genetically cohesive and evolutionarily stable when compared to more fragmented ranges with less gene flow that is attenuated across distant regions (48). Rates of allopatric speciation should be lower in the first case of nearby regions. Short distances and the absence of barriers should permit widespread ranges to persist, and, conversely, long distances and the presence of barriers should result in rare dispersal events followed by rapid speciation events.

Put more simply, what limits dispersal should also promote allopatric speciation. Looking ahead, we think it will be important for models to distinguish between interpopulation migration, the basis for gene flow, and dispersal, the basis for range expansion. Migration (sensu Wright (49)) is the movement of individuals/genes among established populations, whereas dispersal involves the movement of individuals to establish new populations. It is unclear whether migration rates or dispersal rates should generally be higher given the same set of regional features. For example, divergent ecological selection among demes might limit the entry of migrants and thus limit gene flow. On the other hand, individuals dispersing into new ecosystems might be too few in number to establish new populations, or they might be competitively excluded due to priority effects. Carefully parsing the relationships among migration, dispersal, and speciation will help to unify microevolutionary and macroevolutionary perspectives in phylogenetic biogeography.

Materials and Methods

FIG Model Definition. We developed a hierarchical phylogenetic model (FIG) to relate regional features to evolutionary rates of biogeography. SI Appendix diagrams FIG as a probabilistic graphical model (SI Appendix, Fig. S1) and provides a compact summary of all model variables (SI Appendix, Table S1). FIG is a GeoSSE (15) variant, so it is composed of four biogeographic processes: dispersal (d), extinction (e), within-region speciation (w), and between-region speciation (b). Relationships between regional features and relative evolutionary rates are primarily governed by two sets of parameters. Categorical scaler parameters (σp, σd, σw, σe) rescale the effective value of a quantitative feature (e.g., size or distance) depending on the corresponding categorical feature for a region (e.g., insular region or water barrier). Feature exponent parameters (ξp, ξd, ξw, ξe) control the sign and scale of the relationship between a quantitative regional feature and an effect on the matched evolutionary rate. Values for all eight parameters are estimated from the data during inference, where each parameter can induce a different relationship between one regional feature and one evolutionary rate (Table 2) by defining relationships between features and evolutionary effects using the equations below. This version of FIG assumes that regional feature measurements are constant over time; this assumption will be relaxed in future versions of the model.

Measurements for regional features were transformed into relative evolutionary rates in two steps. To simplify notation, we use the subscript p to indicate variables for processes d, e, w, b. First, we constructed four separate sets of categorically scaled features, gp, for the extinction (p = e) and within-region speciation (p = w) processes as

$$g_p(i) = \begin{cases} y_p(i) & \text{if } y_p(i) \text{ is continental} \\ y_p(i) \times \sigma_p & \text{if } y_p(i) \text{ is insular} \end{cases}$$

where the vector y is a feature (e.g., size) and y encodes categorical values (e.g., insular or continental) for region i, and is the categorical scaler that rescales quantitative features for insular regions when determining relative within-region speciation or extinction rates among regions. For example, if σe = 0.5, then the extinction process will consider an insular region of size 4 and a continental region of size 2 as both having the same effective size.

Similar functions for dispersal (p = d) and between-region speciation (p = b) were defined as

$$g_p(i, j) = \begin{cases} z_p(i, j) & \text{if } z_p(i, j) \text{ is over land} \\ z_p(i, j) \times \sigma_p & \text{if } z_p(i, j) \text{ is over water} \end{cases}$$

where, for each ordered pair of regions, the matrix z quantifies a feature (e.g., distance) and z(i,j) indicates a categorical value (e.g., presence/absence of seaway barrier), and is a categorical scaler that rescales distances over water relative to distances over land for dispersal and between-region speciation. Dispersal would consider distances over water to be effectively 3 times greater than the same distances over land if σd = 3, for instance.

In practice, we normalized y and z by their respective means to simplify how we interpret the scale of each relative to the quantitative features.

