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Research Article

A globally consistent scaling relationship reveals stabilizing effects of dominant species in plant communities

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Despite extensive research, stabilizing mechanisms in ecosystems remain uncertain. Taylor's power law (TPL) is a pervasive ecological pattern that describes how variance scales with mean abundance ($\sigma^2 = a\mu^b$). While TPL has been widely studied within populations, its role across species within communities and its implications for stability remain largely unexplored. A TPL scaling factor (b) < 2 implies an unexplored stabilizing effect of dominant species (hereafter the 'dominance effect'), where community stability arises from dominant species being relatively more stable than subordinates. This study aims to explore the influence of TPL exponent b on the dominance effect on stability and identify the biotic and abiotic community factors shaping it. Using data from over 9000 permanent vegetation plots globally, we investigated within-community TPL, linked it to the dominance effect, and examined drivers of b values. Results reveal a strong contribution of b, together with species evenness, to dominance effects on stability. A ubiquitous TPL (mode $R^2 = 0.92$) with a consistent $b < 2$ highlights widespread dominance effects. Lower b values were linked to resource-conservative strategies and climatic seasonality, reinforcing the role of environmental filtering in stability. These findings highlight the widespread dominance effect on community temporal stability, particularly driven by woody, large-seeded species in cold, seasonal climates. Moreover, results identify the TPL exponent b as a powerful indicator of dominant species' stabilizing effects, complementing the well-known role of species diversity.

Keywords: coefficient of variation, community ecology, dominant species, fluctuation scaling, plant community, stabilizing mechanisms, Taylor's power law, temporal stability

Introduction

The stability of ecological communities and its drivers have been a central topic in ecological research for decades (MacArthur 1955, May 1972, Tilman 1996, Cottingham et al. 2001, Craven et al. 2018). In the face of global changes, it is crucial to understand how different drivers of ecological stability modulate the temporal fluctuations in ecosystem functioning (Su et al. 2022). Despite significant advances, this long-standing query is far from being resolved (McCann 2000, Thibaut and Connolly 2013, de Bello et al. 2021b, Segrestin et al. 2024).

One of the most studied aspects of temporal stability is temporal invariability, often assessed as the inverse of the community coefficient of variation ($CV = \sigma/\mu$, where μ is the mean community abundance across the years and σ its standard deviation). There are two primary biological drivers of community invariability ('stability', hereafter for simplicity): 1) the stability of individual species' populations in the community, particularly dominant ones, and 2) the compensatory dynamics between these populations (Gonzalez and Loreau 2009, Hector et al. 2010, Valencia et al. 2020). Focusing on the first driver, requires considering species' relative abundances and assessing whether dominant species stabilize or destabilize communities. Traditionally, an abundance-weighted average of species' temporal CV has been regarded as a key driver of community stability (Thibaut and Connolly 2013, Segrestin et al. 2024). Evidence suggests that a few highly abundant species can significantly influence overall community stability (Polley et al. 2007, Grman et al. 2010, Sasaki and Lauenroth 2011), a phenomenon referred to as the dominance effect on stability or dominance stabilization effect (Segrestin et al. 2024).

Despite its importance, the effect of dominant species on stability has rarely been explicitly quantified due to the difficulty of isolating this mechanism (Hallett et al. 2014, Lisner et al. 2024, Segrestin et al. 2024). Recently, Segrestin et al. (2024), proposed a novel framework that can estimate dominants' influence on community stability. Following Thibaut and Connolly (2013) and Segrestin et al. (2024), the effect of dominant species on community stability is expected to depend on two key factors: the extent of dominance and the extent of temporal variability of dominant species compared to subordinate ones. First, in more uneven communities dominated by fewer species (lower evenness), fluctuations in the dominant species are likely to have a stronger impact on stability. Second, the intrinsic stability of these dominant species relative to subordinate species will determine whether their effect stabilizes or destabilizes the community. This second aspect can be ideally examined through one of the most pervasive patterns in ecology: Taylor's power law (TPL), which describes how variance scales with mean abundance ($\sigma^2 = a\mu^b$). While TPL has been extensively studied within populations (e.g. assessing the spatial or temporal variation of the same species in different communities), its role within communities (e.g. across dominant and subordinate species within a community) and its implications for stability remain largely unexplored.

Originally, the scaling factor (b) of TPL was used to characterize the spatial aggregation patterns of a population (Taylor 1961). Later, TPL was applied to temporal population variability (from now on, temporal TPL) by fitting it to time-series data of same species population abundances (Taylor and Woiwod 1980, 1982, Kilpatrick and Ives 2003, Kalyuzhny et al. 2014, Xu 2016, Baumgartner and Peláez Zapata 2024). Less frequently, temporal TPL has been used to compare fluctuations of coexisting species (within-community approach to temporal TPL), to link population stability to community stability (but see Ghosh and Matthews 2024 and Ma 2015). Following this approach, temporal TPL at the community level can be expressed as in what Ma (2015) calls a 'mixed-species TPL':

$$\sigma^2_m = a\mu_m^b \qquad m = 1, 2, \ldots, M \tag{1}$$

where σ^2_m and μ_m are the variance and mean of the population abundance of a species m over a time series, and M is the number of species in the community. Each species' mean and variance is calculated over the time series, and the relationship is fitted through all the species (Fig. 1A). This relationship can be expressed as a log–log regression between the mean and variance of species, making it possible to estimate its parameters with simple linear regression methods, as:

$$\log\left(\sigma^2_m\right) = \log\left(a\right) + b \times \log\left(\mu_m\right) \tag{2}$$

