forests

Article

Uncovering Seasonal Heterogeneity in Forest Ecosystem Valuation: Evidence from a Meta-Analysis with Experimental Insights

Chulhyun Jeon [1,2,*] and Danny Campbell [2]

[1] National Institute of Forest Science, Korea Forest Services, Seoul 02455, Republic of Korea
[2] Economics Division, Stirling Business School, University of Stirling, Stirling FK9 4LA, UK; danny.campbell@stir.ac.uk
* Correspondence: ecoecon@korea.kr; Tel.: +82-02-961-2812

Abstract

Seasonal variation not only influences the ecological functioning of forest ecosystems but also alters the benefits people derive from them, ranging from physical to psychological restoration. Ignoring such variation in valuation risks, thereby producing seasonally biased and unreliable estimates, constitutes an issue that previous valuation studies have largely overlooked. This study investigates the extent of seasonal bias in willingness to pay (WTP) for forest ecosystem services using a meta-dataset of 476 observations from Korea. Applying pooled, weighted, and robust mixed-effects models, we uncovered substantial seasonal heterogeneity through our analysis: WTP increases by 67% in autumn but declines by 18% and 65% in the summer and winter, respectively. The robust mixed-effects model provided the best empirical fit, highlighting the methodological value of explicitly modeling temporal effects in meta-regression. These results reflect seasonally differentiated engagement with forests and suggest that individuals implicitly recognize the temporal value of ecosystem services. Nevertheless, limitations remain, particularly the heterogeneity of research designs, survey methods, and elicitation formats, which may introduce variability and potential bias. Therefore, while seasonal differences are statistically significant, the results should be interpreted with caution. Extrapolating annual values from single-season data risks systematic distortion, especially when stated preference methods are used. Beyond methodological implications, the findings also underscore a broader point: seasonal rhythms shape not only ecosystem dynamics but also human well-being. Accurately valuing these shifting benefits is essential for making credible economic assessments and sustaining long-term reciprocity between people and nature.

Keywords: seasonal preferences; forest ecosystem services; meta-analysis; willingness to pay; robust mixed-effects models

check for updates

Academic Editors: Juan Manuel Torres-Rojo, Adan L. Martinez-Cruz and Gustavo Perez-Verdin

Received: 6 August 2025
Revised: 13 September 2025
Accepted: 19 September 2025
Published: 24 September 2025

Citation: Jeon, C.; Campbell, D. Uncovering Seasonal Heterogeneity in Forest Ecosystem Valuation: Evidence from a Meta-Analysis with Experimental Insights. *Forests* **2025**, *16*, 1508. https://doi.org/10.3390/f16101508

1. Introduction

Healthy forest ecosystems deliver a vast array of direct and indirect benefits to human societies. Representing over 60% of the Earth's total biomass and storing more than half of global carbon stocks, forests provide crucial provisioning, regulatory, cultural, and support services [1–6]. However, the value and perception of these ecosystem services are not static—they are deeply influenced by seasonal dynamics. Seasonal variation—driven by the Earth's axial tilt and orbital rotation—is a fundamental ecological force that shapes both the supply and of ecosystem services and humans' experiences relating to them [7,8].

Across the spring, summer, autumn, and winter, ecosystems exhibit cyclical changes in biophysical characteristics such as vegetation cover, biodiversity, and resource availability. These natural cycles, in turn, affect human engagement with forests, influencing outdoor recreational use, cultural activities, mental well-being, and responses to environmental externalities [9–12]. Recognizing and incorporating these seasonal patterns are essential for capturing the true economic and experiential value of forest ecosystem services. A failure to account for seasonality may result in undervaluation or misrepresentation, ultimately weakening the foundation for equitable, time-sensitive, and sustainable forest management strategies [13,14].

