PNAS Nexus, 2023, **2**, 1–9
https://doi.org/10.1093/pnasnexus/pgad384
Advance access publication 5 December 2023
Research Report

Temperature shapes language sonority: Revalidation from a large dataset

Tianheng Wang[a], Søren Wichmann[b], Quansheng Xia[c,*] and Qibin Ran[a,d,*]

[a]School of Liberal Arts, Nankai University, Tianjin 300071, China
[b]Cluster of Excellence ROOTS, Kiel University, 24118 Kiel, Germany
[c]College of Chinese Language and Culture, Nankai University, Tianjin 300071, China
[d]Laboratory of Social Science of Tianjin, Nankai University, Tianjin 300071, China
*To whom correspondence should be addressed: Email: xiaqsh@nankai.edu.cn (Q. Xia); ranqibin@126.com (Q. Ran)
Edited By: Emilio Moran

Abstract

Multiple factors of the natural environment have been found to impact and mold the phonetic patterns of human speech, among which the potential correlation between sonority and temperature has garnered significant attention. We leverage a large database containing basic vocabularies of 5,293 languages and calculate the average sonority for each language by adopting a universal sonority scale. Our findings confirm a positive correlation between sonority and temperature across macroareas and language families, whereas this relationship cannot be discerned within language families. We suggest that the adaptation of the distribution of speech sounds within languages is a slow process which is moreover insensitive to minor differences in temperature experienced by speakers as they carry their languages to new regions. Nevertheless, at the global level a solid relationship emerges. Furthermore, we delve deeper into the nature of the relationship and contend that it is mainly due to cold temperatures having a weakening effect on sonority. This research provides compelling additional evidence that climatic factors contribute to shaping language and its evolution.

Keywords: language, environment, climate, sonority, evolution

Significance Statement

Sounds of human languages can be affected by various factors of the natural environment. One such factor is the mean annual temperature. We analyze the average sonority of basic words of nearly three-quarters of the world's languages, and confirm a positive correlation between sonority and local temperature. Our findings suggest that lower temperatures, over the course of many centuries, lead to decreased sonority. Our research provides further evidence that climate plays a role in shaping the evolution of human languages.

Introduction

Language evolution is a complex and never-ending process that can be affected by a multitude of internal and external factors. One such external factor is the natural environment. A century ago, Edward Sapir investigated the correlation between language and environment, and emphasized the reflection of the environment in the vocabulary of a language. He noted that the phonetic systems, however, are almost immune to environmental conditions, and characterized the development of the speech system as a "quasimechanical" process (1). Regardless of the validity of Sapir's point, the relationship between the phonetic system and the natural environment was generally ignored or even rejected in most subsequent linguistic studies, partially due to the Chomskyan view of language as innate and autonomous (2). In recent years, the presupposition that the phonetic system is insulated from the environment has encountered numerous challenges. Interdisciplinary studies have proposed correlations between the phonetic system and various natural environmental factors, including temperature, humidity, vegetation, altitude, precipitation, terrain, etc. (3–12). How the phonetic system can be affected by the natural environment has become a widely debated topic in linguistics and anthropology.

Contrary to Sapir's assertion, it is almost self-evident that the phonetic system must be affected by the environment, since language communication predominantly relies on sound as the medium, and both the production and transmission of speech sounds are susceptible to external factors. For instance, the physical state of a speaker's vocal organs, which play the central role in speech production, can be impacted by climate conditions (5). Sound transmission is subject to filtering and masking effects brought about by the air, while the strength of these effects depends on the physical properties of the air (13, 14). In other words, it depends on the

Competing Interest: The authors declare no competing interest.
Received: June 24, 2023. **Accepted:** October 27, 2023

climate. Moreover, the natural environment can also influence language indirectly by affecting population size and community activities (9–11, 15, 16). Given the complex interplay between direct and indirect environmental factors, the study of the relationship between language and environment is inherently multifaceted and challenging, but also exciting and intriguing for researchers.

A relationship between sonority and temperature is intuitively to be expected, but fascinating nonetheless. Sonority can be defined in terms of speech production as the loudness of speech sounds or the openness of the vocal tract during sound production, or it may be defined perceptually as the prominence of speech sounds (17, 18). As a linguist, one gets the impression that languages spoken in cold regions possess a higher proportion of consonants and more complex consonant clusters, e.g. Russian *vdrug* "suddenly", sometimes reaching extremes, like Georgian *prckvnis* "to peel". Famously, Salishan languages of the Pacific Northwest are characterized by words sometimes lacking vowels, e.g. Nuxalk *pɬt* "thick" and *pk'm* "mosquito" (19). In contrast, languages spoken in the tropics tend to preserve a more balanced vowel-to-consonant ratio, often displaying strings where single consonants and vowels alternate, e.g. Hawaiian *wehewehe* "to explain", and Edo *okuta* "stone" (20). Systematic studies have confirmed that vowel ratio and the degree of sonority are positively correlated with temperature (8, 21–27).

In order to explain this positive correlation, pioneering studies have proposed a number of possible causal mechanisms from multiple perspectives. Among these, two direct physical effects relating to sound propagation are particularly noteworthy. The first one concerns the air absorption effect. High temperatures boost the air's ability to absorb high-frequency components of sounds (13, 14), which results in more damage to consonants with higher frequency noise. The second one relates to the lapse rate, the rate at which temperature decreases as altitude increases. In the tropics, the lapse rate is generally greater (28), meaning that sound travels much faster in warmer air at lower altitudes, causing sound waves to bend upwards during transmission, and reducing the energy transmitted horizontally (29). Such an environment leads to a preference for louder sounds, which are more resilient to the upward bending effect.

Different speech sounds exhibit different degrees of sensitivity to these disturbances due to their distinct acoustic characteristics. Speech sounds are categorized by phonologists into two main groups based on their sonority: obstruents and sonorants. Obstruents (plosives, fricatives, and affricates) are pronounced by obstructing the airflow, while sonorants (vowels, nasals, liquids, etc.) are pronounced with a relatively free airflow (30). The two categories of sounds are notably different in their timbre: most sonorants are voiced, louder, and without friction, while obstruents are usually noisier and shorter, with their distinctiveness relying heavily on their high-frequency components. As a result, obstruents are less resistant to attenuation effects and high-frequency interference, and more likely to merge with each other or disappear under certain circumstances. Conversely, sonorants are more robust and less prone to distortions.