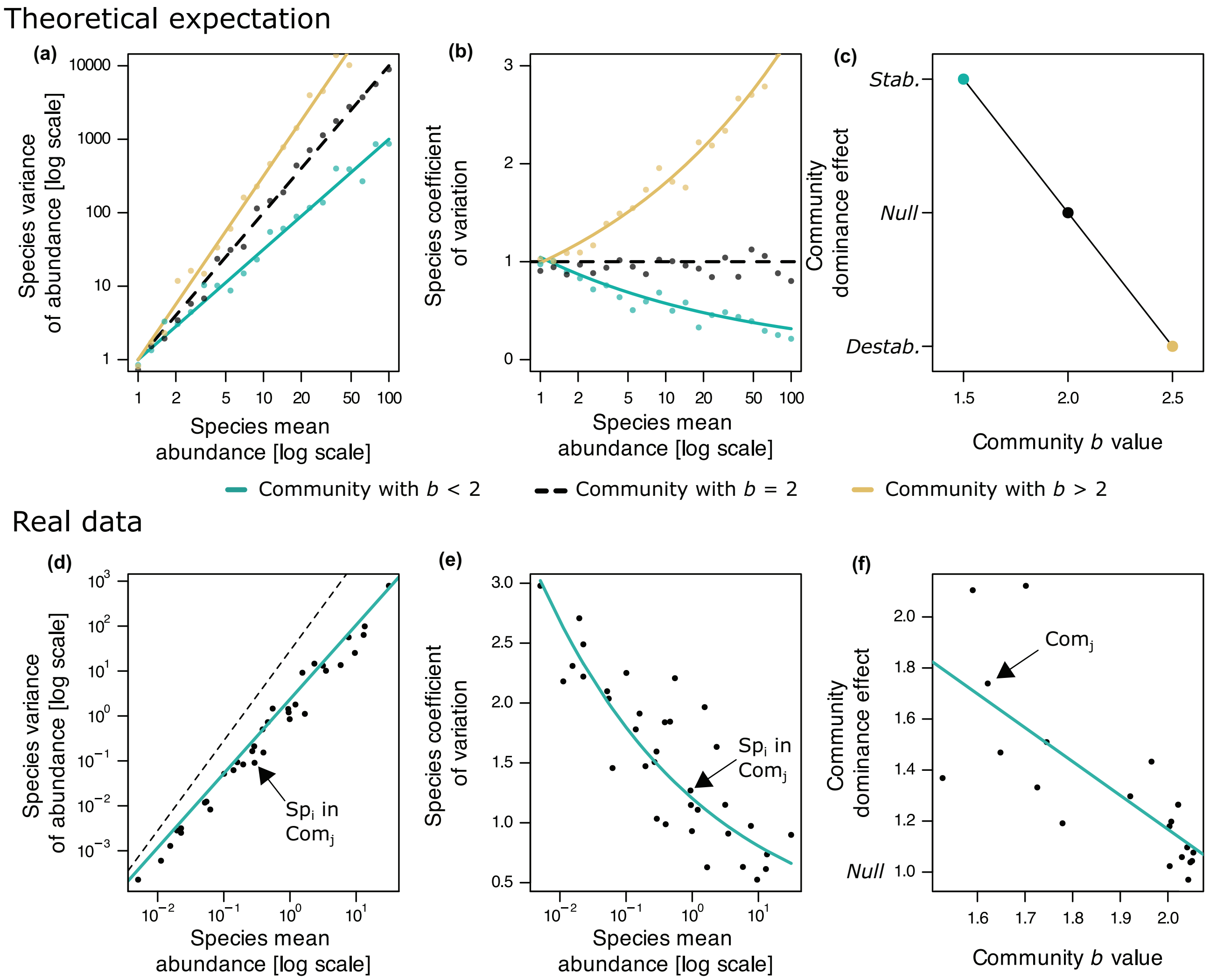

Figure 1. Theoretical expectations and observed data of Taylor's power law and the dominance effect within a community in time. (a) Shows the log–log relationship between the mean and the variance of species abundances within communities with different b values (Eq. 2), and (b) shows the corresponding expected relationship between the species CV and their mean abundance (Eq. 3). (c) Shows the expected dominance effect for the three simulated communities based on their b value. Panel (d) and (e) show the corresponding observed relationship in a real community. Dotted line in panel d shows the $b = 2$, for comparison. Each point in those panels corresponds to the aggregated value of one species in time (variance, mean or CV). (f) Shows the observed relationship between the dominance effect (as $\mathrm{CV_{ratio}}$) and the b value of a sample of 20 communities from the LOTVS database. Note that the dominance effect can be computed by different indexes and the units will depend on that (see Material and methods for more information).

The TPL relationship is mathematically equivalent to a power law predicting species' coefficient of variation ($CV_m = \sigma_m / \mu_m$) from their abundances (Fig. 1) as:

$$CV_m = a^{1/2} \mu_m{}^{b/2-1} \quad (3)$$

From the latter equation, we see that when $b = 2$, CV_m is independent of the mean abundance (Lepš 1993, Doak et al. 1998, Anderson et al. 2013). When $b < 2$, CV_m decreases with increasing mean abundance, meaning that a more dominant species is expected to fluctuate comparatively less in time than subordinate species. Similarly, when $b > 2$, CV_m increases with mean abundance and thus, the more dominant species in the community will tend to fluctuate more, relative to their mean (Fig. 1). Therefore, the observed b in a community, can reflect the relative temporal fluctuation of dominant species compared with subordinate ones. Accordingly, this simple mathematical tool could effectively describe the potential contribution of dominants to community stability. Clearly, such potential will further depend on community evenness because, as mentioned above, lower evenness amplifies the impact of dominant-species fluctuations on stability.

