

Article

Profiling Climate Risk Patterns of Urban Trees in Wuhan: Interspecific Variation and Species' Trait Determinants

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Abstract

Climate change poses significant threats to urban tree health and survival worldwide. This study evaluates climate suitability risks for 12 common tree species in Wuhan, a Chinese metropolis facing escalating climate challenges. We analyzed risk dynamics and interspecific variations across three periods, the baseline (1981–2022), near future (2023–2050), and distant future (2051–2100), quantifying climate risk as differences between local climate conditions and species' climatic niches. We further examined how species' geographic distribution and functional traits influence these climate risks. The results revealed significant warming trends in Wuhan during the baseline period ($p < 0.05$), with projected increases in temperature and precipitation under future scenarios ($p < 0.05$). The most prominent risk factors included the precipitation of the driest month (PDM), annual mean temperature (AMT), and maximum temperature of the warmest month (MTWM), indicating intensifying drought–heat stress in this region. Among the studied species, *Cedrus deodara* (Roxb.) G. Don, *Platanus acerifolia* (Aiton) Willd., *Metasequoia glyptostroboides* Hu & W.C.Cheng, and *Ginkgo biloba* L. faced significantly higher hydrothermal risks ($p < 0.05$), whereas *Koelreuteria bipinnata* Franch. and *Osmanthus fragrans* (Thunb.) Lour. exhibited lower current risks but notable future risk increases ($p < 0.05$). Regarding the factors driving these interspecific variation patterns, the latitude of species' distribution centroids showed significant negative correlations with the risk values of the minimum temperature of the coldest month (MTCM) ($p < 0.05$). Among functional traits, the wood density (WD) and xylem vulnerability threshold (P50) were negatively correlated with precipitation-related risks ($p < 0.05$), while the leaf dry matter content (LDMC) and specific leaf area (SLA) were positively associated with temperature-related risks ($p < 0.05$). These findings provide scientific foundations for developing climate-adaptive species selection and management strategies that enhance urban forest resilience under climate change in central China.

Keywords: urban trees; climate risk quantification; risk growth rates; interspecific variation; geographic distribution; functional traits; central China



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1. Introduction

Climate change stands as one of the most formidable environmental challenges of our era [1]. As vital components of urban green infrastructure, trees play a crucial role in mitigating climate change impacts on human settlements through carbon sequestration

and microclimate regulation [2]. However, the very climate risks trees help ameliorate are simultaneously threatening their own growth, development, and ecological functions.

Climate risks to urban trees primarily emerge from long-term variability in temperature and precipitation patterns, and intensified extreme weather events. Progressive shifts in hydrothermal conditions, especially the global warming trend, have fundamentally altered trees' ecological adaptability [3] by disrupting phenological cycles [4,5], exacerbating pest and disease pressures [6,7], and triggering cascading effects on species distribution and ecosystem services [8,9]. Concurrently, extreme events such as heat waves, droughts, floods, and storms inflict immediate physiological and morphological damage, weaken tree vigor, and dramatically increase trees' environmental vulnerability [10–13]. Furthermore, urban environments amplify these risks through heat island effects and altered surface configurations, which further compromise tree resilience [14,15].

Given the complexity and severity of these impacts, climate risk assessment for urban trees has become a critical research priority. Critically, tree responses to climate stress exhibit considerable interspecific variation. A study in Australia revealed that while over half of examined urban tree species confronted substantial risks from elevated temperatures or drought conditions, others demonstrated remarkable climate resilience [5]. Elucidating species-specific climate risks is therefore fundamental for identifying trees' vulnerability patterns, predicting future risk trajectories, and developing targeted mitigation strategies.

Current approaches to trees' climate risk assessment have evolved from earlier species classifications based on climatic niche characteristics [16,17], such as accessing species' adaptability to urban temperatures based on the 97.5th percentile of the annual mean temperature (AMT) [18]. While these methods effectively revealed cross-species common risk patterns, they provided limited insight into species-specific vulnerabilities. More sophisticated approaches delineated species-specific multidimensional climate risks regarding diverse bioclimatic variables, with particular emphasis on temperature-related and precipitation-related parameters, better capturing interspecific variation in tree responses to comprehensive climate challenges [5,19]. Among prevailing methodologies, habitat suitability modeling provides a critical pathway for evaluating the magnitude of climate risks by quantifying the capacity of local hydrothermal conditions to sustain the survival and reproductive success of target species [3,18,20]. Based on Species Distribution Models (SDMs), climate suitability risk is typically quantified as the deviation of local climatic conditions from species' climatic niches, with greater divergence indicating higher climate risk and reduced habitat suitability [5,21]. Additionally, physiological, morphological, and phenological responses to climate threats (such as extreme weather events) have also been utilized for tree risk evaluation [22]. With the advancement of global climate modeling, projections for future climate risk have become feasible and even prevalent in recent decades [17,23]. The studied temporal periods typically extend from baseline to the near future and distant future [24,25], with risk dynamics often projected under various climate scenarios such as Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs).

Species-specific climate risks were found to associate with species' functional traits, such as leaf morphology, hydraulic properties, photosynthetic capacity, and xylem anatomical features, which govern how trees acquire resources and respond to environmental stresses [12,24]. Additionally, biogeographic origin serves as a key predictor of species' climatic vulnerability, with species originating from climatically disparate regions often exhibiting heightened risks [25]. However, these correlations exhibit considerable complexity owing to site-specific climate conditions and species-specific response mechanisms, necessitating further investigation. Systematic analysis of climate risk–trait associations within

regional contexts can provide essential foundations for predicting climate vulnerability across numerous tree species.

Despite notable advances in climate risk identification for urban tree species in North America and Australia [26], the risk profiles of common tree species in regions facing geographically distinct climate challenges, such as China, remain poorly understood. This knowledge gap constrains the application of climate-resilient species in regional urban forests. Wuhan, as a representative megacity in central China, confronts amplifying challenges from its subtropical monsoon climate with more extreme hydrothermal conditions anticipated under future scenarios, thereby intensifying risks for urban trees [22,27]. However, current local urban forest management, which relies heavily on historical experience, is inadequate for addressing these emerging climate challenges due to insufficient species-specific risk recognition and corresponding adaptation strategies. Therefore, comprehensive species-level climate risk assessment is critical for enhancing the overall climate resilience of urban forests in Wuhan.

This study aims to elucidate the species-specific climate risk characteristics and temporal dynamics of common urban tree species in Wuhan under current and projected future climatic scenarios. Building on this analysis, we investigate how biogeographic distribution and functional traits drive interspecific variations in climate risks. The findings will provide empirical evidence for climate-adaptive species selection in Wuhan and climatically analogous cities, thereby enhancing urban forest resilience against accelerating climate change.

2. Materials and Methods

2.1. Research Site

The research site is located in the Central Urban Area of Wuhan (30.52° – 30.70° N, 114.25° – 114.48° E), a megacity in central China, as shown in Figure 1. The Central Urban Area covers the spatial extent of seven core urban districts, characterized by the highest urbanization level and most pronounced urban heat island effects. Situated in the hinterland of the middle and lower Yangtze River basin, Wuhan experiences a humid northern subtropical monsoon climate with distinct seasonal variations. The multi-year average temperature ranges from 16.5°C to 17.5°C , featuring cold, dry winters with extreme lows below -10°C during cold snaps, and hot, humid summers that average 28.7°C but can reach 37 – 39°C during heatwaves. Annual precipitation averages approximately 1100 mm, with over 40% concentrated in the rainy season from June to August, when flooding events are frequent. The regional vegetation is dominated by mixed evergreen and deciduous broad-leaved forest communities.

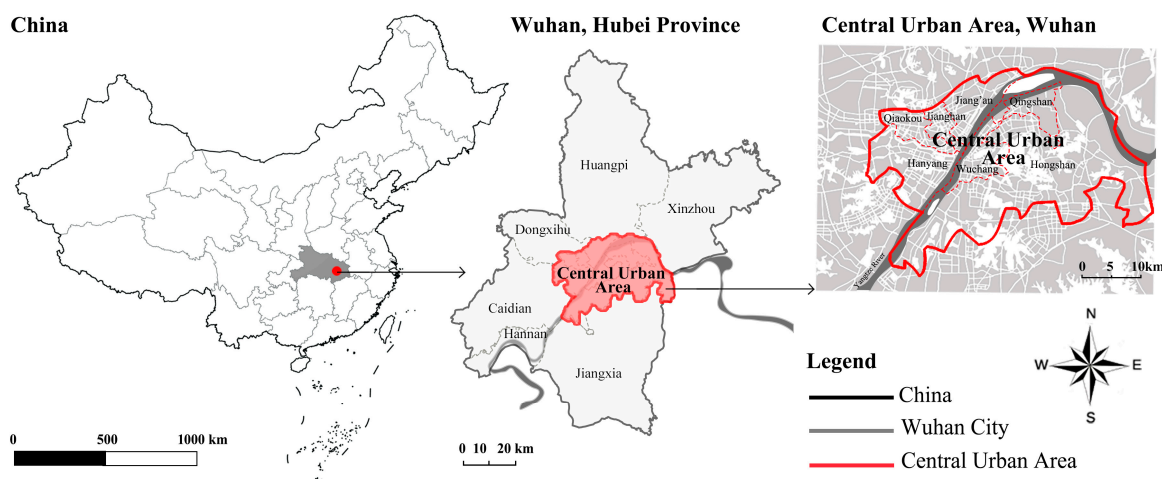


Figure 1. Location of research site (Source: Google Maps).

2.2. Research Objects

This study selected twelve urban tree species as research subjects. The species include *Taxodium distichum* var. *imbricatum* (Nutt.) Croom (pond cypress), *Prunus* × *yedoensis* Matsum. (Japanese cherry), *Platanus acerifolia* (Aiton) Willd. (London plane), *Cedrus deodara* (Roxb.) G. Don (deodar cedar), *Magnolia grandiflora* L. (southern magnolia), *Acer palmatum* Thunb. (Japanese maple), *Osmanthus fragrans* (Thunb.) Lour. (sweet osmanthus), *Sapindus mukorossi* Gaertn. (soapberry), *Metasequoia glyptostroboides* Hu & W.C.Cheng (dawn redwood), *Camphora officinarum* Nees (camphor tree), *Koelreuteria bipinnata* Franch. (bougainvillea goldenrain tree), and *Ginkgo biloba* L. (ginkgo), as detailed in Table 1. The species selection was based on two criteria. First, all species are extensively planted in urban forests across Wuhan and other cities in the middle and lower Yangtze River basin, ensuring research findings provide practical reference for urban forest development in climatically similar regions. Second, the selected species represent diverse life forms and biogeographic origins, with previous studies demonstrating substantial variations in climate adaptability among these species.