Forest ecosystems in Korea, a country in the Northern Hemisphere, provide seasonally dependent public services and functions, covering more than 64% of the country's land area [15,16]. The sustained delivery of these services is critical to public well-being [17,18]. According to the National Institute of Forest Science and the Korea Forest Service (2023) [15], Korean forests contribute to 12 major ecosystem functions—including carbon sequestration, recreation, and landscape esthetics—generating an estimated annual value of approximately KRW 259 trillion (or, as of 2020, approximately USD 224 billion) [15,19]. Despite these substantial benefits, the valuation of forest ecosystem services in Korea exhibits significant seasonal variation [19]. Korea's distinct four-season climate—characterized by hot, humid summers (June–August) and cold, dry winters (November–February)—results in marked differences in recreational use and tourism demand [20,21]. During the summer, vacationers flock to coastal and forested regions to escape the heat, while vibrant autumn foliage attracts large numbers of visitors to mountainous areas [22,23]. In the winter, recreational preferences shift toward snow-based activities, particularly in ski resorts. These seasonal patterns influence not only outdoor recreation behavior but also the perceived esthetic and cultural value of forest landscapes [9,10].

Previous research on forest ecosystem benefits primarily examined recreational values, public goods, biodiversity conservation, and the valuation of protected areas [22]. This research focuses on Korea's high engagement in mountain-related activities, with an estimated 23 million annual visits for hiking, camping, healing, and outdoor pursuits [15]. The 2023 National Travel Survey (allowing multiple responses) found that the most common travel activities in Korea included nature and landscape appreciation (78.3%), rest and relaxation (60.8%), food tourism (60.2%), visiting family and friends (13.7%), and historical-site exploration (7.7%) [20]. These results highlight a strong national preference for nature-based recreation. Analysis of domestic travel experience rates (2019–2023, excluding 2020–2021 because of COVID-19 disruptions) reveals further seasonal trends. The highest travel experience rates were recorded in the fall (53.7%), followed by the summer (51.8%), winter (51.0%), and spring (50.2%). The lowest travel participation occurred in colder months such as March 2022 (41.9%), February 2023 (46.6%), and January 2019 (48.1%), while peak travel was observed in September 2022 (54.3%), September 2023 (56.5%), and February 2019 (62.8%). These trends demonstrate strong seasonal variations in recreational demand, with the highest activity in the fall and the lowest in early spring and winter [21].

Given these seasonal fluctuations, there is potential for seasonal bias in willingness-to-pay (WTP) estimates for forest ecosystem benefits. If seasonal variations in recreation patterns, tourism behavior, and landscape valuation are not properly accounted for, WTP estimates may be distorted, leading to the over- or underestimation of ecosystem benefits [9,14,23]. Due to time and cost constraints, many environmental valuation studies extrapolate annual benefit estimates from surveys conducted in a single season or a limited timeframe [24,25]. This approach can introduce measurement errors, reducing the accuracy of cost–benefit analyses for forest policies and increasing the risk of market and policy failures [26,27].

To address this issue, we compiled a meta-dataset of 476 WTP observations from 90 Korean valuation studies and applied robust mixed-effects meta-regression to statistically verify seasonal heterogeneity in preferences. To the best of our knowledge, this is the first meta-analysis that systematically quantifies seasonal variation in WTP for forest ecosystem services in Korea. Whereas previous meta-analyses have synthesized valuation studies under the assumption of temporally static preferences [22,28,29], this study uniquely incorporates the seasonal dimension, revealing how the autumn, summer, and winter yield markedly different WTP outcomes. This explicit treatment of seasonality not only strengthens methodological rigor but also provides novel insights into how temporal dynamics shape valuation outcomes and forest-related behaviors.

While stated preference methods dominate the dataset (368 estimates: 296 contingent valuation and 72 choice experiments), a smaller number of revealed preference estimates were also included, primarily based on the travel cost method and hedonic pricing. However, because the number of revealed preference studies is relatively limited, our main statistical analysis relies on the stated preference, with revealed preference results reported descriptively for context. This distinction ensures clarity while acknowledging the complementary value of both approaches.

The originality of this study lies in three aspects. First, it empirically demonstrates that ignoring seasonality can introduce systematic bias into benefit transfer and cost–benefit analysis, a point rarely addressed in previous meta-analyses [29,30]. Second, it introduces a conceptual framework linking ecological seasonality, human behavior, and economic valuation, thereby bridging ecological and behavioral economics perspectives [30,31]. Third, it provides policy-relevant recommendations on how forest management, pricing, and marketing strategies can be designed in a season-sensitive manner [32]. In doing so, this study extends the broader literature that underscores the economic and organizational significance of environmental values [31,32] while remaining grounded in the core tradition of WTP-based environmental valuation. By integrating these contributions, this paper advances both methodological innovation and policy discourse on ecosystem service valuation.