While some empirical examples reported $b < 2$ within communities (Eisler et al. 2008, Taylor 2019), $b > 2$ was found for North Sea fish (Cobain et al. 2019) and vole communities (Cohen and Saitoh 2016). Also, Ghosh and Matthews (2024) showed, using 1694 community time series across multiple taxa, that the b value can exceed 2. It remains unclear how this variation in b can influence the stabilizing effects of biodiversity, despite earlier theoretical predictions (Tilman 1999, Thibaut and Connolly 2013). In this context, the potential role of TPL in revealing the drivers of ecological stability has been generally overlooked. Moreover, some studies have implicitly assumed b equals 2, which would potentially lead to overestimations of diversity's stabilizing effects (Doak et al. 1998, Anderson et al. 2013). An empirical evaluation of TPL parameters in real-world communities is therefore needed to draw realistic conclusions about the mechanisms modulating community stability.

While *b* can theoretically be considered an indicator of the dominance effect, the factors that explain its variation remain unclear. Community structural and functional attributes are likely to play a role. For instance, it has been shown that population stability relates to the species ecological strategies, with species with more resource-conservative functional traits usually being more temporally stable (Májeková et al. 2014, Conti et al. 2023, Ren et al. 2023). Thus, in environments with climatic conditions that select for dominant species that are resource conservative, *b* might be lower than in environments that select for fast-growing strategies in its dominant species. Therefore, the type of dominant species, and the environmental conditions driving its selection, should influence *b*. Moreover, species richness may influence *b*, beyond species evenness, possibly due to increased estimation precision with increased number of observations within a community. Similarly, other methodological factors, such as the amount of sampling years or the plot size, may also cause deviations in *b* values.

In this study, we used data from > 9000 plots (communities) in a global dataset of long-term vegetation community sampling studies (LOTVS, https://lotvs.csic.es) to 1) test the relationship between the exponent *b* of TPL and the strength of the dominance effect on stability, 2) test the prevalence of $b < 2$ in temporal TPL across a variety of plant communities, and 3) study the environmental and biotic factors that mediate the *b* value in the community. We expected to show how the dominance effect on stability depends on two main drivers: TPL *b* value and evenness of the community – i.e. an estimate of the dominance structure. In addition, we expected to observe a strong and frequent TPL relationship in time series within communities. Based on previous work at the population level (Eisler et al. 2008) and demography models (Keil et al. 2010), we also expected to see a tendency for $b < 2$, reflecting the stabilizing effect of dominant species in many communities (Segrestin et al. 2024). We also expected that colder or more predictable climates should favour dominance of species with resource-conservative traits (Grime 2001, Díaz et al. 2016) thus causing lower *b* values of the TPL. Similarly, community-based indices like community weighted mean (CWMs; de Bello et al. 2021a, 2021b) of traits associated with more resource-conservative strategies, such as high leaf dry matter content and specific leaf area (Conti et al. 2023) or high seed mass would exhibit lower *b* values for the TPL.

Material and methods

Data acquisition and processing

We combined data from temporal times series in plant community datasets contained in the LOTVS (https://lotvs.csic.es) database of permanent plots of natural and seminatural vegetation sampled over a period of at least 6 years, with a maximum of 99 years (mean = 14.3). We focused our analyses on vascular plants. These datasets have different methods to quantify abundance (e.g. aboveground biomass and species cover estimates), different plot sizes (median = 1 m^2, range = 0.04 to 3000 m^2), vegetation types (grassland, shrubland, savanna, forest understory, tundra and salt marsh vegetation) and management regimes (e.g. grazing, fertilization, burning). The total number of individual plots was 11 676 across 92 localities (total number of abundance observations = 1 216 339).

Different data filtering criteria were considered to minimize biases. Species that occurred in less than 15% of the sampling years within each plot were deemed 'transient species', since measures of temporal variability can be highly volatile with data containing excessive zeros (Májeková et al. 2014, Valencia et al. 2020). An excess of zeros in the temporal series of a species could inflate their variance, causing transient species to underestimate the community TPL (Taylor and Woiwod 1982). Species exhibiting no variance across all years were also excluded because these zero values are probably caused by insufficient precision in the sampling method. This filtering aimed to prevent both underestimation and overestimation of variance, which could bias the estimation of TPL parameters (Clark and Perry 1994). To ensure that this step did not bias our conclusions, we conducted a sensitivity analysis using more inclusive thresholds by including all species and found that our main results remained qualitatively robust.

Taylor's power law regression was further calculated only for communities with a minimum of four species. Additionally, we excluded communities with abundance estimates derived from frequency methods (e.g. point-quadrats, point-intercept, pin-point methods) due to the abnormal b values observed ($b < 1$). This decision was informed by common b ranges found in literature (Eisler et al. 2008, Taylor 2019, Ghosh and Matthews 2024) and our distribution of b values (Supporting information). We expect that frequency methods, can underestimate the variance of dominant species, as their frequency can remain fairly constant, while their cover or biomass can fluctuate. The resulting dataset comprised 9145 plots across 63 localities (total number of abundance observations = 1 032 422).