Table 1. Tree species information.

Latin Name	Origin	Life Form
<i>Taxodium distichum</i> var. <i>imbricatum</i> (Nutt.) Croom	Southeastern North America	Deciduous Conifer
<i>Prunus</i> × <i>yedoensis</i> Matsum.	Japan	Deciduous Broadleaf
<i>Platanus acerifolia</i> (Aiton) Willd.	United Kingdom	Deciduous Broadleaf
<i>Cedrus deodara</i> (Roxb.) G. Don	Northern India and surrounding regions (Himalayas)	Evergreen Conifer
<i>Magnolia grandiflora</i> L.	Southeastern North America	Evergreen Broadleaf
<i>Acer palmatum</i> Thunb.	Japan, Korea, and East-Central China	Deciduous Broadleaf
<i>Osmanthus fragrans</i> (Thunb.) Lour.	Yangtze River basin to South and Southwest China	Evergreen Broadleaf
<i>Sapindus mukorossi</i> Gaertn.	Eastern and Southwestern China	Deciduous Broadleaf
<i>Metasequoia glyptostroboides</i> Hu & W.C.Cheng	Central China	Deciduous Conifer
<i>Camphora officinarum</i> Nees	Yangtze River basin southwards in China and East Asia	Evergreen Broadleaf
<i>Koelreuteria bipinnata</i> Franch.	South-Central China	Deciduous Broadleaf
<i>Ginkgo biloba</i> L.	Central China	Deciduous Broadleaf

Species geographic origins were sourced from multiple authoritative botanical databases, primarily including Plants of the World Online (POWO, <https://powo.science.kew.org/>), maintained by the Royal Botanic Gardens, Kew; the Tropicos database (<https://www.tropicos.org/>) of the Missouri Botanical Garden; and the relevant taxonomic literature.

2.3. Species Geographic Distribution Data and Climatic Niche Construction

Geographic distribution data (species occurrence records) for the studied tree species were retrieved from the Chinese Virtual Herbarium (CVH, <http://www.cvh.ac.cn/>) and the Global Biodiversity Information Facility (GBIF, <https://www.gbif.org/> [28]). After excluding invalid and anomalous coordinate data, the arithmetic mean of all valid occurrence coordinates was defined as the geographic distribution centroid for each species, representing the geometric center of a species' geographic distribution [25].

Six bioclimatic variables were selected for climate change analysis and climatic niche construction: the annual mean temperature (AMT, °C), minimum temperature of the coldest month (MTCM, °C), maximum temperature of the warmest month (MTWM, °C), annual precipitation (AP, mm), precipitation of the wettest month (PWM, mm), and precipitation of the driest month (PDM, mm). These variables capture key aspects of species' climatic adaptation: AMT and AP represent average thermal and moisture conditions, MTCM and MTWM represent extreme cold and heat thresholds, and PWM and PDM represent seasonal precipitation extremes [16,17].

Climate data for these variables at species' distribution sites during the baseline period (1981–2022) were extracted from the WorldClim database version 2.1 (<https://www.worldclim.org/>). The 5th to 95th percentiles were used as valid ranges to construct species-specific climatic niches, with the median value representing the optimal climate conditions for species growth [16,21].

2.4. Historical Climate Data Acquisition and Climate Simulation for Wuhan

Historical temperature and precipitation data of Wuhan during the baseline period (1981–2022) were obtained from the China Surface Climate Daily Data (V3.0) provided by the National Meteorological Science Data Center (NMSDC, <https://data.cma.cn/>). Future climate data are obtained through simulations using global climate models (GCMs). To distinguish the varying degrees of climate change impacts across different temporal scales, and following the World Meteorological Organization (WMO) standard of 30-year periods for climate averages, this study established two projection periods: the near future (2023–2050) and distant future (2051–2100) [29]. The simulation data were derived from the High-resolution CMIP6 Statistical Downscaled Climate Projection Dataset for China 1979–2100 (HiCPC) from the National Tibetan Plateau Science Data Center (NTPSSDC, <https://data.tpsc.ac.cn/>). The dataset features a horizontal spatial resolution of 0.1° and a temporal resolution of 1 day, making it suitable for urban-scale climate simulation.

Two climate models with demonstrated superior performance in simulating China's hydrothermal changes were selected: MPI-ESM1-2-HR and MRI-ESM2-0 [30,31]. Four carbon emission scenarios under Shared Socioeconomic Pathway (SSPs) were employed: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. The SSP framework represents the standardized scenario approach for the Coupled Model Intercomparison Project Phase 6 (CMIP6) and formed the core foundation for the IPCC Sixth Assessment Report (AR6). The selection of these four scenarios covers a broad range of radiative forcing, from strong mitigation (SSP1-2.6) to very high emissions (SSP5-8.5), enabling comprehensive assessment of climate change trends under different policy contexts and subsequent risk evaluation. Future climate values were calculated as the ensemble mean of the two climate models, with all simulation processes conducted using ArcGIS Pro 3.4. Based on daily climate data, the annual or annual mean values of the following bioclimatic variables were calculated for both baseline and future periods: AP, PWM, PDM, AMT, MTWM, and MTCM.

2.5. Calculation of Climate Suitability Risk Values and Risk Growth Rates

For each bioclimatic variable (v_i), the baseline climate suitability risk value for a given species (R_b) was calculated as the difference between the median value of Wuhan's multi-year baseline climate data and the optimal value of the species' climatic niche (m_i). Similarly, species' climate risk values for near-future and distant-future periods (R_{nf} , R_{df}) were calculated as the differences between Wuhan's simulated climates under four SSP emission scenarios and m_i .

The standardized climate risk value (R') for each bioclimatic variable was obtained through min–max normalization. Using Euclidean distance measures, comprehensive risk values were calculated for temperature (R_{temp} , combining standardized AMT, MTWM, and MTCM risks), precipitation (R_{prec} , combining standardized AP, PWM, and PDM risks), and overall hydrothermal conditions (R_{hy-th} , combining all six standardized risk variables) [17], as detailed below.

$$R_{temp} = \sqrt{\left[\left(Sr'_{\{MAT\}} \right)^2 + \left(Sr'_{\{MTWM\}} \right)^2 + \left(Sr'_{\{MTCM\}} \right)^2 \right]} \quad (1)$$

$$R_{prec} = \sqrt{\left[\left(Sr'_{\{AP\}} \right)^2 + \left(Sr'_{\{PWM\}} \right)^2 + \left(Sr'_{\{PDM\}} \right)^2 \right]} \quad (2)$$

$$R_{hy-th} = \sqrt{\sum \left(Sr'_{\{v_i\}} \right)^2} \quad (i = 1, 2, \dots, 6) \quad (3)$$

Risk growth rates (ΔR) across different temporal periods were defined as the relative change of later-period risk values compared to earlier-period ones. The calculation formulas for the risk growth rates from the baseline to near future (ΔR_{B-NF}) and from the near future to distant future (ΔR_{NF-DF}) are as follows:

$$\Delta R_{B-NF} = \frac{(Sr_{nf} - Sr_b)}{Sr_b} \quad (4)$$

$$\Delta R_{NF-DF} = \frac{(Sr_{df} - Sr_{nf})}{Sr_{nf}} \quad (5)$$

2.6. Data Acquisition for Species' Functional Traits

To investigate the association between climate risk characteristics of the studied tree species and their functional traits, six functional traits were selected for this study: the specific leaf area (SLA), leaf dry matter content (LDMC), xylem vulnerability threshold (P50), wood density (WD), leaf area (LA), and leaf thickness (LT). The selection of these functional traits was based on their established regulatory roles in trees' responses and adaptation to hydrothermal stresses [32]. Trait data were primarily obtained from the TRY Plant Trait Database v5.0 (<http://www.try-db.org> [33]), supplemented by the Xylem Functional Traits Fatabase (XFT; <https://xylemfunctionaltraits.org>) and published literature datasets [34]. The functional trait information of tree species is provided in Supplementary Table S1.

2.7. Data Statistics and Analysis

For climate trend analysis, Sen's slope estimator (Theil–Sen median slope) was employed to quantify interannual trends in temperature and precipitation, with statistical significance of trends assessed using the Mann–Kendall test. Trends with $|Z| \geq 1.96$ ($p < 0.05$) were considered statistically significant [35].

The Kruskal–Wallis non-parametric test was used to assess significant differences in climate variables among the four SSP emission scenarios. One-way ANOVA followed by Fisher's least significant difference (LSD) test was used to analyze interspecific differences and temporal variations in climate risk characteristics. The influence of species' geographic distribution centroids and functional traits on climate risks was investigated through Pearson's correlation analysis and linear regression. All statistical analyses were conducted using R version 4.3.1.

3. Results

3.1. The Hydrothermal Dynamics in Wuhan: Baseline and Future Trends

During the baseline period (1981–2022), both the annual mean temperature (AMT) and maximum temperature of the warmest month (MTWM) exhibited significant increasing trends ($p < 0.05$) at $0.033^\circ\text{C}/\text{year}$, while the minimum temperature of the coldest month (MTCM) showed a non-significant decrease ($p > 0.05$). No significant trends were observed in precipitation variables, demonstrating that Wuhan experienced substantial warming over the past four decades with much more stable precipitation patterns.