Against this backdrop, this study addresses the following research questions:

- To what extent does willingness to pay (WTP) for forest ecosystem services vary across different seasons (spring, summer, autumn, and winter)?
- How robust are these seasonal differences in WTP once socioeconomic, methodological, and regional moderators are controlled for in a meta-regression framework?
- What are the implications of seasonal heterogeneity in WTP for policy design, benefit transfer, and sustainable forest management strategies?

By answering these questions, this paper makes three contributions: (i) it provides empirical evidence that overlooking seasonality can bias benefit transfer and policy evaluation, (ii) it provides a robust modeling framework for capturing temporal heterogeneity, and (iii) it offers policy-relevant insights into season-sensitive forest management. We further applied diagnostic tests to validate the choice of model and propose methodological improvements for benefit transfer. The remainder of this paper is structured as follows: Section 2 reviews the theoretical background and prior research; Sections 3 and 4 present the empirical analysis; and Section 5 provides our conclusions along with policy implications.

2. Literature Review on Seasonal Preferences and the Application of Mixed-Effects Models

2.1. Seasonal Preferences

Despite the growing interest in environmental valuation, little attention has been paid to seasonal preferences. This section first reviews the previous literature on seasonal preferences and then expands the discussion to meta-analyses of environmental services and benefits, given the importance of seasonality in natural recreation demand—a key research topic in environmental economics and tourism. Although seasonality plays a crucial role in environmental valuation and consumer behavior in forest-related activities, studies explicitly addressing seasonal variations remain scarce [33,34]. For example, Bartczak et al. (2012) [33] developed a single-site travel cost model for urban forests in Poland to estimate seasonal recreation demand based on travel frequency data. Using a Poisson count data model, they estimated consumer surplus per trip as follows: EUR 2.43 in the summer, EUR 3.68 in the fall, EUR 2.85 in the winter, and EUR 2.60 in the spring. Their findings indicate that fall was the most preferred season, followed by winter, spring, and finally summer. While the average consumer surplus was EUR 2.89, seasonal variations ranged from −15.9% to +27.3%, suggesting that tourists' satisfaction levels fluctuate significantly across seasons.

Similarly, a contingent valuation study on Haeundae Beach in Busan, Korea, found a 20% difference in WTP between peak and off-peak seasons. Specifically, the WTP for preserving the beach's scenic beauty was KRW 16,917 (USD 14.63) per person per visit during peak season and KRW 14,099 (USD 12.19) during off-peak season [35]. This discrepancy underscores the impact of seasonal variation on WTP estimates, potentially leading to differences in valuation outcomes.

Since the 1990s, meta-analysis has been playing an increasingly important role in environmental research [36]. For environmental policymakers and natural resource managers managing non-market resources—such as forests, rivers, wetlands, and other natural assets—conducting original empirical valuations can be both time-consuming and costly [37,38]. As these non-market goods and services are non-excludable and non-rivalrous, researchers often rely on benefit transfer, involving the application of empirical estimates from previous studies to new contexts [39]. For instance, Grammatikopoulou et al. (2021) [40] conducted a meta-analysis on forest ecosystem services using a dataset of 30 studies (71 observations) primarily from Europe. They applied benefit transfer techniques to the Czech Republic, demonstrating forest ecosystem services' substantial economic contribution to the national GDP. Newbold and Johnston (2020) [41] estimated the value of information using meta-analysis for water quality improvement, while Roldan et al. (2021) [42] examined WTP differences for drinking water quality between developed and developing countries, highlighting the influence of income levels on valuation outcomes.