Taylor's power law fitting and dominance effects

Temporal means and variances were calculated for every species in the community (plot) using their abundances across all years. Log-transformed variances were regressed on log-transformed means of all species in each community. Based on the existing literature, we used both ordinary least square (OLS) and standard major axis (SMA) methods (Warton et al. 2006, Taylor 2019).

The dominance effect on stability in each community was calculated using two approaches to assess the consistency of the results. First, Segrestin et al. (2024) proposed an index (Δ) that quantifies the overall effect and directionality of dominant species effect on the community stability. This is obtained by comparing the expected community CV if all species had the same abundance and were perfectly synchronised (CV_e, Eq. 4a; see Segrestin et al. (2024) and R package 'comstab' for details, www.r-project.org), against the community CV that would be expected if all species were perfectly synchronous but after accounting for the observed distribution of abundances (calculated as the abundance-weighted mean of species CVs: CV_w; Thibaut and Connolly 2013). Since the index decreases with greater stabilizing effects of dominants, we used the complement of delta (Δ_{comp}) so high values represent high stabilizing effects and negative values mean destabilization:

$$CV_e = a^{\frac{1}{2}} \times \left(\frac{1}{M} \sum_{m=1}^{M} \mu_m \right)^{\frac{b}{2}-1} \tag{4a}$$

$$\Delta_{comp} = 1 - \Delta = 1 - \frac{\sum_{m=1}^{M} p_m CV_m}{CV_e} = 1 - \frac{CV_w}{CV_e} \tag{4b}$$

Where M is the number of species in the community and p_m the relative abundance of each species. Hence, Δ_{comp} measures the degree to which the community stability is affected by dominant species.

Second, for simplicity of interpretation, we also considered a less sophisticated but ideally more intuitive approach to quantify dominance effects. We considered the ratio between the unweighted arithmetic mean of species CV (CV_a) and the abundance-weighted average population CV at the community level (CV_w):

$$CV_{ratio} = \frac{\frac{1}{M} \sum_{m=1}^{M} CV_m}{\sum_{m=1}^{M} p_m CV_m} = \frac{CV_a}{CV_w} \tag{5}$$

Any decrease from CV_a to CV_w would suggest that dominant species exhibit relatively greater stability. As such, a CV_{ratio} higher than 1 indicates a stabilization effect of dominant species, while values lower than 1 indicate a destabilization due to dominants. Ideally, a CV_{ratio} of 1 or a Δ_{comp} of 0, corresponds to a $b = 2$.

It should be noted that both indices follow a similar logic and produce correlated values (Supporting information). Each quantifies the change in average species CV when species' contributions are, or are not, weighted by their relative abundance. This reflects the potential role of dominant species in community stability under an ideal case of no compensatory dynamics effects between species (i.e. perfect synchrony). This does not imply that the indices represent the unrealistic case of perfect synchrony among species, but that synchrony between species is not accounted for in their formulation and, therefore, synchrony effects should be quantified independently, using dedicated metrics (Segrestin et al. 2024).

Delta (Δ) was conceived to estimate the role of dominant species on community stability and, as such, is less sensitive to the influence of rare species. In contrast, CV_{ratio} is mathematically more sensitive to variations in community evenness and in the scaling of CV with abundance (i.e. b values). This is because CV_{ratio} rests on the assumption that species' CVs are comparable regardless of their abundances, implying that CVs do not necessarily scale with mean abundance. When $b = 2$, CV_a approximates the community CV_w. This property makes CV_{ratio} particularly useful for assessing deviations from $b = 2$ and thus, the influence of TPL on dominance effect. By contrast, Δ integrates the observed TPL scaling within each community. While this makes it more accurate for estimating dominance effects and for broader ecological interpretation, it may also reduce its sensitivity to variation in b itself (see mathematical demonstration in the Supporting information). We therefore adopted the CV_{ratio} as our primary index of dominance effect in the main analysis, while presenting results based on Δ_{comp} in the Supporting information.

Climatic data

We collected 19 bioclimatic variables for each of the 9145 plots using WorldClim (www.worldclim.org). Plots from the same experimental setup (i.e. identical location coordinates within a dataset) were assigned identical climatic values. We used a principal components analysis (PCA) to reduce dimensionality of climatic data. The first axis encompassed temperature and aridity during the hottest quarter of the year (positive values indicate hotter and drier places), while the second axis reflected seasonality and extreme minimum temperatures in the coldest quarter of the year (positive values indicate more seasonal and cooler places; Supporting information). The first and second axes, explaining 41.5 and 30.1% of variability, respectively, were used as predictors of *b* values for each community.

Biotic attributes

For each plot, we calculated the average species richness (average number of species across all years), maximum species richness (maximum of species richness in any year) and Pielou's evenness index ($E = \frac{H}{\log S}$ where H is Shannon's diversity index and S is the number of species). Pielou's index aims to represent the dominance structure of the community, independently from the number of species (Pearson's $r = 0.2$; Supporting information), with 1 representing a perfectly even community, where there is no dominance structure and all species have the same mean abundance. We also calculated the mean relative abundance and the mean coefficient of variation of each species across the years to analyse their relationship in each community. Finally, we calculated the total community CV, as a measure of community stability, using the sum of species abundances per year to estimate the mean and SD of yearly total abundance.