Multiple-scenario climate simulations project significant increases ($p < 0.05$) in temperature variables for both the near-future (2023–2050) and distant-future (2051–2100) periods, as shown in Figure 2. The greatest warming trends are projected for AMT and MTCM under the high-emission SSP5-8.5 scenario in the distant future (0.049 and 0.038 °C/year with an R^2 of 0.821 and 0.221, respectively), while MTWm peaks under the low-emission SSP1-2.6 scenario in the near future (0.042 °C/year, $R^2 = 276$). Similarly, precipitation metrics are projected to increase significantly in the distant future ($p < 0.05$), with AP, PWM, and PDM exhibiting their most significant increases under the moderate-emission SSP2-4.5 scenario (5.783, 2.844, and 0.174 mm/year, with $R^2 = 0.202$, 0.154, and 0.138, respectively). These projections indicate upward trends in both temperature and precipitation in Wuhan's future climate, with temperature changes being more pronounced. Although simulated climate values showed numerical differences among emission scenarios, these differences were not statistically significant ($p > 0.05$). To reduce uncertainty and improve prediction robustness, subsequent risk analyses used ensemble averages of the four scenarios as future climate projections.

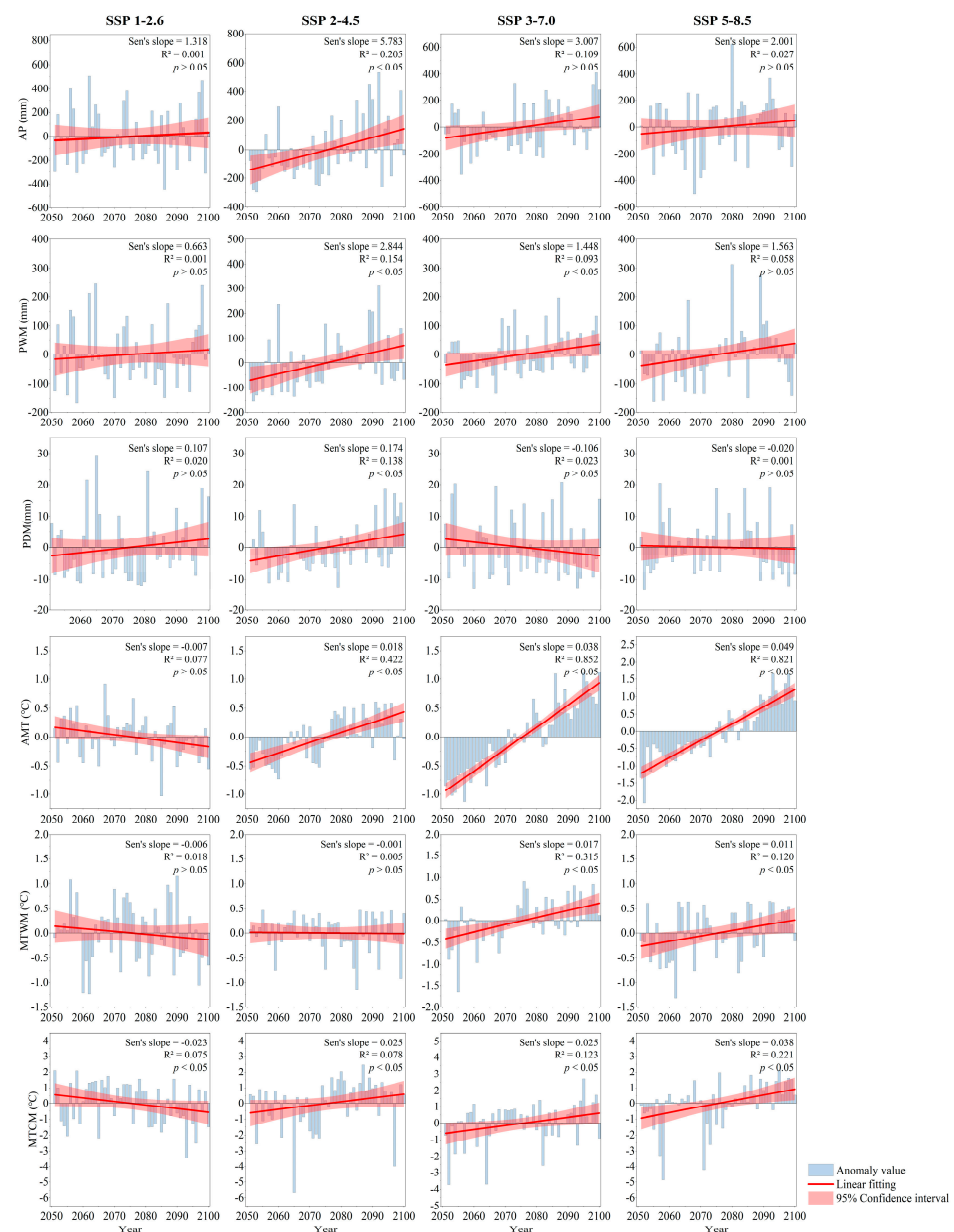


Figure 2. Interannual trends of projected hydrothermal variables in Wuhan under various emission scenarios in the distant future (2051–2100). AMT, annual mean temperature; MTWm, maximum

temperature of the warmest month; MTCM, minimum temperature of the coldest month; AP, annual precipitation; PWM, precipitation of the wettest month; PDM, precipitation of the driest month. Corresponding trends for the baseline period (1981–2022) and the near future (2023–2050) are provided in Supplementary Figures S1 and S2, respectively.

3.2. Varied Climate Risk Values Among Different Species and Bioclimatic Variables

During the baseline period, the species exhibiting high-level (above the 75th percentile) comprehensive temperature risks included *S. mukorossi*, *C. deodara*, and *A. palmatum*, with risk values of 1.01–1.41. Those facing high-level comprehensive precipitation risks included *C. deodara*, *P. acerifolia*, and *M. glyptostroboides* (1.32–1.48). Species experiencing substantial comprehensive hydrothermal risks comprised *C. deodara*, *P. acerifolia*, *M. glyptostroboides*, and *G. biloba* (1.62–1.93). In contrast, *K. bipinnata* and *O. fragrans* exhibited the lowest comprehensive climate risk values of 0.46–0.51.

Future risk projections revealed significant interspecific variations ($p < 0.05$), as shown in Figure 3, but no significant differences between near and distant future periods. Four species—*C. deodara*, *G. biloba*, *M. glyptostroboides*, and *P. acerifolia*—exhibited prominent risks in projected climate scenarios, consistent with those in the baseline period, suggesting their persistent vulnerability to hydrothermal stresses. In near-future projections, specifically, these species demonstrated significantly higher comprehensive temperature risks of 1.10–1.38 (vs. *M. grandiflora* 0.23, $p < 0.05$), higher comprehensive precipitation risks of 1.36–1.48 (vs. *S. mukorossi* 0.06, $p < 0.05$), and higher comprehensive hydrothermal risks of 1.76–2.02 (vs. *K. bipinnata* and *O. fragrans* 0.46–0.47, $p < 0.05$).

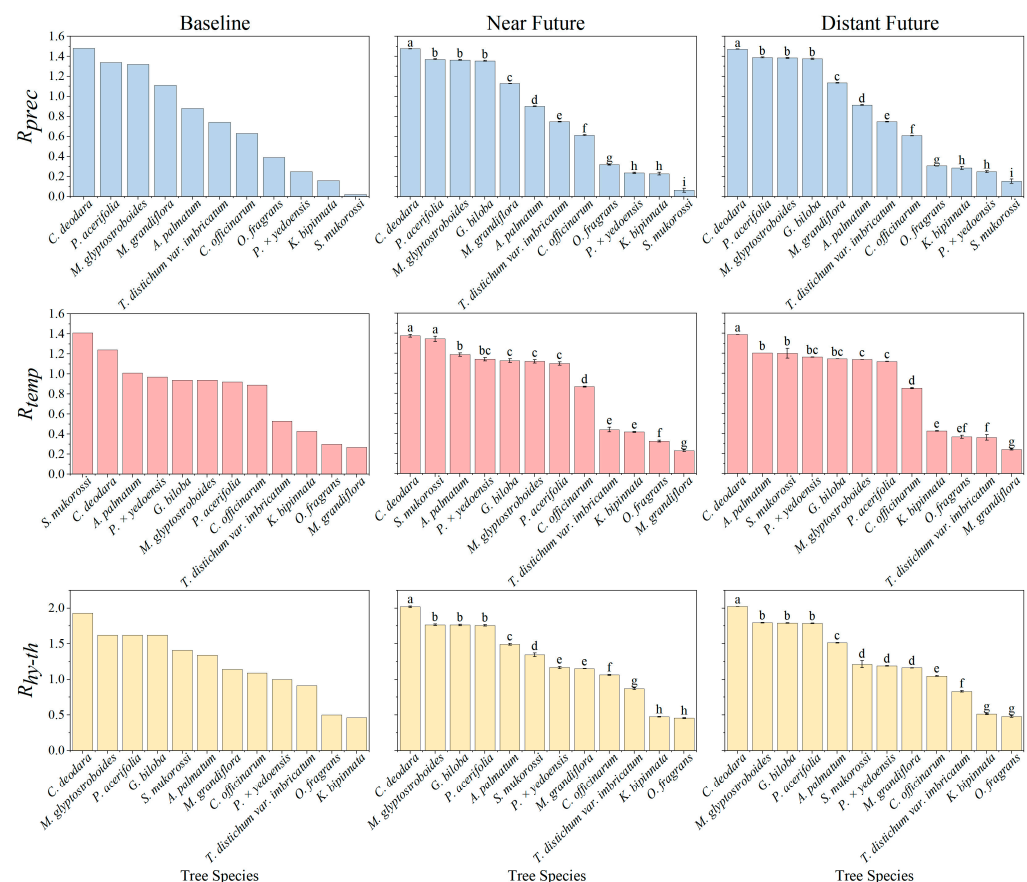


Figure 3. Interspecific variation in comprehensive climate risk values for baseline and future periods. Species labeled with different letters indicate statistically significant differences ($p < 0.05$). R_{prec} , R_{temp} , and R_{hy-th} represent the comprehensive temperature, comprehensive precipitation, and comprehensive hydrothermal risk values, respectively.

Notably, *C. deodara* consistently ranked highest in climate risks across temperature, precipitation, and comprehensive hydrothermal dimensions under both current and projected climates, demonstrating exceptional susceptibility to climate stress.