Besides temperature, other ecological and socioecological influences on sonority have been noted as well. Precipitation and humidity are positively correlated with vowel ratio, and it has been claimed that the effect of humidity on vowel ratio is stronger than that of temperature, with the latter considered epiphenomenal (6). Vegetation may affect as well: the presence of tall and dense plants can dampen high-frequency sound and increase sonority (7), and also reduce the impact of coldness on sonority (10). Literacy levels and baby holding practices have also been suggested as relevant variables (21, 24). What the dominating factors are might vary across regions or languages. Given the inherent complexity of the issue, it is unlikely that a single factor can be considered the ultimate, overarching determinant of sonority. Despite the multifaceted nature of environmental influences on sonority, temperature, as one of the most salient and variable climate parameters, remains a prominent factor that warrants in-depth exploration. This study specifically focuses on temperature to investigate its impact on sonority.

Many earlier studies in this area used small language samples (≤ 100), which limited the generalizability and robustness of their conclusions. In recent decades, linguistics research has witnessed a shift towards the use of large-scale datasets. Studies have emerged that explore methods to investigate language adaptation employing big data and computer simulations (31, 32). In this study, we utilized vocabulary lists of basic words of 9,179 language varieties from the Automated Similarity Judgment Program (ASJP) database (33) as our source for exploring the effect of temperature on sonority.

An essential question regarding sonority is how to quantify it. Since the first attempt to measure sonority in 1871, various methods of measurement have been proposed (34), but no consensus has been reached yet. In this study, we adapted Parker's "final hierarchy of relative sonority" (34, 35), a sonority scale we consider the most effective and up-to-date, to fit the ASJP transcription system (see the Sonority scale subsection for a discussion on difficulties and methods of quantifying and calculating the sonority).

Results

Global distribution of sonority

We utilized a dataset of 9,179 doculects (i.e. language varieties as defined by specific sources of documentation) extracted from the ASJP database. We computed the mean sonority index (MSI) of each doculect using our revised sonority algorithm, and examined the geographical distribution of MSI values (Fig. 1). As expected, the results showed that languages with higher MSIs are concentrated around the Equator and in the Southern Hemisphere, whereas the Northern Hemisphere is moderately associated with lower MSIs. Specifically, the Austronesian languages in Oceania, known to linguists for their often extremely simple phoneme inventories and a preponderance of CV (consonant–vowel) structures (36), are clearly reflected in the figure with notably higher MSIs.

However, some deviations from the overall trend can be observed in the results. For example, Mesoamerica and Mainland Southeast Asia, despite being tropical regions, exhibit lower MSIs. These deviations can possibly be attributed to linguistic genealogical relationships and language contacts in the regions. In Mesoamerica, Mayan and Totozoquean languages commonly permit consonant clusters (37), which would contribute to lower MSIs. Similarly, many Mainland Southeast Asian languages not only allow syllables ending in obstruents but also have "sesquisyllables" (one-and-a-half syllables) formed by loose consonant clusters at syllable-initial positions (38), both of which lead to lower MSIs. In light of these findings, further research is needed to understand the reasons for the development of certain low-MSI languages in the tropics. Nevertheless, it is clear that genealogical relationships must be taken into account when exploring the correlation between sonority and temperature.

Correlation between sonority and temperature

We collected monthly mean temperature over the period of 1982 to 2022 for every doculect. The range and variation of monthly

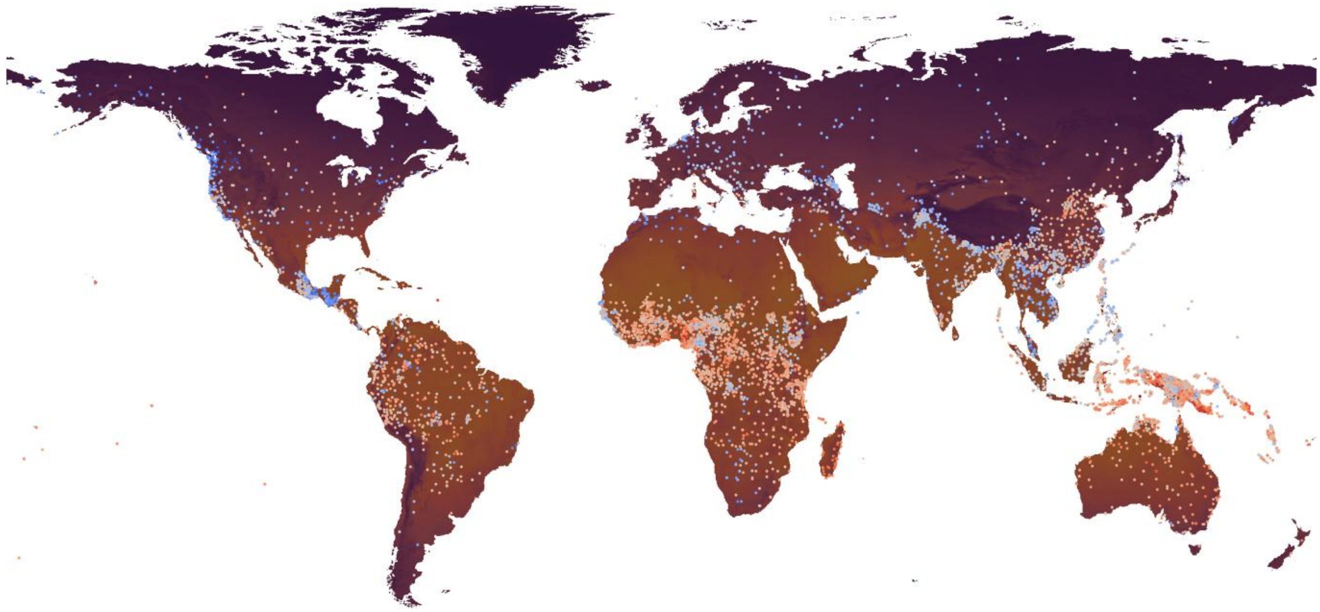

Fig. 1. Global distribution of MSIs across 9,179 language varieties from the ASJP database. Color of dots represents the MSI of the language, with redder dots indicating higher and bluer dots indicating lower indices. The fill color of land areas represents the mean annual temperature.

mean temperature are immense. For example, Yakutsk, Russia, the location of the Sakha language, experiences a monthly mean temperature range from −37°C in January to 19°C in July, while in the lowlands of Papua New Guinea, where a great quantity of languages are located, the monthly temperature remains relatively constant around 27°C with little seasonal variation, and the daily range even approximates the annual range (39). Due to the dispersion of monthly mean temperature, mean annual temperature (MAT) was adopted for further analysis of the correlation between sonority and temperature.