Additionally, Filho et al. (2021) [43] used the Environmental Service Valuation Database (ESVD) to estimate local environmental services across 12 biomes, comparing the performance of meta-analytic transfer versus simple value transfer. In Korea, Kim et al. (2018) [28] conducted a meta-analysis of 51 studies (131 observations) to estimate the marginal WTP and economic benefits of drinking-water-quality improvements. Giergiczny et al. (2014) [44] conducted a meta-analysis of 53 studies (253 estimates) that applied the contingent valuation method (CVM) and travel cost method (TCM) to estimate the recreational value of forests in Europe, including Austria, Germany, Ireland, Italy, Northern Ireland, Poland, and Spain. Their findings indicated that protected areas significantly enhance forest recreational value, emphasizing the ecological and economic importance of conservation efforts.

Although both stated preference and revealed preference methods are increasingly employed in economic valuation research [45], relatively few studies have comprehensively examined the influence of seasonal variations on environmental service valuation. Given the potential for seasonal biases in WTP estimates, addressing these variations is critical for improving the accuracy of benefit assessments. Similar approaches to valuing ecosystem services have been applied in several meta-analyses (Table 1). As shown in Table 1, we identified the key studies that have contributed to this body of research, providing the study author(s), publication year, type of ecosystem services, research areas, and the valuation methodology used, allowing for a clearer understanding of the various approaches and contexts under which seasonal variations in WTP have been analyzed.

Table 1. Summary of major meta-analyses in the ecosystem service valuation literature.

Authors	Ecosystem Services	Scale (Country, Area)	Value Type	Survey Method (Valuation Methods)	Observations (No. of Estimates)
Kim et al. (2018) [28]	Water quality (mainly rivers)	Korea	Indirect use	CVM CE	51 studies, 139 observations
Grammatikopoulou et al. (2021) [40]	Forest ecosystem services	Europe	Indirect use	Stated preference	30 studies, 71 observations
Newbold and Johnston (2020) [41] [b]	Water quality improvement	US	Total (use + non-use)	Stated preference	51 studies, 140 observations
Roldan et al. (2021) [42]	Drinking water quality	30 countries	Indirect use	Face-to-face survey	30 studies, 30 observations
Filho et al. (2021) [43]	Ecosystem services [a]	Global scale	Total (use + non-use)	General valuation method	636 observations (ESVD)
Giergiczny et al. (2014) [44]	Forest recreation	Europe	Direct use	CVM TCM	53 studies, 253 observations

[a] Ecosystem services: provisioning, regulation and maintenance, and cultural services. Biomes: coastal systems, coastal wetlands, coral reefs, cultivated areas, desert, freshwater, grasslands, inland wetlands, marine, temperate or boreal forests, tropical forests, and woodland. [b] Year estimated or published.

Through statistical tests and modeling, this study makes three key contributions to advancing the meta-analysis approach and understanding the significance of seasonal effects, preferences, and WTP variations across the four seasons: (1) it highlights the necessity of incorporating seasonal effects in valuing environmental services, an aspect that has been largely overlooked in previous research; (2) it provides a newly developed robust mixed-effects model to address heterogeneity and heteroskedasticity in meta-regression; and (3) it quantifies WTP variations in percentage terms for each season, providing conclusive justification for coefficient adjustments when using partial datasets across different times of the year.

Beyond these empirical examples, the existing literature remains largely descriptive and fragmented, offering limited integration of ecological, behavioral, and economic perspectives. To provide a more cohesive theoretical foundation, in this study, we propose a conceptual framework that links seasonal dynamics to human behavior and, ultimately, WTP outcomes (Figure 1). Specifically, seasonal variation in ecological conditions—such as vegetation cycles, climatic factors, and landscape esthetics—influences human interactions with forests, including in terms of recreational demand, cultural attachment, and psychological restoration. These behavioral responses then shape stated and/or revealed preferences, as reflected in WTP estimates. This framework highlights why ignoring seasonal dynamics can bias valuation results and underscores the need for meta-analyses that explicitly incorporate temporal variation [12,20,23,33]. By situating seasonality at the intersection of ecology, behavior, and economics, this framework provides a guiding model for the subsequent empirical analysis.