Moreover, climate risk hierarchies varied significantly among bioclimatic variables. During the baseline period, temperature risk patterns differed between species groups: for species with higher risks (*M. glyptostroboides*, *P. acerifolia*, *G. biloba*, *A. palmatum*, and *P. × yedoensis*), AMT and MTCM represented the highest and lowest risks, respectively, while the AMT risks reversed to be lowest in low-risk species (*K. bipinnata*, *O. fragrans*, *C. officinarum*, and *M. grandiflora*), as shown in Figure 4. Across precipitation variables, PDM and AP constituted the highest and lowest precipitation risk factors for 83.3% and 72% of the studied species, respectively, with PDM showing the overall highest risk values (0.58 ± 0.11) among all climatic variables.

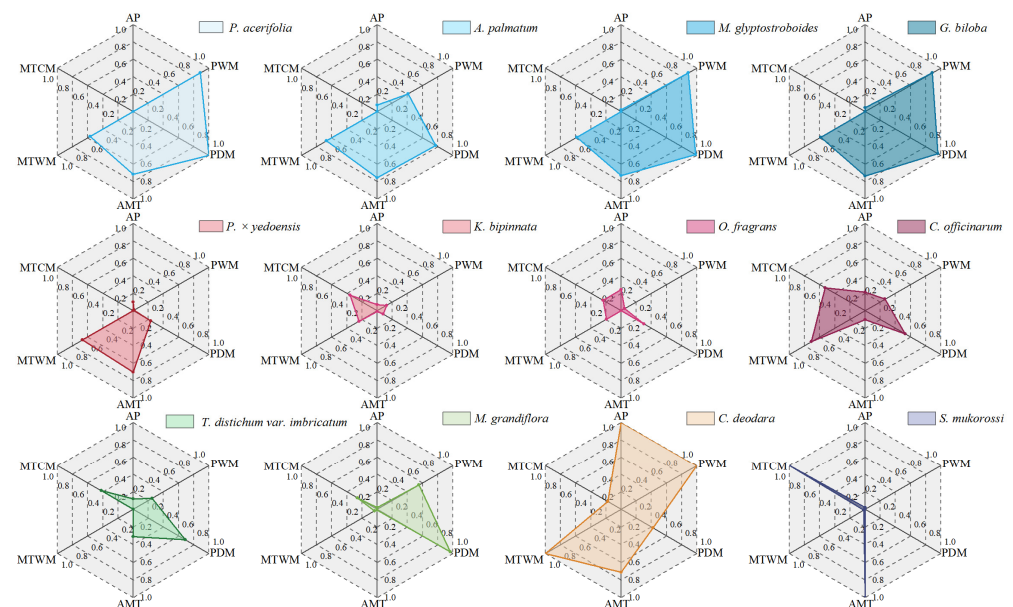


Figure 4. Radar plots of species' standardized risk values for various bioclimatic variables during the baseline period. Corresponding plots for the near future and distant future are provided in Supplementary Figures S3 and S4, respectively.

For the near-future and distant-future periods, the risk values of AMT (0.59 ± 0.06 , 0.60 ± 0.06), PDM (0.58 ± 0.05 , 0.57 ± 0.05), PWM (0.47 ± 0.05 , 0.47 ± 0.05), and MTWM (0.44 ± 0.05 , 0.44 ± 0.05) significantly exceeded those of MTCM (0.23 ± 0.04 , 0.21 ± 0.04) and AP (0.20 ± 0.04 , 0.26 ± 0.04) ($p < 0.05$), as shown in Figure 5. For temperature variables, AMT and MTCM, respectively, remained the highest and lowest risks for the majority of species (58.3%), while PDM and AP retained their positions as the precipitation factors with the highest and lowest risk, respectively, for most species, exhibiting considerable consistency with the baseline period.

Overall, among all bioclimatic variables, PDM and AMT represented the highest risks, spanning the baseline and projected future periods. Additionally, MTWM and PWM also exhibited significantly higher risks, suggesting intensifying extreme thermal and precipitation stresses. The species-specific risk values are detailed in Table 2.

Table 2. Species-specific risk values and risk growth rates for various bioclimatic variables.

Tree Species	Risk Characteristics	Period	Precipitation Variables (mm)			Comprehensive Precipitation Risk	Temperature Variables (°C)			Comprehensive Temperature Risk	Comprehensive Hydrothermal Risk
			AP	PWM	PDM (mm)		AMT	MTWM	MTCM		
<i>T. distichum</i> var. <i>imbricatum</i>	Risk value	B	201.50 (0.12)	108.45 (0.25)	49.20 (0.69)	0.74	2.55 (0.31)	5.00 (0.00)	9.20 (0.42)	0.53	0.91
		NF	137.57 (0.05)	142.01 (0.29)	46.96 (0.69)	0.75	1.50 (0.20)	5.34 (0.00)	8.05 (0.39)	0.44	0.87
		DF	201.27 (0.10)	154.66 (0.29)	46.61 (0.68)	0.75	0.79 (0.06)	5.73 (0.00)	7.63 (0.35)	0.36	0.83
	Risk growth rate	B-NF NF-DF	−0.32 0.44	0.31 0.12	−0.05 −0.01	0.01 0.00	−0.41 −0.46	0.07 0.08	−0.13 −0.05	−0.16 −0.18	−0.04 −0.04
<i>P. × yedoensis</i>	Risk value	B	194.60 (0.10)	78.85 (0.01)	23.20 (0.23)	0.25	5.05 (0.70)	8.90 (0.67)	1.60 (0.00)	0.97	1.00
		NF	137.48 (0.05)	103.01 (0.00)	20.96 (0.23)	0.24	6.09 (0.92)	9.24 (0.67)	1.67 (0.02)	1.14	1.17
		DF	209.61 (0.12)	115.66 (0.00)	20.61 (0.22)	0.25	7.10 (0.95)	9.63 (0.67)	2.19 (0.02)	1.16	1.19
	Risk growth rate	B-NF NF-DF	−0.29 0.55	0.31 0.19	−0.1 −0.01	−0.07 0.06	0.21 0.17	0.04 0.04	0.05 0.33	0.18 0.02	0.16 0.02
<i>P. acerifolia</i>	Risk value	B	166.10 (0.00)	188.45 (0.89)	67.20 (1.00)	1.34	5.16 (0.72)	8.30 (0.57)	1.55 (0.00)	0.92	1.62
		NF	249.92 (0.28)	222.01 (0.89)	64.96 (1.00)	1.37	6.20 (0.94)	8.64 (0.57)	1.47 (0.00)	1.10	1.76
		DF	339.90 (0.36)	234.66 (0.89)	64.61 (1.00)	1.39	7.21 (0.96)	9.03 (0.57)	2.01 (0.00)	1.12	1.78
	Risk growth rate	B-NF NF-DF	0.51 0.37	0.18 0.07	−0.03 −0.01	0.03 0.01	0.2 0.16	0.04 0.05	−0.05 0.39	0.20 0.02	0.08 0.02
<i>K. bipinnata</i>	Risk value	B	186.00 (0.07)	92.95 (0.12)	14.35 (0.08)	0.16	0.60 (0.01)	6.40 (0.24)	8.00 (0.36)	0.43	0.46
		NF	172.69 (0.12)	126.51 (0.18)	11.62 (0.07)	0.23	0.90 (0.10)	6.74 (0.24)	6.85 (0.32)	0.42	0.47
		DF	261.40 (0.21)	139.16 (0.18)	11.70 (0.06)	0.29	1.90 (0.20)	7.13 (0.24)	6.43 (0.28)	0.43	0.51
	Risk growth rate	B-NF NF-DF	−0.07 0.53	0.36 0.14	−0.19 0.02	0.41 0.26	0.51 1.36	0.05 0.06	−0.14 −0.06	−0.04 0.03	0.03 0.08
<i>M. grandiflora</i>	Risk value	B	171.60 (0.02)	146.45 (0.55)	65.20 (0.97)	1.11	0.62 (0.01)	5.20 (0.03)	6.30 (0.26)	0.27	1.14
		NF	142.30 (0.05)	180.01 (0.58)	62.96 (0.97)	1.13	0.53 (0.04)	5.54 (0.03)	5.15 (0.22)	0.23	1.15
		DF	227.17 (0.15)	192.66 (0.58)	62.61 (0.96)	1.14	1.48 (0.14)	5.93 (0.03)	4.73 (0.17)	0.24	1.16
	Risk growth rate	B-NF NF-DF	−0.17 0.6	0.23 0.09	−0.04 −0.01	0.01 0.01	−0.15 2.45	0.07 0.07	−0.18 −0.08	−0.14 0.05	0.01 0.01
<i>O. fragrans</i>	Risk value	B	237.55 (0.25)	83.45 (0.05)	27.20 (0.30)	0.39	0.55 (0.00)	6.10 (0.19)	5.80 (0.24)	0.30	0.50
		NF	122.38 (0.02)	117.01 (0.11)	24.96 (0.30)	0.32	1.38 (0.18)	6.44 (0.19)	4.65 (0.19)	0.32	0.46
		DF	144.02 (0.00)	129.66 (0.11)	24.61 (0.29)	0.31	2.39 (0.27)	6.83 (0.19)	4.23 (0.14)	0.37	0.48
	Risk growth rate	B-NF NF-DF	−0.49 0.2	0.4 0.16	−0.08 −0.01	−0.19 −0.04	1.51 0.79	0.06 0.06	−0.2 −0.09	0.07 0.13	−0.08 0.05

Table 2. Cont.