For each species in the dataset, we extracted up to 12 plant traits from the TRY database (www.try-db.org): leaf dry matter content (LDMC), total plant height, vegetative-part height, generative-part height, seed dry mass, leaf area, leaflet area, specific leaf area (SLA), plant longevity, plant life form from Raunkier classification, plant growth form and plant woodiness (see Garnier et al. 2017 for trait definitions). We calculated community weighted means (CWM) for each of these traits using the function *functcomp* in the R package 'FD' (Laliberté et al. 2014). If the coverage of species with available trait value was < 80% of the total abundance of species in the community, CWM was not considered (Pakeman and Quested 2007; Supporting information). Because of this, only woodiness and seed dry mass (log-transformed) were used because they were available for most communities (~ 84% of the base-filtered dataset), and were less correlated (Pearson's $r = -0.5$; Supporting information). Nevertheless, we conducted additional analyses of SLA and LDMC for the 4079 plots where these traits were available.

Analyses

To test how *b* value modulated the dominance effect we used linear mixed-effects models (LMM) ('lmer' function in R package, ver. 1.1-26; Bates et al. 2015) with both Δ_{comp} and CV_{ratio} as response variables. As fixed predictors we included *b* and evenness to account for the dominance structure and the dataset identifier as random effect to compare between regions. Importantly, we tested that there is no correlation between *b* and community evenness (Pearson's $r = 0.008$, p-value = 0.373).

To examine how the dominance effect contributes to the whole community stability, we used LMM with the community CV as response variable and CV_{ratio} or Δ_{comp} as fixed predictors. Again, we used the dataset identifier as random effect.

To test whether *b* values across communities were significantly different from the null value of $b = 2$, we used the method from Warton et al. (2006), checking the correlation between residuals and fitted values, which can be used to test the slope obtained with OLS and SMA methods. To determine the robustness of our results, we conducted a series of data subsetting steps and explored the consequences of different data structures in the calculations of temporal TPL. First, we selected plots with an increasing minimum mean number of species, ranging from 4 to 40 species and calculated mean *b* values by OLS and SMA for each selection. Second, we explored the effects of removing plots with 1) poorer model fitting (TPL $R^2 < 0.7$), 2) temporal gaps between sampling years greater than 2 years, and 3) both. Third, we tested for differences in *b* values obtained from biomass and cover data, using a LMM with dataset identifier as a random factor.

To test whether lower *b* values are related to dominant species with resource-conservative traits or harsher environments, we used LMM, as well. Since the estimation method for *b* (OLS and SMA) produced similar results, we used *b* estimated using OLS as the response variable, as it is used more frequently in the literature. Although using the result from a regression as a response variable may introduce a statistical bias, the high fit in the TPL models and especially the low variation across sites in the TPL fit (see Results) should mitigate this problem. We fit a full model incorporating CWMs of seed size and woodiness, climatic PCA's 1 and 2, and ancillary predictors (number of years of sampling, plot size, type of management, changes in management across years, and averaged species richness). We then used backward selection procedure based on both the variance explained and the significance of each predictor, using Satterthwaite's method with the package 'lmerTest' (Kuznetsova et al. 2017). Dataset identifier was included as a random factor. This analysis was conducted using the entire dataset, for subsets based on the filters described earlier and for the smaller subset including leaf traits. We checked the compliance of all of the models' residuals with normality and homoscedasticity and calculated the standardized coefficients of each predictor. To assess the goodness-of-fit of the models, marginal (i.e. fixed effects) and conditional (i.e. total effects) R^2 were calculated, as well as AIC scores.