Each set of scaled features (gp) was then transformed into a set of exponentiated features, mp, for extinction (p = e) and within-region speciation (p = w) as

$$m_p(i) = \left[ g_p(i) \right]^{\frac{\phi_p}{\sigma_p}}$$

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Table 2. FIG hypothesis testing

| Parameter | Interpretation |
|-----------|----------------|
| Feature exponent | -∞ < φ_p < ∞ |
| Size has no effect on extinction (φ_p = 0) or within-region speciation rate (φ_p = 0) |
| Distance has no effect on dispersal (φ_d = 0) or between-region speciation rate (φ_d = 0) |
| Size decreases extinction (φ_p < 0) or within-region speciation rate (φ_p < 0) |
| Distance decreases dispersal (φ_d < 0) or between-region speciation rate (φ_d < 0) |
| Size increases extinction (φ_p > 0) or within-region speciation rate (φ_p > 0) |
| Distance increases dispersal (φ_d > 0) or between-region speciation rate (φ_d > 0) |
| Categorical scaler | 0 < σ_p < ∞ |
| Insular region sizes unchanged for extinction (σ_p = 1) or within-region speciation (σ_p = 1) |
| Over water distances unchanged for dispersal (σ_d = 1) or between-region speciation (σ_d = 1) |
| Insular region sizes effectively decreased for extinction (σ_p < 1) or within-region speciation (σ_p < 1) |
| Over water distances effectively decreased for dispersal (σ_d < 1) or between-region speciation (σ_d < 1) |
| Insular region sizes effectively increased for extinction (σ_p > 1) or within-region speciation (σ_p > 1) |
| Over water distances effectively increased for dispersal (σ_d > 1) or between-region speciation (σ_d > 1) |

Different values for the four feature exponent (φ_p, φ_d, φ_b, φ_s) and four categorical scaler (σ_p, σ_d, σ_m, σ_e) parameters determine if and how regional features (size, distance, region type, barrier type) influence biogeographic rates. Larger quantitative features (size, distance) increase the relevant regional rates when φ_p > 0, decrease rates when φ_p < 0, and leave rates unchanged when φ_p = 0. Categorical features (insularity, ocean barrier presence) effectively increase the corresponding quantitative feature (size, distance) value when σ_p > 1, effectively decrease the value when σ_p < 1, and leave values unchanged when σ_p = 1. Additional detail is provided in Materials and Methods.

and, similarly, for dispersal (p = d) and between-region processes (p = b) as

\[ m_p(i,j) = \left[ \frac{g_p(i,j)}{gm(g_p)} \right]^{\phi_p} \]

where gm(g_p) is the geometric mean for the scaled features, g_p. For example, suppose that the scaled feature for extinction in region A was g_p(A) = 4, and the corresponding geometric mean across all scaled features for extinction was gm(g_p) = 2. If the feature exponent φ_p = -1, then the exponentiated feature m_p(A) = [4/2]^{-1} = 1/2; that is, the extinction rate in region A would be half that for any region whose size equaled the geometric mean of all region sizes.

Absolute state-dependent rates of evolution (τ_u, τ_v, τ_w, τ_r) are then computed as the product of a base rate parameter (ρ_u, ρ_v, ρ_w, ρ_r) and a term involving the respective exponentiated features (m_u, m_v, m_w, m_r) for each event type: \( τ_u(i) = ρ_u × m_u(i) \) is the rate of within-region speciation in region \( i \); \( τ_v(i) = ρ_v × m_v(i) \) is the rate of extinction in region \( i \); \( τ_r(i,j) = ρ_r × m_r(i,j) \) is the rate of dispersal from region \( i \) to \( j \); and \( τ_d(s,t) = τ_b(s,t) = m_b(s,t) \) is the rate at which the ancestral range, \( s \cup t \), splits into the non-empty and complementary daughter ranges \( s \) and \( t \); the range split score function, \( m_b \), is defined below. All rates are then assigned to a GeoSSE process for simulation and inference.

Range Split Scores. The range split score computes the relative rate of between-region speciation, where higher scores accelerate speciation. Range split scores treat each range as a fully connected graph, with nodes corresponding to inhabited regions and edge weights measured by the parametrized geography matrix, \( m_u \). The cutset, \( E(u) \), defines the minimal set of edges that must be removed (cut) from the ancestral range graph, \( u \), to fully separate the daughter ranges \( s \) and \( t \), into distinct components. We then define the range split score function as

\[ f_b(s,t; m_b) = \frac{1}{gm(f_b)} \times \left( \sum_{\{u,v\} \in E(u)} m_b'(u,v) \right)^{-1}, \]

which is the inverse sum of inverse weights between all pairs of regions in the cutset, with edge weights between nodes \( u \) and \( v \) equaling \( m_b'(u,v) = m_u(u,v) + m_v(u,v)/2 \), normalized by the geometric mean of all range split scores. Each additional edge in the cutset for a particular split decreases its corresponding range split score (e.g., increases range cohesion).