Tree Species	Risk Characteristics	Period	Precipitation Variables (mm)			Comprehensive Precipitation Risk	Temperature Variables (°C)			Comprehensive Temperature Risk	Comprehensive Hydrothermal Risk
			AP	PWM	PDM (mm)		AMT	MTWM	MTCM		
A. palmatum	Risk value	B	188.50 (0.08)	128.45 (0.41)	54.20 (0.77)	0.88	5.41 (0.76)	8.90 (0.67)	1.55 (0.00)	1.01	1.34
		NF	175.19 (0.12)	162.01 (0.44)	51.96 (0.77)	0.9	6.45 (0.98)	9.24 (0.67)	1.47 (0.00)	1.19	1.49
		DF	263.90 (0.22)	174.66 (0.44)	51.61 (0.77)	0.91	7.46 (1.00)	9.63 (0.67)	2.01 (0.00)	1.21	1.51
	Risk growth rate	B-NF NF-DF	−0.07 0.52	0.26 0.1	−0.04 −0.01	0.03 0.02	0.19 0.16	0.04 0.04	−0.05 0.39	0.17 0.02	0.11 0.02
M. glyptostroboides	Risk value	B	172.55 (0.02)	188.45 (0.89)	66.20 (0.98)	1.32	5.25 (0.73)	8.40 (0.59)	1.55 (0.00)	0.94	1.62
		NF	264.92 (0.31)	222.01 (0.89)	63.96 (0.98)	1.37	6.29 (0.95)	8.74 (0.59)	1.39 (0.00)	1.12	1.77
		DF	354.90 (0.39)	234.66 (0.89)	63.61 (0.98)	1.38	7.30 (0.98)	9.13 (0.59)	1.95 (0.00)	1.14	1.79
	Risk growth rate	B-NF NF-DF	0.54 0.35	0.18 0.07	−0.03 −0.01	0.03 0.01	0.2 0.16	0.04 0.05	−0.10 0.40	0.19 0.02	0.09 0.02
S. mukorossi	Risk value	B	172.60 (0.02)	77.50 (0.00)	9.85 (0.00)	0.02	6.97 (1.00)	5.10 (0.02)	19.60 (1.00)	1.41	1.41
		NF	142.30 (0.05)	106.01 (0.02)	7.74 (0.00)	0.06	5.93 (0.90)	5.44 (0.02)	18.45 (1.00)	1.34	1.35
		DF	226.42 (0.15)	118.66 (0.02)	8.53 (0.00)	0.15	4.92 (0.65)	5.83 (0.02)	18.03 (1.00)	1.20	1.21
	Risk growth rate	B-NF NF-DF	−0.18 0.6	0.37 0.18	−0.22 0.11	1.8 2.3	−0.15 −0.17	0.07 0.07	−0.06 −0.02	−0.05 −0.11	−0.05 −0.10
C. officinarum	Risk value	B	227.80 (0.21)	110.45 (0.26)	40.20 (0.53)	0.63	1.20 (0.10)	9.10 (0.71)	11.10 (0.53)	0.89	1.09
		NF	131.04 (0.03)	144.01 (0.31)	37.96 (0.53)	0.61	0.39 (0.02)	9.44 (0.71)	9.95 (0.50)	0.87	1.06
		DF	177.36 (0.06)	156.66 (0.31)	37.61 (0.52)	0.61	0.92 (0.06)	9.83 (0.71)	9.53 (0.47)	0.85	1.05
	Risk growth rate	B-NF NF-DF	−0.43 0.37	0.3 0.12	−0.06 −0.01	−0.03 −0.01	−0.67 1.98	0.04 0.04	−0.1 −0.04	−0.02 −0.02	−0.02 −0.01
C. deodara	Risk value	B	457.55 (1.00)	202.45 (1.00)	34.20 (0.42)	1.48	5.14 (0.71)	10.80 (1.00)	4.70 (0.17)	1.24	1.93
		NF	594.92 (1.00)	236.01 (1.00)	31.96 (0.42)	1.48	6.18 (0.94)	11.14 (1.00)	3.55 (0.13)	1.38	2.02
		DF	684.90 (1.00)	248.66 (1.00)	31.61 (0.41)	1.47	7.18 (0.96)	11.53 (1.00)	3.13 (0.07)	1.39	2.02
	Risk growth rate	B-NF NF-DF	0.3 0.15	0.17 0.06	−0.07 −0.01	0 0	0.2 0.16	0.03 0.04	−0.25 −0.12	0.11 0.01	0.05 0.00
G. biloba	Risk value	B	178.90 (0.04)	188.45 (0.89)	65.20 (0.97)	1.31	5.30 (0.74)	8.40 (0.59)	1.55 (0.00)	0.94	1.62
		NF	271.92 (0.32)	222.01 (0.89)	62.96 (0.97)	1.36	6.34 (0.96)	8.74 (0.59)	1.39 (0.00)	1.13	1.76
		DF	361.90 (0.40)	234.66 (0.89)	62.61 (0.96)	1.38	7.35 (0.98)	9.13 (0.59)	1.95 (0.00)	1.15	1.79
	Risk growth rate	B-NF NF-DF	0.52 0.34	0.18 0.07	−0.03 −0.01	0.03 0.02	0.2 0.16	0.04 0.05	−0.10 0.40	0.19 0.02	0.09 0.02

Note: Values in () denote standardized values of climate risks. B, NF, and DF represent the baseline period, the near future, and the distant future, respectively.

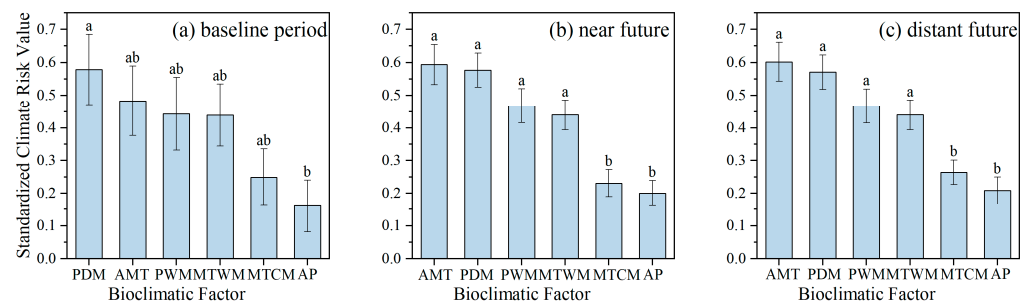


Figure 5. Variation in risk values among bioclimatic factors during three temporal periods: (a) baseline period (1981–2022), (b) near future (2023–2050), and (c) distant future (2051–2100). Different lowercase letters above bars indicate significant differences among groups as determined by one-way ANOVA followed by LSD post-hoc test at the $p < 0.05$ level.

3.3. Varied Climate Risk Growth Rates Among Species and Bioclimatic Variables

Significant interspecific variations were observed in the risk growth rates of comprehensive climatic variables during the transitions from baseline to near future (B-NF) and from near future to distant future (NF-DF) ($p < 0.05$), as shown in Figure 6.

The growth patterns of comprehensive temperature risk varied markedly among species. During B-NF transitions, 58.3% of species exhibited increased risks, with *P. acerifolia*, *M. glyptostroboides*, and *G. biloba* showing significantly higher growth rates (0.20–0.19) than *M. grandiflora* and *T. distichum* (−0.14 and −0.16) ($p < 0.05$). The proportion of species with rising risks increased to 75% during the NF-DF transition, with *O. fragrans* demonstrating the highest growth rate (0.13) compared to *S. mukorossi* and *T. distichum* (−0.11 and −0.18) ($p < 0.05$).

For comprehensive precipitation risk, 66.7% and 75% of studied species showed increased risks during B-NF and NF-DF transitions, respectively. Notably, *S. mukorossi* consistently exhibited exceptionally high growth rates (1.80, 2.30) during both transition periods, significantly exceeding all other species (−0.19 to 0.41) ($p < 0.05$). Regarding comprehensive hydrothermal risk, 66.7% of species showed increased risks during both transition periods. During B-NF transitions, *P. × yedoensis* led with the highest growth rate (0.16) compared to *O. fragrans*, *S. mukorossi*, and *T. distichum* (−0.08 to −0.04) ($p < 0.05$). During NF-DF transitions, *K. bipinnata* and *O. fragrans* exhibited the highest risk growth rates (0.08 and 0.05) versus *S. mukorossi* (−0.10) ($p < 0.05$).

These findings suggest that over half of the studied species will face increasing climate risks in the future, exhibiting distinct risk change patterns. Moreover, several species displayed significantly varied risk growth rates between B-NF and NF-DF transitions ($p < 0.05$). For instance, the comprehensive hydrothermal risk accelerated in the NF-DF transition compared to the B-NF transition for low-risk species (*K. bipinnata* and *O. fragrans*), while high-risk species (*G. biloba*, *M. glyptostroboides*, and *C. deodara*) showed the opposite pattern.

Risk growth rates also varied significantly among bioclimatic variables. During both transition periods, AMT and MTCM consistently represented the temperature variables with the highest and lowest risk growth rates, respectively, for most species ($p < 0.05$). Among precipitation factors, PWM and AP alternately dominated the highest risk growth between B-NF and NF-DF transitions, while PDM consistently exhibited the weakest risk growth. The species-specific risk growth rates are detailed in Table 2.