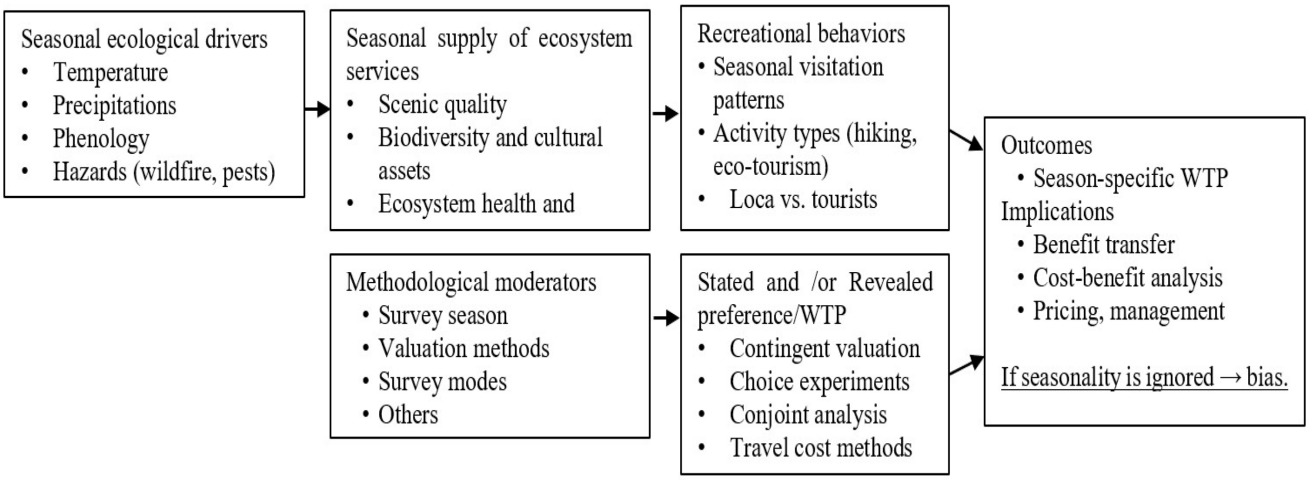

Figure 1. Conceptual framework linking seasonal dynamics, behavior, and valuation for forest ecosystem services.

2.2. Meta-Analysis Framework and the Role of Mixed-Effects Modeling

Meta-analysis is widely used in environmental economics to synthesize WTP estimates for ecosystem services across multiple primary studies [25,29,31,38–40]. Unlike conventional cross-sectional data, meta-analytic datasets typically have an unbalanced panel structure, where multiple value estimates are extracted from the same studies using different methods or sample designs, and the basic framework for the panel structure consists of a regression model [46]. This hierarchical data structure requires more flexible modeling approaches that account for both within- and between-study variation [39]. Nelson et al. (2009) [47] summarized a few key points as part of a meta-analysis: sample selection criteria, basic data summary, primary data heterogeneity, heteroskedasticity, and non-independence of multiple observations from primary studies. They also suggested a set of best-practice guidelines for other areas of economics and indicated that with some solutions, sample heterogeneity can be explained by the binary dummy and random effect. Second, the heteroskedasticity of effect-size variance should be a high priority in collecting primary data on variance and sample sizes. Finally, the non-independence of primary estimates can be addressed using panel data methods and other econometric methods for managing correlated data.

Mixed-effects models are increasingly applied in meta-analyses to address these complexities. These models incorporate both fixed effects (explaining overall trends) and random effects (capturing unobserved heterogeneity across studies). This structure allows for the inclusion of clustered data, missing values, and unbalanced designs while also improving model robustness and predictive performance. Robust mixed-effects models can handle study-specific deviation and reduce residual variance through random slopes and intercepts [48–51].

In this study, random intercepts were specified for both study year and region. The temporal random effect captures unobserved heterogeneity across time, such as macroeconomic shifts or evolving methodological standards, while the regional random effect accounts for contextual differences in forest ecosystems, cultural preferences, and policy environments that may systematically influence WTP estimates. Compared to fixed-effects or single-level specifications, this structure provides greater flexibility in partitioning variance and improves the generalizability of results across different spatiotemporal contexts [44,52]. To ensure the reliability of this specification, model diagnostics were conducted. In addition, sensitivity analyses with alternative specifications (e.g., random intercepts for either time or region only) produced consistent seasonal patterns, though with slightly different effect magnitudes, supporting the robustness of the chosen specification [53].