Temperature and sonority data were divided geographically into six largely independent linguistic macroareas: North America, South America, Eurasia, Africa, Greater New Guinea, and Australia (26, 40, 41). A preliminary positive correlation can be discerned across macroareas (Fig. 2). It should be noted that the internal dispersion of monthly temperature is great for the Eurasian macroarea, apparently because it straddles diverse climate zones from Siberia to the Indian Peninsula.

We investigated the existence and the universality of the positive correlation between MSI and MAT in R (42) using linear modeling and linear mixed effects modeling (43). To account for the effect of genealogical relationship properly, we included language family, as defined in the World Atlas of Language Structures (WALS) classification (26), as random intercept and random slope in our mixed effects model. We also performed Box–Cox transformation (44) on MSI and MAT data to ensure the normality of distribution before fitting the model, as raw MAT data deviate from normal distributions.

The results of the linear regression analysis (Fig. 3) demonstrate a positive correlation between mean MSI and mean MAT averaged by language family ($R^2 = 0.239$). The significance of the relationship, which would be $P < 0.001$, is compromised by the fact that families are far from independent units. The linear mixed model fitting with family as the random effect also shows a significant correlation ($P < 0.001$). However, its slope is relatively small (the brown line in Fig. 3) for the transformed data, raising doubts about the existence of a general positive correlation within families. Upon examining the coefficients of 16 individual families with more than 100 doculects, it is observed that 9 families exhibit positive correlations between MSI and MAT, while 7 families exhibit negative correlations (Supplementary Table S4 and Fig. S2). The correlations fluctuating around zero indicate that the correlation between sonority and temperature is largely absent within language families. There is no need to investigate families with fewer than 100 doculects, as their speakers do not experience sufficient temperature variation to reflect any potential influence of temperature on sonority.

The statistical findings obtained, indicating that temperature primarily exerts its influence on sonority at an inter-family level rather than within language families, suggest that the process whereby sound structures of languages relating to sonority adapt to the environment is a slow process. Its effect is evident only through centuries or even millennia of evolution temporally spanning both languages ancestral to the world's current language families and languages having diversified in historical times. The time represented by currently identifiable language families, which only represents the tip of the iceberg of evolution, has not produced sufficient variance in the temperature or sonority parameters and sufficient accommodation between the two to allow for the effect to become apparent.

In addition, we explored the possible impact of annual temperature variation on sonority. To investigate this, we added the mean annual range of temperature (from 1982 to 2022) as another fixed effect into the model by language family. We found a significant negative correlation between MSI and mean annual range ($P = 0.006$; besides, $P < 0.001$ for MAT in this model). Alternatively, similar results can be obtained by using the standard deviation of monthly temperature, as the standard deviation and mean annual range are highly correlated (Supplementary Fig. S4). The findings indicate that sonority is also influenced by temperature fluctuations. Nonetheless, there is a moderate negative correlation between mean annual range and MAT ($R^2 = 0.503$ by family or $R^2 = 0.483$ for all locales; both $P < 0.001$). The correlation arises from the trend that, for areas with human habitation and language use, warmer regions generally tend to have more stable temperatures throughout the year, whereas colder regions

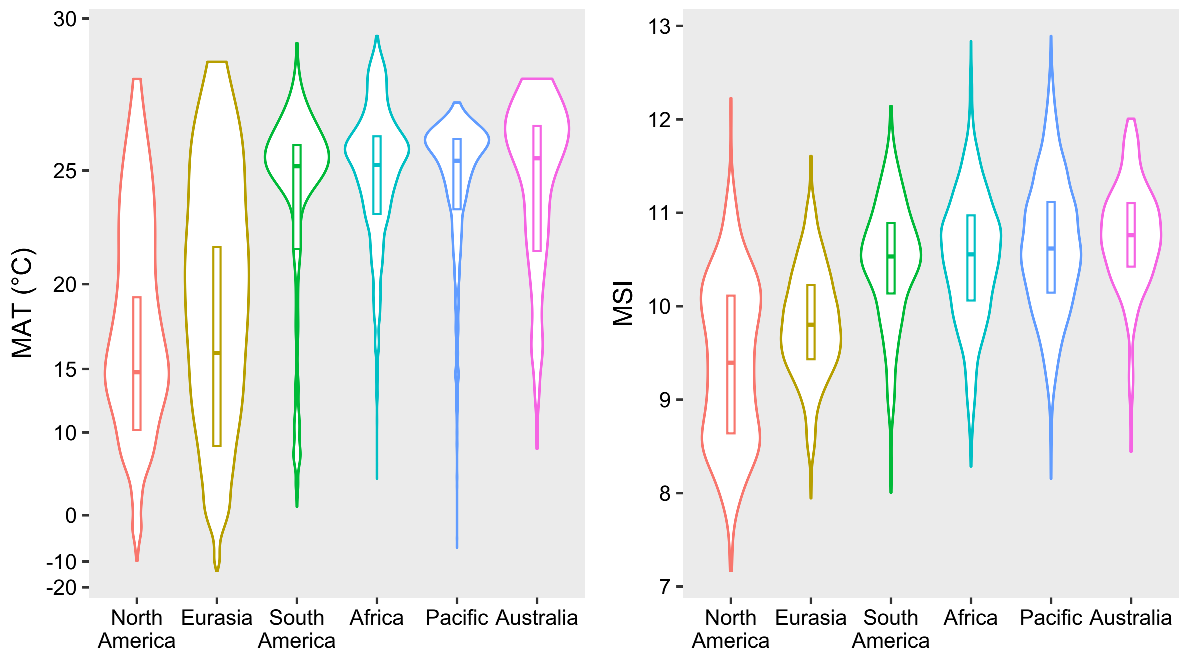

Fig. 2. Distribution of mean annual temperatures (MATs) over the period of 1982 to 2022 and distribution of MSIs, grouped by macroarea. The box inside each macroarea represents the interquartile range, and the thick line through the box represents the median. Macroareas are arranged in ascending order of medians of MATs or medians of MSIs in Parker's scale. Medians of MATs and medians of MSIs in Parker's scale are in the same order across six macroareas, suggesting a potential positive correlation.

can experience large temperature fluctuations between the summer and winter seasons. Therefore, by summarizing the two interconnected factors, we can conclude that lower sonority is associated with colder temperatures.