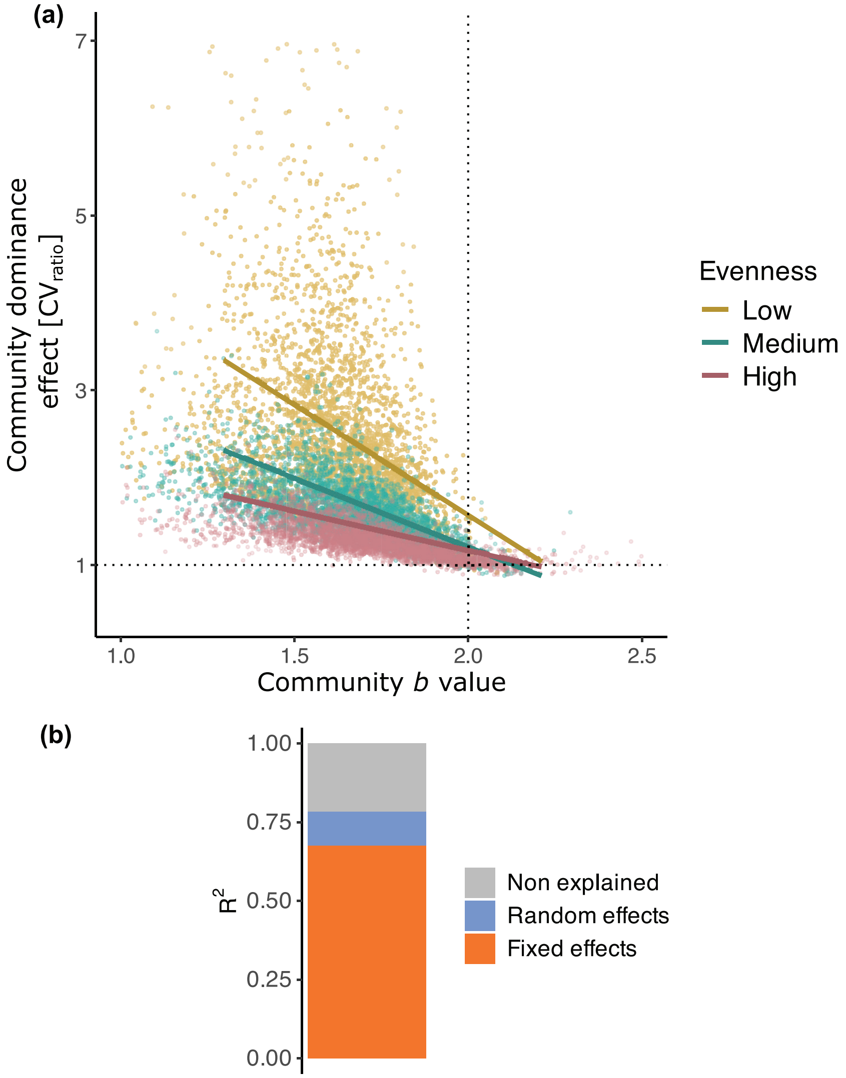

Figure 2. Effect of TPL exponent *b* and the dominance structure (evenness) on the dominance stabilization effect, estimated by the CV_{ratio} (results of the model with Δ_{comp} can be found in the Supporting information). (a) Shows the scatterplot of the relationship. In the original model, evenness is treated as a continuous variable, but for graphical purposes it was converted to categorical. (b) Shows the variation explained by fixed and random effects of a model (see the Supporting information for more details) with both predictors and data identifier as a random effect.

Results

Across the LOTVS database, we found that the exponent *b* of TPL was closely linked to the extent to which dominant species influence community stability, as measured by both CV_{ratio} and Δcomp, particularly when $b < 2$ (Fig. 2, Supporting information). The two models differed in the variance explained, with fixed predictors explaining 68 and 55% of CV_{ratio} and Δ_{comp}, respectively. Estimates and details of the models can be found in the Supporting information showing, particularly for CV_{ratio}, that TPL effects were stronger with greater dominance (i.e. lower evenness) in species abundances within communities. We found a strong negative relationship between the total community stability and the dominance effect (CV_{ratio} estimate = −0.23, $F_{1,10541} = 4967$, p-value < 0.001), showing that the dominance effect has a widespread contribution to overall community stability.

We also detected ubiquitous and strong Taylor's power law relationships (mode of R^2 distribution = 0.92; Fig. 3a; for TPL examples, see the Supporting information). The OLS estimation method gave slightly lower *b* than SMA method, as expected (mean OLS *b* value = 1.65, mean SMA *b* value = 1.71; paired t-test: mean difference = −0.06, t = −77.44, df = 9144, p-value < 0.001; Fig. 3b). With OLS, around 53% of the plant communities had a *b* significantly < 2 (p-value < 0.05; each *b* tested individually; see Methods – Analysis), and this value reached 87% for communities with average richness > 20 species (Table 1). With SMA, around

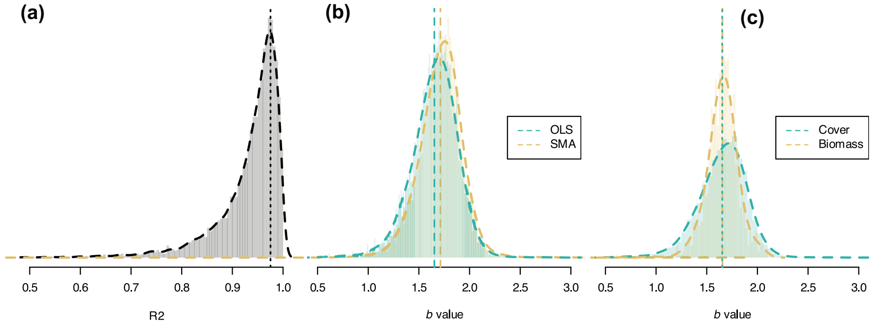

Figure 3. Distribution of TPL models regarding (a) R^2, the dotted line represents the mode, (b) b values with different regression methods, and (c) b values with different data type; dashed lines represent the mean of each group.

42% of communities had a b significantly < 2, reaching 72% for communities with average richness > 20 species. The percentage of communities with a b significantly > 2 was statistically negligible ($< 5\%$) with both OLS and SMA (but see Discussion). Similarly, $b < 1$ was found only in 1.2% of communities, well within the expected statistical error.

We found no significant difference in the b values between sampling methods as biomass and cover data generally produced similar mean values ($F_{1,60} = 1.33$, p-value $= 0.254$), and thus, both types of data were used together in the full model. Nevertheless, cover data tended to produce more variable b values than biomass data (Fig. 3c). Species richness had a two-sided effect on b; while it slightly increased the mean b value, it also increased the percentage of plots with $b < 2$ (Supporting information). This is due to the increasingly precise estimate with smaller confidence intervals resulting from the higher number of observations. When exploring other types of filtering of the data that could represent confounding effects for slope estimates ($R^2$and temporal gaps in time series), the mean slope slightly increased with filters, while the percentage of plots with values statistically different from 2 did not significantly vary (Table 1).

All LMMs indicated that climatic factors and species traits influenced TPL. Specifically, lower b values were associated with communities dominated by resource-conservative species, such as those with greater woodiness, higher seed mass, and, where data were available, low SLA (Supporting information). A lower b was detected in regions with greater seasonality and low minimum temperatures (2nd axis of climatic PCA; Fig. 4). In contrast, higher species richness was associated with higher b values, while a longer sampling duration had a negative effect on b. In a representative model (see model f2 in the Supporting information; Fig. 4), dataset identity explained 47% of the variance while fixed effects explained 14%.