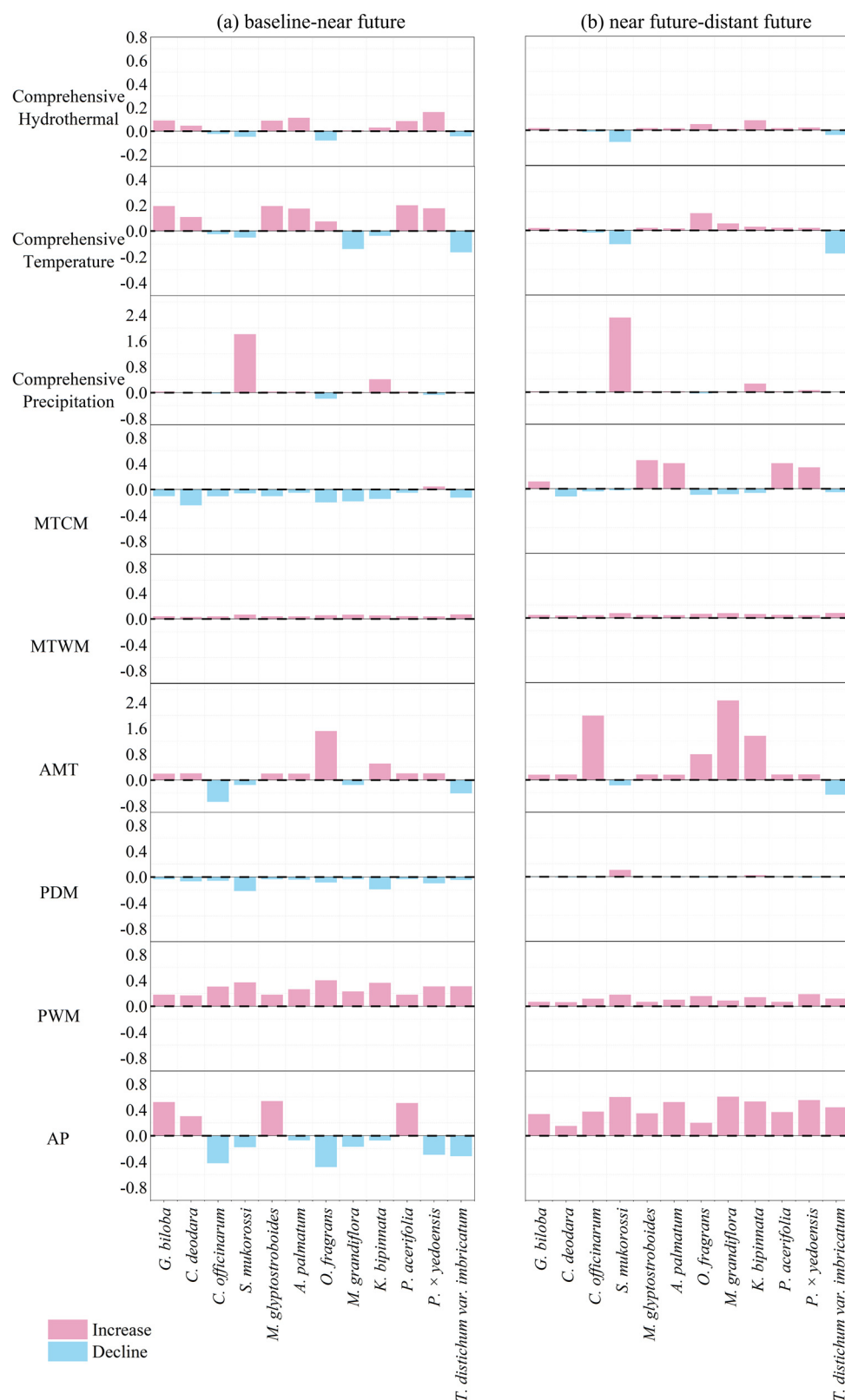


Figure 6. The species-specific risk growth rates for various bioclimatic variables during the (a) baseline-near future transition and (b) near future-distant future transition.

3.4. Determinants of Interspecific Variation in Climate Risk Characteristics

3.4.1. Influence of Species' Geographic Distribution

Pearson correlation analyses and linear regression were employed to assess how latitudinal, longitudinal, and altitudinal coordinates of species' geographic distribution

centroids affect their climate risk values and growth rates. Of these factors, latitude and elevation showed significant correlations with species' climate risk parameters ($p < 0.05$), with latitude demonstrating stronger effects, as shown in Figure 7 and Table 3.

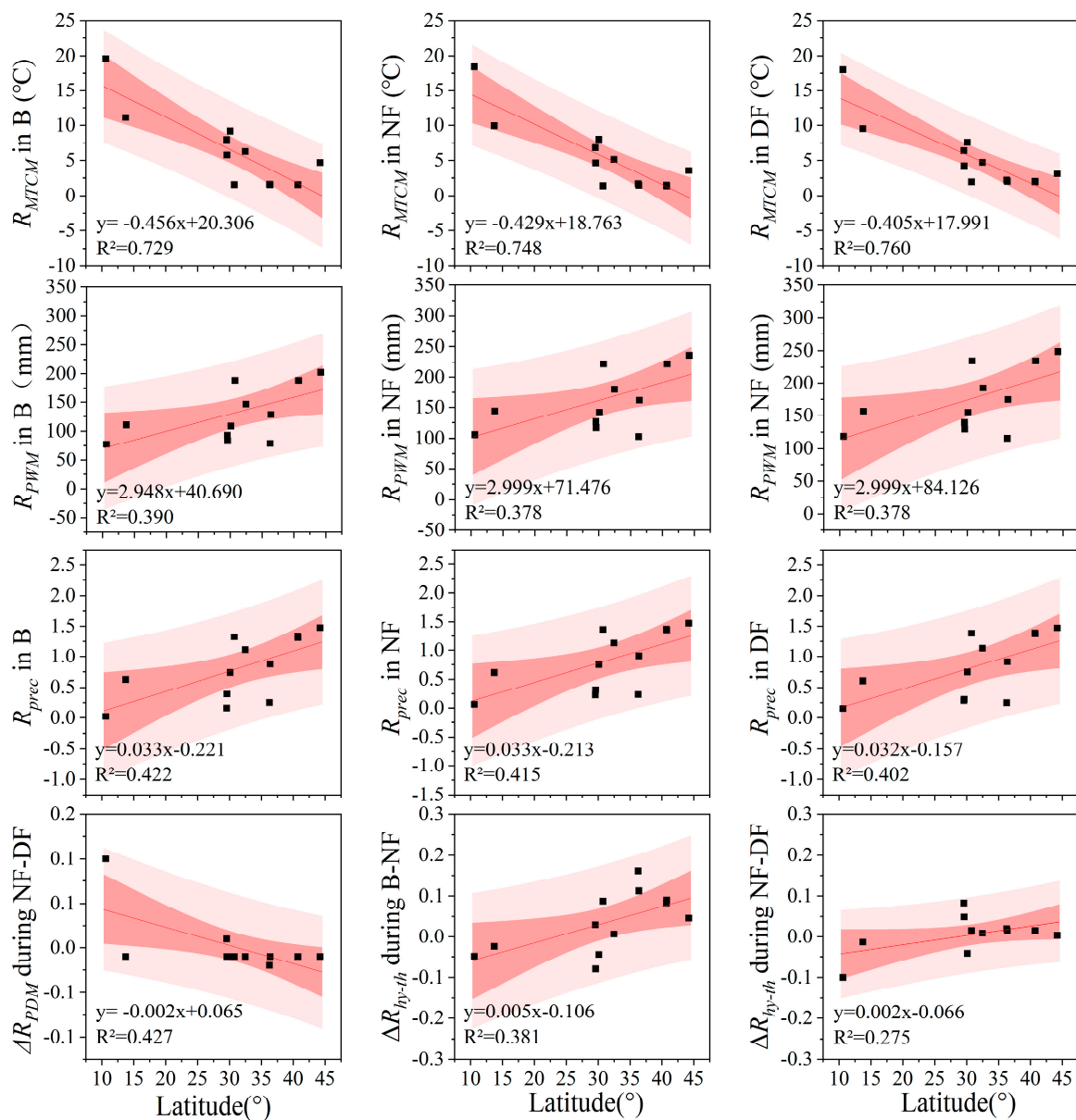


Figure 7. Linear regression between the latitudes of species' distribution centroids and their climate risk parameters, showing significant correlations. B, NF, and DF represent the baseline period, the near future, and the distant future, respectively. R_{MTCM} , R_{PWM} , and R_{prec} represent the MTCM, PWM, and comprehensive precipitation risk value, respectively, while ΔR_{PDM} and ΔR_{hy-th} represent the PDM and comprehensive hydrothermal risk growth rate, respectively.

Latitude significantly influenced both temperature and precipitation risks. For temperature variables, latitude exhibited significant negative correlations with MTCM risk values across all temporal periods ($r = -0.86 \pm 0.01$, $p < 0.05$). For precipitation, latitude showed significant positive correlations with AP risk in the distant future ($r = 0.60$, $p < 0.05$), and with PWM and comprehensive precipitation risks across all periods ($r = 0.62 \pm 0.01$, 0.64 ± 0.01 , $p < 0.05$). These findings indicate that lower-latitude species face greater cold temperature stress but reduced precipitation risk compared to higher-latitude species. By comparison, elevation effects were primarily related to precipitation. Elevation of species'

distribution centroids demonstrated significant positive correlations with AP risk values across all temporal periods ($r = 0.62 \pm 0.04$, $p < 0.05$), suggesting that species from higher elevations are more vulnerable to precipitation stress in Wuhan's climate.

Table 3. Pearson correlation coefficients between geographic factors of species' distribution centroids and the climate risk characteristics for various bioclimatic variables.

Geographic Factors	Risk Characteristics	Period	AP (mm)	PWM (mm)	PDM (mm)	AMT (°C)	MTWM (°C)	MTCM (°C)	Comprehensive Precipitation Risk	Comprehensive Temperature Risk	Comprehensive Hydrothermal Risk
Latitude	Risk value	B	0.31	0.62 *	0.47	0.18	0.46	−0.85 **	0.65 *	−0.08	0.33
		NF	0.56	0.62 *	0.46	0.41	0.46	−0.87 **	0.64 *	0.12	0.43
		DF	0.58 *	0.62 *	0.46	0.54	0.46	−0.87 **	0.63 *	0.21	0.49
	Risk growth rate	B-NF	0.56	−0.64 *	0.53	0.34	−0.46	−0.12	−0.62 *	0.54	0.62 *
		NF-DF	−0.35	−0.57 *	−0.64 *	−0.18	−0.46	0.41	−0.63 *	0.36	0.53
Longitude	Risk value	B	0.08	−0.32	−0.33	−0.18	0.39	−0.26	−0.32	−0.05	−0.37
		NF	−0.13	−0.32	−0.33	−0.04	0.39	−0.26	−0.34	0.02	−0.30
		DF	−0.17	−0.32	−0.33	0.07	0.39	−0.27	−0.36	0.08	−0.25
	Risk growth rate	B-NF	−0.27	0.31	−0.10	0.38	−0.47	0.15	−0.30	0.35	0.25
		NF-DF	−0.17	0.31	−0.33	0.19	−0.46	0.12	−0.27	0.47	0.52
Elevation	Risk value	B	0.66 *	0.12	−0.44	−0.18	0.24	0.02	0.00	−0.01	−0.06
		NF	0.60 *	0.12	−0.44	−0.09	0.24	−0.02	0.01	−0.02	−0.06
		DF	0.59 *	0.12	−0.45	−0.02	0.24	−0.07	0.02	0.00	−0.04
	Risk growth rate	B-NF	0.12	0.00	−0.39	0.26	−0.18	−0.55	0.02	−0.07	−0.01
		NF-DF	−0.27	−0.09	−0.06	0.16	−0.18	−0.45	−0.02	0.18	0.41

* $p < 0.05$, ** $p < 0.01$. B, NF, and DF represent the baseline period, near future, and far future, respectively. The color bar indicates the magnitude and direction of the correlation coefficient (r). Red indicates a positive correlation, while blue indicates a negative correlation. The color intensity varies proportionally with the absolute value of the correlation coefficient.