Correlation with word length

As a further factor possibly related to sonority, we also considered word length, as defined by the mean length of words found in the ASJP database for a given language. Differences in word length are expected to contribute to differences in MSI through word structure. For example, when looking at general phonotactic patterns (patterns of distributions of speech sounds over syllables and words), we see that the prevailing structure of a 3-segment word is CVC (consonant–vowel–consonant), whereas a 4-segment word commonly follows a CVCV structure. Consequently, we anticipate that a 3-segment word, with fewer opportunities for vowels, will tend to have a lower sonority index compared to a 4-segment word. Additionally, examining word length provides insight into the inherent characteristics of language families, as different families exhibit preferences for different word structures and word lengths.

After extracting the mean word length of each doculect, a modest positive correlation ($R^2 = 0.045$) was observed between MSI and mean word length of language families, and the correlation between mean word length and MAT is weaker ($R^2 = 0.020$) (Supplementary Fig. S1). This suggests that word length is an intrinsic factor that impacts sonority besides temperature. The positive correlation can be elucidated by considering phoneme inventory size and word structure. Languages with smaller phoneme inventories tend to have longer words (45–47), because they require more segments to convey the same information and to maintain word distinctiveness. At the same time, languages with smaller inventories often possess lower syllable complexity, i.e. fewer consonants in a syllable (48, 49). This association between sonority and word length gives rise to the observed positive correlation. Additionally, the two most frequently occurring word structures in all doculects are CVCV (69,943 words) and CVC (43,807 words), which further biases the data to show correlations in favor of longer words with more vowels (i.e. higher sonority).

A linear model fitting with MAT and mean word length as independent variables, across families, revealed that both factors are significantly correlated with MSI ($P < 0.001$ for MAT and $P = 0.0046$ for word length). Given the strong association of word length with phoneme inventory and syllable structure (46, 49), the findings of the linear model suggest that, in addition to temperature (and other environmental factors), sonority is also governed by the intrinsic characteristics of the language family, such as phoneme inventory and syllable structure. Consequently, it is plausible to propose that the potential influence of temperature within a language family is attenuated by intrinsic characteristics.

Discussion

In this study, the engagement of big data provided detailed observations on the previously established notion of a positive correlation between sonority and temperature. The positive trend is confirmed across macroareas and across language families, implying that temperature shapes sonority on a macroscopic scale. However, the trend is not apparent within individual language families, suggesting that the time scale at which the effect of adaptation of language structures to temperature builds up is usually greater than the few thousand years that language families typically span (50, 51). Nonetheless, the absence of a signal within families does not undermine the overall trend; on the contrary, the influence of temperature on prehistoric languages is strong enough that the positive correlation between sonority and temperature across language families is not obliterated or overridden by subsequent language development.

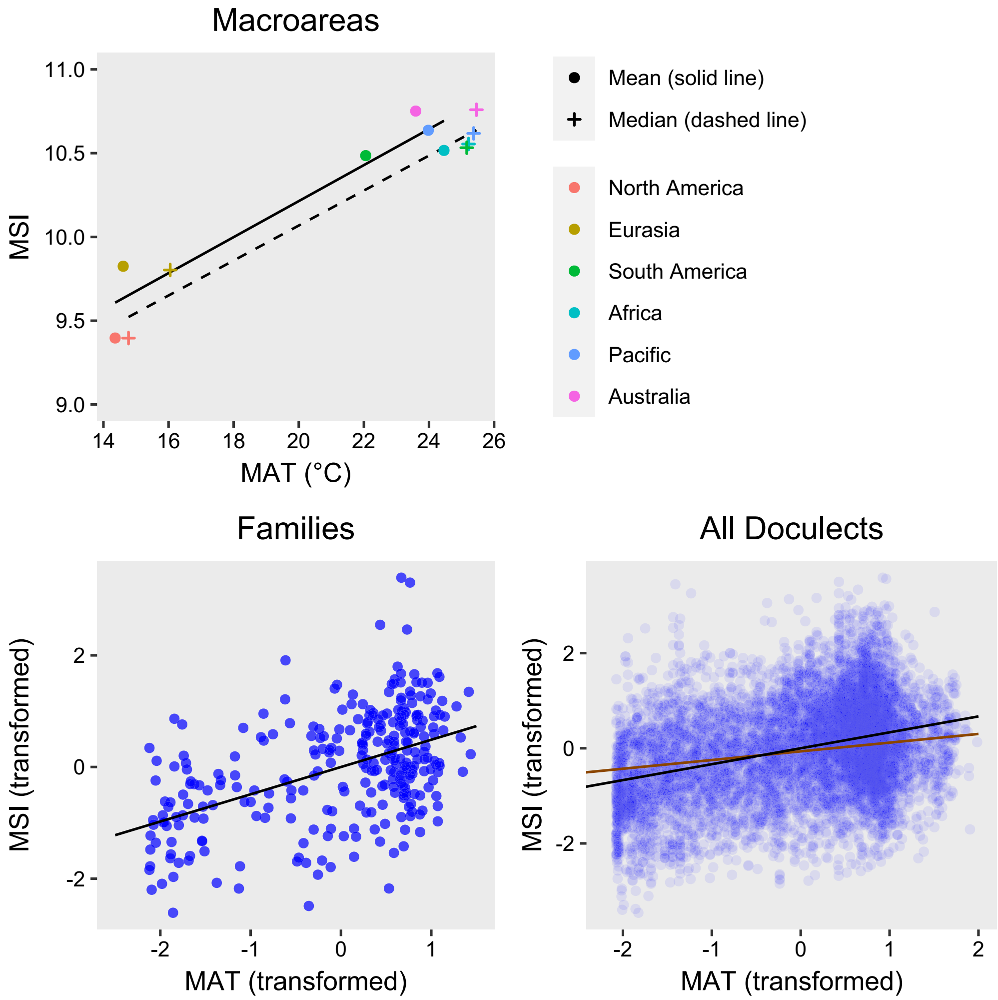

Fig. 3. Relationship between means or medians of MSI and MAT of macroareas ($R^2 = 0.904$, $P = 0.0036$ for means; $R^2 = 0.959$, $P = 0.0006$ for medians), between mean MSI and mean MAT of language families ($R^2 = 0.239$), and between MSI and MAT of all doculects (the steeper line represents the prediction of linear regression, $R^2 = 0.112$; and the less steep line represents the prediction of the linear mixed model with language family as the random effect). Box–Cox transformation was applied to data of the last two plots to ensure homoscedasticity.