Discussion

Our analysis revealed a widespread and remarkably strong relationship between the temporal mean and variance of coexisting species in plant communities, consistent with Taylor's power law. This greatly overlooked relationship within communities has a direct impact on the drivers of community stability. Specifically, the TPL b exponent, by being frequently $<$ 2, has a clear role in modulating the dominant species effects on community temporal stability. Such an effect is further influenced by the type of dominant species in a community, with stronger effects in communities dominated by more resource-conservative species.

Following expectations, the stabilizing effects of dominant species in communities becomes particularly apparent as the slope b deviates from and decreases below the value of 2. Since we found that most b values were lower than 2, this provided evidence of a widespread potential stabilizing dominance effects in plant communities worldwide. Such potential for stabilizing effects materializes with increased dominance structure (i.e. lower evenness), where the greater temporal stability of dominant species can contribute more substantially

Table 1. Mean slope values with OLS and SMA method for each data subset (f0–f5) based on different filters. Base filter involves the filtering carried out to avoid confounding effects (rare species and variances = 0; see Methods – Data acquisition and processing). Mean b CI = average of the min/max confidence interval of the estimate in each community model.

			OLS method			SMA method		
Subset	Filter	No. communities	Mean b	Mean b CI 2.5%	Mean b CI 97.5%	Mean b	Mean b CI 2.5%	Mean b CI 97.5%
f0	Base filter	10 544	1.615	1.316	1.913	1.684	1.358	2.168
f1	Frequency data	9145	1.653	1.357	1.949	1.713	1.385	2.192
f2	$R^2 > 0.70$	8985	1.661	1.377	1.946	1.715	1.397	2.167
f3	Temporal gaps < 2y	7754	1.652	1.349	1.954	1.711	1.373	2.210
f4	$R^2 > 0.70$ + Temporal gaps < 2y	7609	1.661	1.370	1.952	1.714	1.386	2.187
f5	$R^2 > 0.70$ + Temporal gaps < 2y + No. species ≥ 20	1379	1.682	1.514	1.851	1.743	1.579	1.926

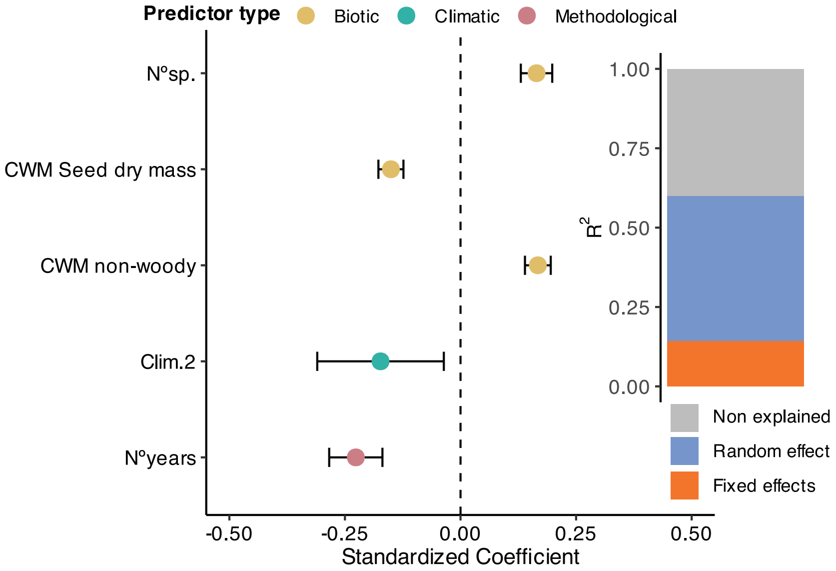

Figure 4. Standardized coefficient and variation explained by the model as R^2. Negative values mean the factor tends to reduce *b* and vice versa. N°sp = average species richness; CWM seed dry mass = community weighted mean of the seed dry mass in log scale; CWM non-woody = community weighted mean of the non-woody plants, – i.e. percentage of non-woody plants in the community. Clim.2 = Community scores on the second axis of the PCA for climatic variables accounting mainly for the temperature seasonality and minimum temperatures (Supporting information); N° years = number of sampling years. The full model and the rest of reduced models are detailed in the Supporting information.

to overall community stability. In other words, the potential stabilizing dominance effects are possible only when $b < 2$ and are stronger in communities with higher dominance by fewer species. Theoretically, when $b = 2$, regardless of community evenness, the stabilization effect of dominance should be zero, resulting in a CV_{ratio} of 1. However, there could be various sources of error, some linked to sampling biases, that could decrease the precision of estimation of both dominance structure and *b* values, resulting in some partial deviation from the expectations (below). Nonetheless, the overall pattern observed for both CV_{ratio} and Δ_{comp} (Fig. 4, Supporting information), illustrate *b* value as a foundational component of one of the least understood stability mechanisms.

While existing studies have already shown the importance of TPL in temporal variation within species across populations (Döring et al. 2015), our results demonstrate that TPL is also strong across species within plant communities worldwide, providing a link between population ecology and community stability. Furthermore, we demonstrate that TPL *b* value can be used to investigate the stabilizing role of dominant species, as we found this relationship to have a considerable prevalence of slopes (*b* values) lower than 2, demonstrating that dominant species typically fluctuate relatively less in time than subordinate species (Supporting information), leading to dominance stabilizing effects. Finally, we found that the dominance effect reaches its greatest potential, i.e. lower *b* values, in communities where species have resource-conservative functional traits (woodiness and high seed mass) and inhabit more extreme weather conditions of high seasonality and low minimum temperatures.