Given the nested nature of the meta-dataset—476 value estimates from 90 studies—this study specifies the following linear mixed-effects regression model (1), which is well suited for continuous outcomes such as the natural logarithm of WTP [48,49,53]. A linear specification is appropriate because the dependent variable is continuous and log-transformed, allowing effect sizes to be interpreted in relative percentage terms. The mixed-effects framework is further justified by the hierarchical structure of the data: multiple observations are clustered within individual studies, inducing within-study correlation that cannot be captured by simple linear regression. By combining fixed effects (to estimate average moderator impacts) with random effects (to capture study-level heterogeneity), the model reduces residual correlation and improves the generalizability of the results for benefit transfer applications.

$$y_{in}= \alpha + \sum_{k=1}^{K} \beta_k x_{k,\ in} + \varepsilon_i + \mu_n \tag{1}$$

where y_{in} represents the n^{th} WTP estimate from study i; β^k denotes fixed-effect coefficients for explanatory variables $x_{k,\ in}$; ε_i denotes the study-level random effect; and μ_n is the estimate-level residual. This structure enables us to account for both study-specific clustering and observation-level noise, thereby improving the reliability of the valuation estimates [53].

3. Empirical Analysis

3.1. Systematic Review

We first applied a systematic review to identify empirical research estimating willingness to pay (WTP) for forest resources and ecosystem services. The review was conducted following a stepwise approach consisting of three stages: (1) identifying and screening relevant studies, (2) compiling a structured meta-database of WTP estimates and explanatory variables, and (3) applying regression models to account for heterogeneity across studies [25,54,55].

To ensure comprehensiveness, we searched multiple databases and academic sources, including RISS, DBpia, the Korea Environment Institute's EVIS system, major university library sites, and key journal publisher websites, for reports published between 1999 and 2022. The search involved the use of predefined keywords related to forest ecosystems (e.g., forest, mountain, and parks), non-market valuation methods (e.g., WTP, contingent valuation, and choice experiment), and environmental valuation themes (e.g., recreation, biodiversity, and preservation) [54,56–58]. A summary of the databases, keywords, and scope is presented in Table 2.

We compiled a meta-dataset from 90 studies on forest ecosystem services in Korea. Table 2 presents a summary of the data sources, selection criteria, and meta-data coverage. The table includes information on the number of studies, the research fields covered, the methodologies used, and the temporal and seasonal characteristics of the data. These elements were crucial for ensuring the comparability and robustness of the meta-analysis.

Each study had to report at least one WTP estimate for forest ecosystem services, obtained through stated or revealed preference methods. Abstracts were initially screened to exclude irrelevant studies, such as those not focused on forest resources, those lacking valuation estimates, or those based solely on value transfer methods. We searched the gray literature to find as many estimates as possible and test the influence of the gray reports; however, this research was excluded from the final model. Full texts were then reviewed to confirm eligibility. The inclusion criteria were defined in accordance with the MAER-Net guidelines [24,25] to ensure the validity and replicability of the meta-analysis, as emphasized in [47,59–61].

Table 2. Overview of systematic review procedure and metadata coverage.

	Content
Main databases	EVIS (http://riss.or.kr/index.do; accessed on 25 August 2022), major academic sites (riss.or.kr; DBpia), relevant journal websites, major university library sites, National assembly libraries, and relevant research institute reports
Main relevant keywords	Main natural resources: forests, mountains, wetlands, parks (national, provincial, local, etc.), and forest-dependent animals Non-market valuation: willingness to pay, willingness to accept, stated preference, revealed preference, contingent valuation, choice experiment/modeling, travel cost, hedonic price, and conjoint analysis Meta-topics: environment, economic value, non-market values, use value, non-use value, preservation value, environmental services, recreation, tours, visits, satisfaction, healing, education, and biodiversity
Types of prominent journals and research institutes	Environmental economics, agricultural economics, economics, tourism and applied fields, marine economics, forest economics, forest management, and relevant natural science and public organizations
Number of studies	93 (initial) → 90 (after screening)
Number of estimates	485 (initial) → 476 (after screening)
Timespan	1999~2022