The reason why the time scale of a language family does not suffice to yield a signature of adaptation to temperature must be sought in the sources of variance of the variables involved, namely the sound patterns by which sonority is measured and temperature. As far as the sound patterns are concerned, it is not unexpected that they should be slow in changing. While language change is ubiquitous, aspects of language structure, both lexical (52) and structural (53), can be highly conservative. Sound patterns mainly develop through linguistically motivated mechanisms that linguists have been studying for two centuries, ever since the discovery of the regularity of sound changes. Since phonemes typically do not change in isolation from the systems that they are part of, there is an inherent inertia to sound change. On the ecological side of the adaptation process, changes are slowed down because the annual temperature variation experienced by speakers belonging to one and the same language family is limited. For those families that have a small geographical range, which is the typical pattern, the majority of their members pertain to places with similar temperatures, so there will be no impetus for adaptive change. Even large families that extend across ecologically diverse regions exhibit limitations with regard to temperature variation. For instance, many Indo-European languages are concentrated in relatively cold places, whereas many Austronesian languages are concentrated in relatively warm regions. In general, there seems to be a tendency for populations to spread within similar climatic zones rather than across zones (54). Thus, it is not a surprise that intrafamily correlations between sonority and temperature are obscured, if they ever existed.

The introduction of large databases like ASJP has proven to be an invaluable asset for research, enabling deeper analyses that were previously unfeasible or unreliable. More data, however, comes with more room for flaws and inconsistencies. As an example, vowel length is ignored in the ASJP database, which could potentially impact the accuracy of MSI calculations, since both short and long vowels are transcribed with the same number of tokens. Nonetheless, our experimental investigations verified that an inclusion of vowel length would not appreciably alter the correlations with MSIs (Supplementary Fig. S5). Another example pertains to the treatment of semivowels. In Sinitic languages, gliding semivowels are often regarded as vowels (e.g. Lichuan Gan [nje] "fish" transcribed as *nie*), resulting in a higher calculated MSI. In contrast, in Slavic languages, such gliding components are often integrated into consonants (e.g. Russian [nje] "not" transcribed as *n*e*), leading to a lower calculated MSI. Such flaws are usually rooted in complex phonetic and phonological considerations and are thus hard to resolve. Despite the difficulties, we are confident that they do not undermine the final conclusions since the dataset is large and robust enough to withstand occasional inaccuracies. Undeniably, using large databases offers significant benefits.

In our study, we focused on the average sonority index of the entire vocabulary for each language. It is an intriguing question whether temperature or other factors of the environment might influence sonority to varying degrees depending on the meaning or grammatical category of the word. Exploring this aspect would require further investigation, but it is beyond the scope of this study.

Back to the question of how temperature affects sonority, in addition to the aforementioned effects of temperature on sound propagation, some other conjectures about the temperature's effects on sonority can be proposed. Cold air is always dry because of its low water vapor capacity (55), causing water evaporation from the vocal cords' surface, which makes phonation control difficult (5, 56) and frustrates the production of sonorants, because sonorants are commonly voiced, requiring the vibration of vocal cords. Besides, in colder climates, especially at higher altitudes, wind chill is severe and might necessitate people keeping their mouths more closed, leading to a reduction of sonorant usage (3). It has also been also suggested that colder climates discourage outdoor activities and that indoor communication at close distances would lead to better preservation of obstruent sounds (23).

Do cold climates affect sonority more than warm climates do? Contradictory answers have been given in the literature (3, 21–23). Here, based on the global temperature distribution, we suggest that colder climates have a greater effect on sonority than warmer climates. We have observed that among geographic locations of ASJP doculects, the global variation of minimum monthly temperature is plainly greater than that of maximum monthly temperature. During winter months, the equator-to-pole temperature gradient of the corresponding hemisphere reaches its maximum due to the lower sun angle and fewer daylight hours in regions farther from the Equator (57). During summer months, however, these regions can experience the same high temperatures as tropical areas. Therefore, it is hard to conceive that the almost ubiquitous warmer climates should be the main driver of the regression. Conversely, cooler climates, whose characteristics are limited to certain regions, are more likely to be responsible for the sonority variation.

Several studies have affirmed the idea that language adapts to or is shaped by the environment (10, 11, 16, 27). This idea is in line with the predictions of the Acoustic Adaptation Hypothesis, which posits that animal acoustic signals for communication should be adapted to transmit effectively within the surrounding environment where they evolved (8, 58). The present study adds further support to previous studies on the influence of multiple environmental factors on language, enhancing the credibility of the idea of language adaptation. However, we contend that "language *shaped* by the environment" (11, 16) is a more accurate expression than "language *adapting* to the environment" (10, 27). Regarding temperature and sonority, it has been observed that warm climates limit the appearance of obstruents (21, 23), while cold climates limit the appearance of sonorants (3, 22). Such observations suggest that language evolution is more likely shaped and driven by environmental factors, rather than language actively changing itself to adapt to the environment.

Materials and methods

Word list

We utilized word lists extracted from the ASJP database version 20 (33), a collection of basic vocabulary lists of 10,168 doculects. In ASJP, all words are given in a special but unified transcription system known as the ASJPcode, which omits some phonetic details but is informative enough for characterizing phonetic features and for cross-linguistic comparison (59, 60). Typically, each doculect is represented by a vocabulary of 40 basic meanings, which is a subset of the 100-item Swadesh list (61), including "I", "person", "tree", "eye", "hear", "new", etc. The lists vary in the degree to which these 40-item lists are complete. For 2,469 doculects (approximately one-quarter of the database), whose word lists are based on the complete 100-item Swadesh list, only a 40-item subset was taken to ensure consistency across all doculects. One meaning may be represented by multiple synonyms.