Risk growth patterns also varied with species' geographic distribution. Specifically, species from lower latitudes exhibited significantly higher PDM risk growth rates during the NF-DF transition ($r = -0.64$, $p < 0.05$). Conversely, latitude showed a positive correlation with the growth rates of comprehensive hydrothermal risks during the B-NF transition ($r = 0.62$, $p < 0.05$), indicating that lower-latitude species will experience more moderate increases in overall hydrothermal stress in the future.

Additionally, native versus exotic status showed no significant influence. No statistically significant differences were found between native and exotic species in either climate risks or risk growth rates, suggesting that biogeographic origin relative to China does not significantly affect species' climate vulnerability in Wuhan.

3.4.2. Influence of Species' Functional Traits

Pearson correlations revealed that species' climate risk values were significantly affected by four key functional traits, as detailed in Table 4: the xylem vulnerability threshold (P50), wood density (WD), specific leaf area (SLA), and leaf dry matter content (LDMC) ($p < 0.05$). Temperature-related risks showed distinct associations with leaf morphological traits. SLA demonstrated consistent positive correlations with AMT risk values across all temporal periods ($r = 0.62 \pm 0.01$, $p < 0.05$), with an explanatory power (R^2) of 0.325 ± 0.016 . LDMC emerged as a stronger predictor of temperature risks, exhibiting robust positive correlations with MTWM risks across all periods ($r = 0.61 \pm 0.00$, $R^2 = 0.372 \pm 0.01$, $p < 0.05$).

Precipitation-related risks were primarily governed by hydraulic and structural traits. P50 showed significant negative correlations with AP risk across all periods and comprehensive precipitation risk in the near future ($r = -0.67 \pm 0.04$, -0.41 , $p < 0.05$), indicating that species with more vulnerable xylem face greater precipitation stress. Similarly, WD negatively influenced precipitation risks, with significant correlations with PDM risk values across all periods and comprehensive precipitation risk in the distant future ($r = -0.63 \pm 0.00$, -0.60 , $p < 0.05$). The explanatory power of functional traits for precipitation risks reached a maximum of 0.4, considerably weaker than that for temperature risks. Additionally, comprehensive hydrothermal risks were jointly affected by leaf morphology

and hydraulic traits, with WD as the primary determinant during the baseline period ($r = -0.38$, $R^2 = 0.102$, $p < 0.05$) and P50 becoming more influential in the near future ($r = -0.59$, $R^2 = 0.282$, $p < 0.05$).

Table 4. Pearson correlation coefficients between species' functional traits and the climate risk characteristics for various bioclimatic variables.

Traits Factors	Risk Characteristics	Period	AP (mm)	PWM (mm)	PDM (mm)	AMT (°C)	MTWM (°C)	MTCM (°C)	Composite Precipitation Risk	Composite Temperature Risk	Composite Hydrothermal Risk
P50	Risk value	B	−0.63 *	−0.51	−0.01	−0.34	−0.52	−0.11	−0.41	−0.57	−0.65
		NF	−0.71 *	−0.51	−0.01	−0.33	−0.52	−0.10	−0.41 *	−0.55	−0.59 *
		DF	−0.68 *	−0.51	−0.01	−0.33	−0.52	−0.10	−0.41	−0.56	−0.57
	Risk growth rate	B-NF	−0.4	0.41	−0.05	0.08	0.45	0.42	−0.15	−0.26	0.06
		NF-DF	0.57	0.43	−0.17	0.05	0.45	0.09	−0.14	−0.09	0.23
WD	Risk value	B	0.08	−0.54	−0.63 *	−0.13	−0.29	0.45	−0.57	−0.02	−0.38 *
		NF	−0.24	−0.54	−0.63 *	−0.15	−0.29	0.45	−0.6	−0.10	−0.43
		DF	−0.31	−0.54	−0.62 *	−0.19	−0.29	0.43	−0.60 *	−0.13	−0.46
	Risk growth rate	B-NF	−0.47	0.67 *	−0.52	0.54	0.27	−0.10	0.37	−0.08	−0.53
		NF-DF	−0.18	0.59 *	0.41	0.06	0.27	−0.41	0.44	−0.27	−0.09
SLA	Risk value	B	−0.41	0.24	0.32	0.61 *	0.29	−0.31	0.18	0.46	0.4
		NF	−0.05	0.22	0.32	0.63 *	0.29	−0.25	0.21	0.55	0.46
		DF	0.03	0.22	0.33	0.62 *	0.29	−0.19	0.23	0.56	0.46
	Risk growth rate	B-NF	0.46	−0.32	0.11	−0.1	−0.35	0.66 *	0.13	0.57	0.58
		NF-DF	0.24	−0.21	0.13	−0.37	−0.35	0.76 **	0.11	−0.05	−0.05
LA	Risk value	B	−0.27	0.31	0.39	0.07	0.01	−0.23	0.29	−0.05	0.20
		NF	−0.02	0.31	0.38	0.12	0.01	−0.21	0.30	0.01	0.21
		DF	0.01	0.31	0.39	0.16	0.01	−0.20	0.31	0.04	0.23
	Risk growth rate	B-NF	−0.38	−0.22	0.17	−0.74	−0.65	0.04	−0.11	−0.86	−0.55
		NF-DF	0.46	−0.32	0.11	−0.10	−0.35	0.66	0.13	0.57	0.58
LT	Risk value	B	−0.19	−0.16	0.01	−0.30	−0.5	0.27	−0.13	−0.36	−0.35
		NF	−0.22	−0.14	0.01	−0.42	−0.5	0.25	−0.11	−0.44	−0.39
		DF	−0.21	−0.14	0.01	−0.52	−0.5	0.23	−0.11	−0.50	−0.40
	Risk growth rate	B-NF	−0.15	0.23	−0.10	−0.24	0.43	−0.11	0.05	−0.55	−0.39
		NF-DF	0.19	0.05	0.04	−0.23	0.53	−0.28	−0.01	−0.62 *	−0.1
LDMC	Risk value	B	0.48	0.44	0.06	−0.05	0.61 *	−0.07	0.35	0.26	0.36
		NF	0.55	0.44	0.05	0.00	0.61 *	−0.08	0.36	0.27	0.35
		DF	0.54	0.44	0.05	0.09	0.61 *	−0.10	0.36	0.31	0.37
	Risk growth rate	B-NF	0.31	−0.41	0.06	−0.24	−0.59 *	−0.33	−0.13	0.14	0.16
		NF-DF	−0.31	−0.47	−0.15	0.40	−0.51	−0.11	−0.18	0.22	0.20

* $p < 0.05$, ** $p < 0.01$. SLA, specific leaf area; LDMC, leaf dry matter content; P50, xylem vulnerability threshold; WD, wood density; LA, leaf area; LT, leaf thickness. B, NF, and DF represent the baseline period, near future, and far future, respectively. The color bar indicates the magnitude and direction of the correlation coefficient (r). Red indicates a positive correlation, while blue indicates a negative correlation. The color intensity varies proportionally with the absolute value of the correlation coefficient.

Similarly, risk growth rates correlated significantly with the functional traits of WD, SLA, LT, and LDMC ($p < 0.05$). For temperature-related risks, LDMC showed a significant negative correlation with the risk growth rates of MTWM during the B-NF transition ($r = -0.59$, $R^2 = 0.352$, $p < 0.05$). LT demonstrated a negative correlation with the growth rates of comprehensive temperature risk during NF-DF transition ($r = -0.62$, $R^2 = 0.300$, $p < 0.05$). With a higher R^2 of 0.456 ± 0.109 , SLA demonstrated significant positive correlations with MTCM risk growth rates ($r = 0.71 \pm 0.07$, $p < 0.05$). For precipitation-related risks, WD showed significant positive correlations with PWM risk growth rates ($r = 0.63 \pm 0.05$, $p < 0.05$) with R^2 of 0.339 ± 0.076 .

These results collectively indicate that functional traits serve as key determinants of species-specific climate risk patterns. Species with lower WD and P50 demonstrated more pronounced precipitation risks but slower risk growth in the future, while those with higher SLA and LDMC face more intense temperature risks over time. Notably, no significant correlations were found between geographic factors (latitude, longitude, and elevation) of species' distribution centroids and their functional traits, suggesting that functional trait influences on risk patterns operate independently of biogeographic origin.

4. Discussion

4.1. Hydrothermal Change Trends and Key Climate Risk Factors in Wuhan

Our results revealed a significant warming trend during 1981–2022 in Wuhan, while precipitation showed no significant change, consistent with climate change patterns reported for the middle and lower Yangtze River region during 1961–2022 [36]. Climate projections indicate that both temperature and precipitation in Wuhan will increase significantly by the end of this century, with temperature rises being more pronounced, continuing historical trends. This finding aligns with previous research projecting significant future warming across China [37,38] and increases in both temperature and precipitation across the Yangtze River region during the 21st century, though precipitation increases remain more limited [39]. Such trends reflect the severe climate challenges facing Wuhan, posing continued threats to natural ecosystems, including urban forests.

Building on the climate trend analysis, this study identified distinct risk hierarchies among climatic variables. PDM (precipitation of the driest month) emerged as the most prominent precipitation risk factor, highlighting significant drought challenges under both current and future climates. This finding is consistent with extensive research identifying drought as a critical threat to tree survival [5,40,41]. Regarding temperature variables, AMT (annual mean temperature) and MTWM (maximum temperature of the warmest month) exhibited significantly higher risks than MTCM (minimum temperature of the coldest month), suggesting that elevated temperatures, particularly extreme dry heat, will pose substantial threats to tree growth. These results align with broader research demonstrating that climate extremes, particularly heat and drought, present persistent challenges to global forest ecosystems [18,42,43].

As global warming intensifies both the frequency and severity of extreme heat and drought events [44,45], existing vegetation becomes increasingly susceptible to severe damage or mortality [11–13]. Moreover, distinctive urban environments further amplify these climate risks. Heat island effects cause urban temperatures to be 2–5 °C higher than surrounding areas, significantly intensifying heat stress [14]; meanwhile, soil pollution and compaction limit root development and water uptake capacity, aggravating trees' hydraulic failure [15]. This warming and drying urban microclimate forms compound pressures with global climate change, which must be comprehensively considered in species selection and management strategy formulation.