Small range split scores are dominated by those cut edges with the smallest weights (e.g., nearby region pairs), while larger-valued weights further decrease the split score only marginally.

Power Analysis for Hypothesis Testing. We analyzed 200 simulated datasets using FIG to assess how reliably the model correctly detected the effect of regional features on evolutionary rates. All simulations used the same five-region system that contained variation in region size, distance, region type (continental vs. insular), and barrier type (over land vs. over water; SI Appendix, Fig. S2). All simulations ran for ten units of evolutionary time under the same base rates (\( ρ_u = 0.1, ρ_v = 0.1, ρ_w = 0.1, ρ_r = 0.2 \)), but each simulation randomly sampled its own effect strengths for feature exponent (\( φ_u, φ_v, φ_w, φ_r \)) and categorical scaler (\( σ_u, σ_v, σ_m, σ_e \)) parameters. Our simulations (but not inferences) assumed that larger region sizes decreased extinction rate, \( ψ_u \sim Unif(−3,0) \), and increased within-region speciation rate, \( ψ_v \sim Unif(0,3) \), and insular region size was effectively reduced relative to equivalent continental region sizes, \( σ_m \sim Logunif(0.2,1.0) \). Longer distances between regions decreased dispersal rates, \( ψ_r \sim Unif(−3,0) \), and increased between-region speciation rates, \( ψ_b \sim Unif(0,3) \), and distances over water were effectively increased relative to equivalent distances over land, \( σ_d \sim Logunif(1,5) \). We obtained 50 simulated datasets for each of four tree size categories: 20 to 49 species, 50 to 99 species, 100 to 174 species, and 175 to 250 species. We then estimated the marginal posterior model probabilities that the correct signed nonzero estimate was obtained for each \( φ \) and \( σ \) parameter using FIG with RJMCMC. Model probabilities greater than 0.95 were used to classify when FIG correctly detected the effect of a regional feature on an evolutionary rate. Simulated datasets were analyzed using RevBayes (50).

Maximum Range Cohesion Distance. We predicted the maximum distance at which dispersal rates exceeded between-region speciation rates (\( r_b/r_s > 1 \)) using the y-intercept estimate of the log-linear model, \( \log10(r_b/r_s) = \log10(ε_2/ε_3) + ε \). Separate posterior means and HPDs for range cohesion distances were computed for continental and insular regions. We preferred the HPD upper bound as a conservative estimator for MRCD.

Anolis Biogeography. We reanalyzed the Poe et al. (21) Anolis lizard dataset, which described 379 anole species ranges across 14 neotropical regions. We collapsed their regions into a system with five continental regions (Mexico and Upper Central America [A]; Lower Central America [B]; the Chocó and Interoceanic Valleys [C]; the Andes [D]; Amazonia [E]) and four insular regions (the Lesser Antilles and Puerto Rico [F]; Cuba, Jamaica, and the Caymans [H]; Hispaniola [G]; and the Bahamas [I]). Region sizes and spatially averaged distances were computed using modern day features of geography and anole ranges (SI Appendix). Maximum range sizes were limited to four regions (255 possible range states). All species ranges from Poe et al. (21) were translated directly into our collapsed system of regions, except for four that required minor manual adjustments. SI Appendix describes the dataset treatment and the phylogenetic uncertainty analysis in detail and expands on our interpretation of our Anolis results and ancestral range estimates (SI Appendix, Fig. S4).

Bayesian Model Design and Inference. Model design and inference was performed in RevBayes (commit 724fadab204 [50]). SSE model likelihoods were computed using the TensorPhylo plugin for RevBayes (commit 5cd26b9f3 [51]). All simulated and empirical analyses used the same priors: \( ρ_u \sim Exp(1) \), \( φ_u \sim Norm(0,1) \), and \( ψ_u \sim Lognorm(0.172, 0.587) \). Standard MCMC was used to generate the main empirical results and parameter estimates. RJMCMC analyses were conducted to estimate the model probabilities for \( φ_u \neq 0 \).
and $\sigma_f \neq 1$ for the simulation study and for the empirical analysis. MCMC mixing and convergence for the Anolis parameter estimates and reversible-jump probabilities (Table 1) were validated by visual inspection and through small potential scale reduction factors ($\leq 1.05$) (52).

**Data Availability.** RevBayes analysis scripts, R plotting scripts, 200 simulated datasets, two versions of the Anolis dataset, and the MCMC results for the simulation study and empirical study are hosted through the public GitHub repository (https://github.com/mlandis/fig_model) (53).

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