Our results are important in the context of identifying the role of different stabilizing mechanisms, because in communities with stronger stabilization by dominance there is less scope for the stabilizing effect of species diversity (Doak et al. 1998). This is due to the larger contribution of dominants to stability, compared with communities in which species abundance and temporal variability characterized by CV are independent (which corresponds to $b = 2$; Fig. 1), where there is greater potential for diversity to generate a stronger portfolio effect (Tilman 1999). Time-series analyses aimed at understanding community stability have possibly overlooked the mean–variance relationship predicted by Taylor's power law, sometimes implicitly assuming a theoretical $b = 2$ (Anderson et al. 2013, Thibaut and Connolly 2013) and sometimes missing its influence on the dominance effect (Hallett et al. 2014). Alternative frameworks for understanding community stability that consider the stabilizing role of dominant species in the community have been developing (Polley et al. 2007, Sasaki and Lauenroth 2011, Segrestin et al. 2024). Our results underscore the importance of fully considering the TPL *b* value from the time-series data to better understand the effects of different components of stability and specifically the stabilizing effect of dominant species.

In this sense, our models shed new light on factors influencing the potential for stabilization by dominant species. Substantial variance was explained by the region identifier, highlighting the context-dependence of *b* values. Nevertheless, key ecological predictors of *b* were significant as well. Our results indicate that in communities dominated by small woody and large-seeded species, and communities in more extreme and seasonal environments (e.g. tundra and boreal forests), dominant plant species often play stabilizing roles. These results are consistent with earlier predictions linking the dominance effects to harsh (although predictable) environments (Gao et al. 2022). These results also support the expectation that resource-conservative functional traits (higher seed mass, more woodiness and lower SLA; Díaz et al. 2016) are associated with species being both more dominant and more temporally stable (Conti et al. 2023). Nevertheless, our study is limited to communities of low stature (mostly grasslands and shrublands), and whether the same conclusions apply to forests remains to be tested.

While less than 5% (400 of 9144) of our plots exhibited $b > 2$, not considerably exceeding the Type I error rate, it is notable that 92% of these communities are in deserts or semi-desert environments (harsh and highly unpredictable environments). In desert annuals, some species remain in the seed bank and germinate en masse in years of high rainfall (Guo and Brown 1996), potentially leading to high mean abundance coupled with high variability. Cobain et al. (2019) attributed high b values ($b > 2$) in North Sea fish communities to the effects of a fluctuating environment. Other notable instances of $b > 2$ in the literature include ruderal moth communities (Lepš 1993) and vole populations (Saitoh and Cohen 2018). Together, these results suggest the possibility that stochastic temporal environmental variation, as opposed to regular seasonality, may be associated with highly fluctuating dominant species and therefore with unusually high b values. However, in such communities, estimating dominance structure may be partially unreliable, as dominant species may only appear sporadically, making the average evenness index misleading. This could explain why most cases of the $b > 2$ occur in communities with higher evenness (Fig. 2). Furthermore, in these cases, it is also possible that despite $b < 2$, the dominant species deviates significantly from the community main mean-variance trend, meaning that b does not accurately capture its behavior. Generally, for these types of communities it would be advisable to examine the role of individual species. To do this, it could be used the stability measure developed by Döring et al. (2015), based on the residuals of the TPL that can reflect single-species deviations from the community trend.

Estimates of b may be influenced both by number of species (number of observations) and number of years (from which to calculate mean and variance) (Giometto et al. 2015), and we found small but significant influences of these factors in our results. Nonetheless, our main results were robust to our different data filters and regression approaches. When means or variances are calculated from < 15 years, SMA regression may provide a more robust estimate of the b value, representing an upper limit for estimates by OLS (Perry 1981). However, when the correlation coefficient is sufficiently high ($R^2 > 0.95$), the difference between the OLS estimate of b and the SMA estimate is small (Perry 1981, Taylor 2019; Supporting information). We used OLS for ease of comparison with the majority of existing TPL literature (Taylor 2019) and because our mean temporal series spans 15 years. Similarly, the statistical estimation of b can be influenced by species evenness, since high evenness reduces the range of variation in species means and variances. Our analysis found no correlation between b and evenness. However, we did observe that community evenness affects the R^2 of the TPL regression, with lower R^2 values more common in highly even communities. This suggests that b estimates are less precise for even communities, underscoring the importance of relying on well-supported TPL fits (high R^2), as well as sufficient species richness and temporal replication when estimating scaling parameters.

A key question that this study helps to raise for future research is the extent to which this dominance effect scales up to influence overall community stability. Our results demonstrate that the dominance effect is associated with higher stability across a vast number of plant communities worldwide. However, fully understanding how this relationship is influenced by b and how it interacts with other stabilizing mechanisms, such as species synchrony, warrants further theoretical and empirical investigations.

Our results shed light on a frequently overlooked aspect of temporal stability of natural communities. We find that the stabilization by dominant species is widespread in plant communities worldwide and its potentiality depends on the community TPL. These results imply that ecologists need to pay more systematic attention to the role that dominant species play in stabilizing communities and the ecosystem services that communities provide in a rapidly changing world. Devising ways to more thoroughly quantify and analyse this contribution of dominant species to community properties is an important future challenge.

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Author contributions

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Data availability statement

Data and R code are available from the Dryad Digital Repository: https://doi.org/10.5061/dryad.msbcc2g7f (Gracia et al. 2026).

Supporting information

The Supporting information associated with this article is available with the online version.

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