For each doculect, we calculated the average sonority index of all meanings it contains as its MSI. If a meaning was represented by multiple words (synonyms and phonological variants), we used the average sonority index of these words as the sonority index of the meaning.

To ensure the reliability of our data, we excluded creoles, pidgins, reconstructed languages, and artificial languages. We also eliminated doculects with less than 20 words or recording no vowels. As a result, we obtained 9,179 doculects, corresponding to 5,293 distinct ISO 639-3 languages and 296 families in WALS (26) or 389 families in Glottolog (62). The filtered doculects include 345,681 words representing 315,145 sets of synonyms in total, with an average of 34.3 meanings attested per doculect. For all doculects, latitudes and longitudes representing their approximate centroid locations are supplied in the database. We used these coordinates as a basis for collecting climate data for this study.

Temperature data

Monthly mean temperatures from 1982 to 2022 were retrieved from the Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System (FLDAS) (63). The FLDAS data encompasses the global landmass with a spatial resolution of 0.1° latitude $\times$ 0.1°longitude. Few doculects with locations on sea islands lack corresponding temperature data and were also excluded during doculect filtering.

Sonority scale

As mentioned previously, no consensus has been reached in sonority measurement. The lack of consensus mainly arises from two challenges: the difficulty in quantifying the sonority of phonetic segments, and the uncertainty of how to average the sonority of a word.

Earlier studies exploring the impact of climate on language have relied on the CV structure index (21, 24) or the vowel index (6). However, these indices have been argued to be inappropriate, as sonorant consonants are affected by temperature in ways similar to vowels, rather than obstruent consonants (25). Therefore, a detailed quantification of the sonority of speech sounds is required to overcome the limitations of the consonant–vowel dichotomy. By investigating constraints on the arrangement of segments in a syllable, phonologists have proposed the Sonority Sequencing Principle, a near-universal sonority hierarchy shared by most languages (64). However, this hierarchy is a categorical arrangement, not a numerical scale, thus not directly quantifiable.

Table 1. Sonority scale adapted and supplemented from Parker (34, 35).

Natural class	Index
Voiceless plosives and clicks	1
Voiceless affricates	2
Voiceless fricatives	3
Voiced plosives	4
Voiced affricates	5
Voiced fricatives	6
Nasals	7
Laterals	9
Rhotics	10
Semivowels	12
Interior vowels	13
High peripheral vowels	15
Mid peripheral vowels	16
Low vowels	17

To address this issue, Fought et al. (23) have adapted an early measurement of the energy of American English phonemes into a numerical sonority scale to study the relationship between sonority and climate, but the universality of the measurement is questionable. Instead, List (65) introduced a more universal sonority scale for sequence modeling and cognate detection, and integrated the sonority algorithm in the LingPy tool (66). In this study, we take a further step by employing Parker's "final hierarchy of relative sonority" (34, 35) as our scale (Table 1), which is more detailed than List's scale. In addition to sonority scales, other methods also have been proposed to avoid the difficulties of quantification, e.g. calculating a sonorant index—the proportion of sonorants in a word (27).

Ways of quantifying sonority depend not only on theoretical choices, but are also restricted by empirical materials at disposal. For example, when extracting a measure of sonority from a speech recording, we are prone to take an average of intensity over the entire recording or to extract the peak intensity of each segment (67), whereas when working with a phonetic transcription, we might average over the number of segments. In this study, as we employed vocabulary lists from ASJP as material, we calculated the mean sonority in Parker's scale of all ASJPcode-transcribed segments in a word.

An ASJPcode usually corresponds to multiple International Phonetic Alphabet (IPA) symbols, but most symbols in ASJPcode do not span different sonority values. For instance, *L* represents [ʟ, ɭ, ʎ] in IPA, but they are all lateral approximants and have the sonority index of 8 in Parker's scale. For few ASJPcode symbols that span sonority values, we have made reasonable adjustments based on the frequency of the sounds they may represent (Supplementary Table S1). For instance, *p* represents both the voiceless bilabial plosive [p] and the voiceless bilabial fricative [ɸ], but the latter rarely appears in the world's languages (60), so we properly regarded *p* as a voiceless plosive, whose sonority index is 1 in Parker's scale. Another example is the ASJPcode symbol *r*, which represents all varieties of rhotic sounds, involving trills (index = 8), flaps (index = 10), and rhotic approximants (index = 11) in Parker's original scale. We defined the sonority index of *r* to be 10.

There are also ASJPcode clusters of "digraphs" and "trigraphs" in the database, indicating affricates and various phonetic features. Secondary articulations of labialization, palatalization, velarization, pharyngealization, and glottalization were directly ignored during calculation, and only the sonority index of the primary articulation part was counted. Nasalization of vowels was also ignored. For prenasalized consonants, the average sonority index of the nasal segment and the following segment(s) was taken into account. In other cases (e.g. devoiced consonants, aspirated consonants, and maybe some miscoded complex consonants), the smallest sonority index in the cluster was taken as the index of the cluster.

Here, we illustrate the procedure of calculating the sonority index from ASJPcode using the French word *pw~aso** "fish" as an example, where the symbol ~ denotes a digraph and the symbol * indicates nasalization of the preceding vowel (59). First, the string is divided into four segments employing LingPy (66): *pw*, *a*, *s*, and *o**; alternatively, one can start from the presegmented forms available in the Cross-Linguistic Data Formats (68) version of the ASJP database (33). Following segmentation, these four segments are categorized into phonetic classes: labialized voiceless plosive, low vowel, voiceless fricative, and nasalized mid vowel. Subsequently, they are assigned corresponding sonorant indices: 1, 17, 3, and 16 (with labialization and nasalization ignored). Finally, the sonority index for the entire word is computed by averaging these indices, yielding a value of 9.25.

It is worth noting that Parker's final hierarchy does not involve click consonants. Although clicks can be acoustically loud, almost louder than vowels (69), no compelling evidence exists to help quantify their sonority. Consequently, we were constrained to treat clicks as equivalent to normal voiceless plosives since they both involve complete closure of the vocal tract. Nevertheless, clicks exclusively occur in the Khoisan languages of Southern Africa and a few languages in Tanzania, so they are unlikely to have a significant impact on the outcome.