4.2. Interspecific Differences in Trees' Climate Risk Characteristics

Our study revealed substantial interspecific variation in climate risk values and risk growth rates among the studied tree species. Among high-risk species, *C. deodara* faces the highest comprehensive temperature, precipitation, and hydrothermal risks across all temporal periods. Three additional species—*P. acerifolia*, *M. glyptostroboides*, and *G. biloba*—also demonstrate prominent hydrothermal risks, along with the steepest temperature risk increases from baseline to near-future periods. These findings align with previous research documenting heightened climate sensitivity in these taxa [46–48], suggesting that these species will experience progressively intensifying thermal stress in Wuhan and climatically similar cities.

At the opposite end of the risk spectrum, *K. bipinnata* and *O. fragrans* consistently exhibit the lowest risk values across all climate dimensions in current and future scenarios. This finding corroborates Liu and Zhang [3], who similarly documented lower climatic stress in these species under comparable conditions, reinforcing their apparent suitability for the middle and lower reaches of the Yangtze River region. However, despite their currently favorable risk profiles, both species show pronounced climate risk growth in future projections, indicating that anticipated shifts in hydrothermal conditions may significantly

challenge their adaptive capacity in coming decades. The illustrated interspecific variations in climate risks provide an important scientific basis for species selection in resilient urban forest development.

4.3. Factors Influencing Interspecific Differences in Climate Risk

Our analysis revealed significant correlations between species' climate risk characteristics and the latitude of their geographic distribution centroids. Species of lower latitudinal origin demonstrated higher risks facing low-temperature stress while exhibiting lower precipitation-related risks compared to their higher-latitude counterparts, corroborating recent findings by Cunha et al. [49] and Xu et al. [25]. This differential risk pattern reflects the evolutionary adaptation of low-latitude taxa to warm, humid climate regimes, rendering them inherently more susceptible to cold temperatures below their physiological thresholds. Their lower precipitation risks likely stem from morphological and physiological adaptations including extensive root architecture and optimized hydraulic efficiency, developed through prolonged exposure to their native environments [50,51]. Additionally, species from lower latitudes showed attenuated increases in comprehensive hydrothermal risk under future climate projections, attributed to the compatibility between their evolutionary background in warm, humid environments and anticipated climatic trajectories of increasing temperature and precipitation. Their hydrothermal regulation capacity is expected to remain effective under future climate conditions [52], rendering them more climate-resilient with minimal risk escalation.

This study also revealed close associations between species' climate risks and their functional traits. Although these plant functional traits have been primarily studied in natural ecosystems, they become critical indicators for assessing urban tree responses and predicting their survival capacity under the intensified compound stresses of urban environments, including heat island effects, soil compaction, and air pollution [53,54]. Specifically, precipitation risk was predominantly influenced by wood density (WD) in a negative way, with high-WD species facing lower drought risks, consistent with previous findings [24,32,55,56]. The underlying mechanism involves denser xylem structure in high-WD species, which facilitates reduced water loss and enhanced water-use efficiency under drought conditions [57–60].

Temperature risk, on the other hand, was primarily affected by leaf dry matter content (LDMC). Species with low LDMC exhibited lower increase trends in heat risk, aligning with the observations by Tabassum et al. [12] on Australian perennial vegetation. This adaptive advantage appears related to the deciduous nature of many low-LDMC species, which utilize leaf senescence as a water conservation strategy under extreme thermal stress [61,62]. However, Poorter and Markesteijn [63] reported opposing correlations in humid tropical forests, where high-LDMC species showed stronger heat tolerance. They linked this phenomenon to the reinforced cellular architecture characteristic of dense-leaved taxa, which offers greater structural defense against moisture depletion under extreme temperatures. These contradictory outcomes largely originate from disparities in climatic environments and species taxonomic composition across research locations, emphasizing the importance of conducting region-, climate-, and species-specific investigations to elucidate trees' heat risk and adaptation mechanisms.

Besides LDMC, specific leaf area (SLA) also showed a correlation with species' temperature risk, with low-SLA species facing weaker low-temperature risk, corroborating findings by Zhao and Dixon [64]. They noted that low-SLA taxa typically develop thicker and denser leaf structures with higher organic matter concentrations, enabling greater thermal absorption and retention capacities. Their well-developed palisade mesophyll

effectively reduces internal heat loss, collectively strengthening leaf thermal insulation under cold conditions and achieving risk mitigation [65].

Surprisingly, we found no significant correlations between species' geographic distribution centroids and their functional traits, contrasting with previous studies documenting close biogeography–trait relationships [66–69]. This discrepancy may arise from several factors. First, distribution centroids may inadequately capture environmental complexity across species' ranges. Second, functional traits are influenced by multiple factors beyond climatic origin, including biotic interactions and local environmental conditions in new habitats [70,71]. Additionally, the trait data derived from the TRY database may have geographic coverage limitations that affect trait representativeness for widely distributed species. Future research should integrate more comprehensive geographic and trait datasets to better elucidate the combined effects of biogeography and functional traits on species' climate vulnerability, providing stronger scientific basis for predicting and screening climate-resilient species.

4.4. Practical Implications for Urban Tree Species Selection and Management

Based on the revealed species-specific climate risk patterns and influencing factors, this study provides some practical guidance for climate-resilient species selection and management in cities across the middle and lower Yangtze River basin.

Given that drought and heat emerge as the most prominent climate threats across baseline and future periods, species with strong drought-heat adaptive capacity are recommended in urban environments, especially in heat-island areas, such as *K. bipinnata* and *O. fragrans*. The associations between species' functional traits, geographic origin, and climate risks revealed in this research provide relevant screening criteria for numerous unstudied local species and potential future introductions. For climate-resilient urban forests, priority is suggested for trees with high wood density (enhanced drought resistance) and low leaf dry matter content (improved heat tolerance). Additionally, species of low-latitude origin, which demonstrate higher hydrothermal adaptability under projected climate scenarios, should also be prioritized.

For high-risk species, such as *C. deodara*, *P. acerifolia*, *M. glyptostroboides*, and *G. biloba*, we recommend a hierarchical management strategy. New plantings in highly urbanized areas should be limited, with site selection carefully evaluated. Meanwhile, intensive maintenance should be implemented for existing trees, including supplemental irrigation and shading during heatwave events.

Considering the complexity of urban environments, species' selection and management require comprehensive consideration of urban-specific conditions such as urban heat islands, soil quality, surface characteristics, and anthropogenic disturbances. In addition, establishing long-term monitoring and assessment networks is crucial for validating these strategies. Dynamic assessment of tree health, growth performance, and ecosystem services is recommended, with evidence-based adaptive management to ensure continued ecological benefits under climate change.

4.5. Limitations and Future Perspectives

Although this study provides scientific evidence for climate-adaptive tree species selection in Wuhan and climatically analogous cities, several limitations remain. First, this study considered only temperature and precipitation variables, while other climate risk factors such as extreme weather events (windstorm, etc.) may also influence species' climate adaptability, requiring a more comprehensive climate indicator system in future research.

Second, the analysis was limited to twelve common urban tree species, which may not fully capture the species diversity in climate response and community-level ecological

resilience of urban forests. Furthermore, while the study focused on the central urban area, the comprehensive effects of urban microclimates (such as urban heat islands and wind corridors), artificial habitats (such as limited growth space and impervious surfaces), and anthropogenic disturbances (such as vandalism and maintenance practices) on tree species performance warrant further investigation. Future work will incorporate urban microclimate data and specific habitat conditions into species risk assessments to better capture the compound challenges of urban environments and climate change on tree survival.

5. Conclusions

This study systematically assessed the climate risk characteristics and determinants of 12 common urban tree species in Wuhan across baseline, near-future, and distant-future periods. Our comprehensive analysis revealed several key findings.

Firstly, regarding climate trends and risk factors, Wuhan experienced significant warming during the baseline period with continued warming and increased precipitation projected for the future. Among bioclimatic variables, PDM, AMT, and MTWM emerged as prominent risk factors, indicating intensifying thermal and drought stresses for urban trees. Secondly, the climate risk profiles varied significantly among studied species, with *C. deodara*, *P. acerifolia*, *M. glyptostroboides*, and *G. biloba* facing the most pronounced hydrothermal risks, while *K. bipinnata* and *O. fragrans* showed the lowest current risks but significant risk increases projected for the long term. Thirdly, in terms of the risk determinants, species' geographic distribution and functional traits significantly influenced climate risk patterns. Lower-latitude species demonstrated lower hydrothermal risk growth rates. Hydraulic traits (WD and P50) negatively correlated with precipitation-related risks, while leaf morphological traits (LDMC and SLA) showed positive associations with certain temperature risks.

These findings provide scientific foundations for climate-adaptive species selection and management for urban forests in central China. For resilient species application, priority should be given to currently low-risk species (*K. bipinnata* and *O. fragrans*) while monitoring their future risk dynamics. Based on revealed risk determinants, broader species selection should consider taxa with favorable functional trait combinations. For high-risk species (*C. deodara*, *P. acerifolia*, *M. glyptostroboides*, and *G. biloba*), careful application and enhanced adaptive management are necessary.

While this study advances our understanding of climate risks for urban trees and provides valuable practical insights, several limitations require future attention, including incomplete climate factor coverage, limited species sampling, and insufficient consideration of urban environmental complexities. Continued research is essential to further reveal species-specific comprehensive climate risks and underlying mechanisms in complicated urban settlements, thereby enabling better guidance for resilient urban forest development under escalating climate challenges.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/f16081358/s1>, Figure S1: Interannual trends of hydrothermal variables in Wuhan during the baseline period (1981–2022); Figure S2: Interannual trends of projected hydrothermal variables in Wuhan under various emission scenarios in the near future (2023–2050); Figure S3: Radar plots of species standardized risk values for various bioclimatic variables in the near future (2023–2050); Figure S4: Radar plots of species standardized risk values for various bioclimatic variables in the distant future (2051–2100); Table S1: Functional traits of tree species; Table S2: List of Abbreviations.

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and collected data. L.Z. (Li Zhang) and S.L. analyzed and interpreted data. S.W. and L.Z. (Lu Zhou) prepared visualizations. X.X. and S.L. critically reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

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