We verified the near-equivalence between the various sonority scales. According to the results calculated from our materials, MSIs in Parker's scale have a relatively strong linear correlation with indices in Fought's scale ($R^2 = 0.753$, $P < 0.001$), List's scale ($R^2 = 0.876$, $P < 0.001$), sonorant indices ($R^2 = 0.637$, $P < 0.001$), and vowel indices ($R^2 = 0.768$, $P < 0.001$) (Supplementary Tables S2 and S3).

Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

Funding

This work is supported by a major project from the National Social Science Fund of China (grant no. 19ZDA300), the Academic Innovation Program for Middle and Young Scholars of the International Society for Chinese Language Teaching (grant no. SH23Y11), and the Deutsche Forschungsgemeinschaft (German Research Foundation) under Germany's Excellence Strategy (grant no. EXC 2150 390870439).

Author Contributions

Q.R. designed research; T.W. performed research; S.W. contributed language data; T.W. analyzed data; Q.R. and Q.X. supervised the study; and T.W. wrote the paper with contributions from S.W.

Data Availability

The code and extracted data have been deposited in GitHub (https://github.com/EL-CL/temperature-sonority). The raw temperature data (63) are available from the NASA Goddard Earth

Sciences Data and Information Services Center (https://disc.gsfc.nasa.gov/datasets/FLDAS_NOAH01_C_GL_M_001/summary). The ASJP database (33) is available in Zenodo (https://zenodo.org/record/7079637).

References

1 Sapir E. 1912. Language and environment. *Am Anthropol*. 14(2): 226–242.
2 Winter B, Wedel A. 2016. Commentary: desiccation and tone within linguistic theory and language contact research. *J Lang Evol*. 1(1):80–82.
3 Ember CR, Ember M. 2007. Climate, econiche, and sexuality: influences on sonority in language. *Am Anthropol*. 109(1):180–185.
4 Everett C. 2013. Evidence for direct geographic influences on linguistic sounds: the case of ejectives. *PLoS ONE*. 8(6):e65275.
5 Everett C, Blasi DE, Roberts SG. 2015. Climate, vocal folds, and tonal languages: connecting the physiological and geographic dots. *Proc Natl Acad Sci U S A*. 112(5):1322–1327.
6 Everett C. 2017. Languages in drier climates use fewer vowels. *Front Psychol*. 8:1285.
7 Maddieson I, Bhattacharya T, Smith DE, Croft W. 2011. Geographical distribution of phonological complexity. *Linguist Typology*. 15(2):267–279.
8 Maddieson I, Coupé C. 2015. Human spoken language diversity and the acoustic adaptation hypothesis. *J Acoust Soc Am*. 138(3): 1838–1838.
9 Lupyan G, Dale R. 2010. Language structure is partly determined by social structure. *PLoS ONE*. 5(1):e8559.
10 Lupyan G, Dale R. 2016. Why are there different languages? The role of adaptation in linguistic diversity. *Trends Cogn Sci (Regul Ed)*. 20(9):649–660.
11 Palmer B, Lum J, Schlossberg J, Gaby A. 2017. How does the environment shape spatial language? Evidence for sociotopography. *Linguist Typology*. 21(3):457–491.
12 Liang Y, *et al*. 2023. Languages in China link climate, voice quality, and tone in a causal chain. *Humanit Soc Sci*. 10(1):453.
13 Harris CM. 1966. Absorption of sound in air versus humidity and temperature. *J Acoust Soc Am*. 40(1):148–159.
14 Embleton TFW. 1996. Tutorial on sound propagation outdoors. *J Acoust Soc Am*. 100(1):31–48.
15 Honkola T, *et al*. 2013. Cultural and climatic changes shape the evolutionary history of the Uralic languages. *J Evol Biol*. 26(6): 1244–1253.
16 Nölle J, Fusaroli R, Mills GJ, Tylén K. 2020. Language as shaped by the environment: linguistic construal in a collaborative spatial task. *Palgrave Commun*. 6:27.
17 Laver J. 1994. *Principles of phonetics*. Cambridge: Cambridge University Press. p. 450–510.
18 Ladefoged P, Johnson K. 2014. *A course in phonetics*. 7th ed. Stamford (CT): Cengage Learning. p. 255.
19 Nater HF. 1979. Bella Coola phonology. *Lingua*. 49(2–3):169–187.
20 Agheyisi RN. 1986. *An Ẹdo–English dictionary*. Benin City: Ethiope Publishing Corporation.
21 Munroe RL, Munroe RH, Winters S. 1996. Cross-cultural correlates of the consonant–vowel (CV) syllable. *Cross Cult Res*. 30(1): 60–83.
22 Ember M, Ember CR. 1999. Cross-language predictors of consonant–vowel syllables. *Am Anthropol*. 101(4):730–742.
23 Fought JG, Munroe RL, Fought CR, Good EM. 2004. Sonority and climate in a world sample of languages: findings and prospects. *Cross Cult Res*. 38(1):27–51.
24 Munroe RL, Silander M. 1999. Climate and the consonant–vowel (CV) syllable: a replication within language families. *Cross Cult Res*. 33(1):43–62.
25 Munroe RL, Fought JG, Macaulay RKS. 2009. Warm climates and sonority classes. *Cross Cult Res*. 43(2):123–133.
26 Dryer MS, Haspelmath M. 2022. The world atlas of language structures online (v2020.3). Zenodo [accessed 2022 Dec 1]. https://doi.org/10.5281/zenodo.7385533.
27 Maddieson I. 2018. Language adapts to environment: sonority and temperature. *Front Commun*. 3:28.
28 Mokhov II, Akperov MG. 2006. Tropospheric lapse rate and its relation to surface temperature from reanalysis data. *Izv Atmos Ocean Phys*. 42(4):430–438.
29 Attenborough K. Sound propagation in the atmosphere. 2014. In: Rossing TD, editor. *Springer handbook of acoustics*. New York (NY): Springer. p. 117–155.
30 Gussenhoven C, Jacobs H. 2017. *Understanding phonology*. 4th ed. London: Routledge. p. 30–31.
31 Roberts SG. 2018. Robust, causal, and incremental approaches to investigating linguistic adaptation. *Front Psychol*. 9:166.
32 Nölle J, Spranger M. 2022. From the field into the lab: causal approaches to the evolution of spatial language. *Linguist Vanguard*. 8(s1):191–203.
33 Wichmann S, Holman EW, Brown CH. 2022. The ASJP database (version 20). Zenodo [accessed 2022 Sep 14]. https://doi.org/10.5281/zenodo.7079637.
34 Parker S. 2008. Sound level protrusions as physical correlates of sonority. *J Phon*. 36(1):55–90.
35 Parker S. Sonority. 2011. In: Oostendorp M, Ewen CJ, Hume E, Rice K, editors, *The Blackwell companion to phonology*. West Sussex: John Wiley & Sons. p. 1160–1184.
36 Lynch J, Ross M, Crowley T. 2001. *The oceanic languages*. London: Routledge. p. 169–235.
37 DiCanio C, Bennett R. 2020. Mesoamerica. In: Gussenhoven C. Chen A, editors. *The Oxford handbook of language prosody*. Oxford: Oxford University Press. p. 408–427.
38 Enfield NJ, Comrie B. 2015. *Languages of Mainland Southeast Asia*. Berlin: De Gruyter Mouton. p. 1–28.
39 Jackson RT, Standish W. 2022. Papua New Guinea. *Encyclopedia britannica* [accessed 2022 Nov 20]. https://www.britannica.com/place/Papua-New-Guinea.
40 Hammarström H, Donohue M. 2014. Some principles on the use of macro-areas in typological comparison. *Language Dynamic Change*. 4(1):167–187.
41 Blasi DE, Wichmann S, Hammarström H, Stadler PF, Christiansen MH. 2016. Sound–meaning association biases evidenced across thousands of languages. *Proc Natl Acad Sci U S A*. 113(39):10818–10823.
42 R Core Team. 2022. R: a language and environment for statistical computing [accessed 2022 Jun 23]. https://www.R-project.org/.
43 Kuznetsova A, Brockhoff PB, Christensen RHB. 2017. lmerTest package: tests in linear mixed effects models. *J Stat Softw*. 82(13):1–26.
44 Box GEP, Cox DR. 1964. An analysis of transformations. *J R Stat Soc Series B (Methodol)*. 26(2):211–243.
45 Nettle D. 1995. Segmental inventory size, word length, and communicative efficiency. *Linguistics*. 33(2):359–368.
46 Wichmann S, Rama T, Holman EW. 2011. Phonological diversity, word length, and population sizes across languages: the ASJP evidence. *Linguist Typology*. 15(2):177–197.
47 Wichmann S, Holman EW. 2023. Cross-linguistic conditions on word length. *PLoS ONE*. 18(1):e0281041.

48 Maddieson I. 2005. Correlating phonological complexity: data and validation. UC Berkeley PhonoLab Annual Report. 1:216–229.
49 Fenk-Oczlon G, Pilz J. 2021. Linguistic complexity: relationships between phoneme inventory size, syllable complexity, word and clause length, and population size. *Front Commun*. 6:626032.
50 Holman EW, *et al.* 2011. Automated dating of the world's language families based on lexical similarity. *Curr Anthropol*. 52(6): 841–875.
51 Rama T, Wichmann S. 2020. A test of generalized Bayesian dating: a new linguistic dating method. *PLoS ONE*. 15(8):e0236522.
52 Pagel M, Atkinson QD, Meade A. 2007. Frequency of word-use predicts rates of lexical evolution throughout Indo-European history. *Nature*. 449(7163):717–720.
53 Wichmann S Holman EW. 2009. *Temporal stability of linguistic typological features*. München: LINCOM Europa.
54 Diamond JM. 1997. *Guns, germs, and steel: the fates of human societies*. New York (NY): W. W. Norton & Co.
55 Koskela HO. 2007. Cold air-provoked respiratory symptoms: the mechanisms and management. *Int J Circumpolar Health*. 66(2): 91–100.
56 Leydon C, Sivasankar M, Falciglia DL, Atkins C, Fisher KV. 2009. Vocal fold surface hydration: a review. *J Voice*. 23(6):658–665.
57 Lydolph PE, Temple D, Temple D. 1985. *The climate of the earth*. Totowa (NJ): Rowman & Allanheld. p. 24–30.
58 Morton ES. 1975. Ecological sources of selection on avian sounds. *Am Nat*. 109(965):17–34.
59 Brown CH, Holman EW, Wichmann S, Velupillai V. 2008. Automated classification of the world's languages: a description of the method and preliminary results. *Lang Typology Universal*. 61(4):285–308.
60 Brown CH, Holman EW, Wichmann S. 2013. Sound correspondences in the world's languages. *Language*. 89(1):4–29.
61 Swadesh M. 1971. *The origin and diversification of language*. Chicago (IL): Aldine-Atherton. p. 283.
62 Hammarström H, Forkel R, Haspelmath M, Bank S. 2022. Glottolog database (v4.7). Zenodo [accessed 2022 Dec 5]. https://doi.org/10.5281/zenodo.7398962.
63 McNally A, NASA/GSFC/HSL. 2018. FLDAS Noah Land Surface Model L4 Global Monthly 0.1 × 0.1 degree (MERRA-2 and CHIRPS), NASA Goddard Earth Sciences Data and Information Services Center [accessed 2023 Feb 20]. https://doi.org/10.5067/5nhc22t9375g.
64 Berent I, Harder K, Lennertz T. 2011. Phonological universals in early childhood: evidence from sonority restrictions. *Lang Acquis*. 18(4):281–293.
65 List J-M. 2014. *Sequence comparison in historical linguistics*. Düsseldorf: Düsseldorf University Press. p. 131–133.
66 List J-M, Forkel R. 2021. LingPy. A Python library for historical linguistics (v2.6.8). Zenodo [accessed 2022 Jul 29]. https://doi.org/10.5281/zenodo.5144474.
67 Gordon M, Ghushchyan E, McDonnell B, Rosenblum D, Shaw PA. Sonority and central vowels: a cross-linguistic phonetic study. 2012. In: Parker S, editor. *The sonority controversy*. Berlin: De Gruyter Mouton. p. 219–256.
68 Forkel R, *et al.* 2018. Cross-linguistic data formats, advancing data sharing and re-use in comparative linguistics. *Sci Data*. 5(1):180205.
69 Ladefoged P, Maddieson I. 1996. *The sounds of the world's languages*. Oxford: Blackwell. p. 257–259.