Out of the 93 studies initially identified, 90 were retained after screening, yielding 476 usable WTP estimates. Studies were excluded if they reported negative or inconsistent values (e.g., one negative WTP, six transfer-based values, and two statistical outliers). Such values are typically considered implausible in economic valuation or reflect methodological inconsistencies that compromise comparability across studies. However, we acknowledge that excluding negative or highly inconsistent estimates may introduce upward bias by underrepresenting protest responses or zero-WTP segments, thereby limiting full generalizability of the findings. To address this concern, we conducted sensitivity checks including these excluded studies, and the overall seasonal patterns of WTP were found to remain robust, though the absolute mean levels were slightly lower. This result suggests that the exclusion improved internal consistency and comparability across studies while only marginally affecting external validity. Each estimate was subsequently coded with relevant moderator variables, including resource type, valuation method, publication characteristics, and survey timing. Seasonal variables—derived from reported survey months—were also coded to capture seasonal preference effects. Socioeconomic variables were incorporated to enrich the dataset and reduce bias inherent in meta-level data [48,62].

The final dataset averages 5.2 estimates per study and includes a mix of published articles, gray literature, and reports. All moderator variables were coded systematically, primarily as dummy variables (0, 1), to facilitate empirical analysis. Table 2 summarizes the data sources, selection criteria, and meta-data coverage.

3.2. Database Compilation

Table A1 summarizes the structure of the meta-database used in this study along with the variables, including data sources, coding schemes, valuation methods, seasonal classifications, and regional distributions. This structured dataset was compiled following the screening of 90 primary studies and includes 476 WTP estimates covering forest ecosystem services in Korea from 1999 to 2022. The dataset integrates various sources—including peer-reviewed articles, government reports, and academic theses—and emphasizes seasonal variation as a key moderator variable. In addition to standard meta-regression variables, socioeconomic attributes and valuation design factors were systematically coded to capture heterogeneity in WTP estimates. The database includes peer-reviewed journal articles (405), reports and working papers (52), and dissertations (17), with a focus on forest ecosystem services in Korea. The full structure and coding framework of the meta-database—including all dependent and independent variables—are presented in Appendix A, Table A1.

A major challenge in constructing meta-datasets is the heterogeneity of reporting formats across primary studies [52,57]. To address this, we applied standardized coding procedures based on the guidelines reported by Havranek et al. (2020) and MAER-Net [24,25]. The dependent variable is the natural logarithm of the WTP value, standardized across studies. The independent variables include study-level and observation-level characteristics, with particular attention to seasonal and socioeconomic attributes.

In the Korean case studies included in our analysis, environmental services were monetarily valued through respondents' stated willingness to pay, expressed in Korean Won (KRW). Payment vehicles varied across studies, including entrance fees pertaining to forest sites, annual household taxes, earmarked donations, and restoration funds. The parameters commonly valued included biodiversity conservation, forest restoration cost, landscape esthetics, carbon sequestration, recreational access, and protection against forest disasters such as pests or fire. To enhance comparability across sources, all reported WTP values were adjusted to a common base year (2020) using the Korean Consumer Price Index (CPI), depending on the reporting format of the primary study. Where necessary, lump-sum or monthly contributions were annualized, along with monetary values. This harmonization ensured that variations in WTP reflect genuine preference heterogeneity rather than inconsistencies in valuation metrics or scaling procedures.

Seasonal variation is central to this study: In the spring, plants sprout, leaves unfurl, and flowers bloom, creating landscapes dominated by light green. Summer brings the most daylight and warmth, promoting rapid plant growth and deep-green vegetation. In autumn, falling temperatures lead to color changes in leaves—yellow, orange, and deep red—before they fall. Winter is marked by cold weather, limited daylight, and minimal plant activity. Each observation is categorized by the month in which the original survey was conducted, mapped onto the four-season classification of the Northern Hemisphere. The seasonal distribution of the estimates was as follows: spring (151), summer (201), fall (212), and winter (62). These seasonal classifications allow us to assess their statistical significance in shaping WTP estimates, beyond the effect of other study characteristics.

To enhance the robustness of the analysis, we incorporated socioeconomic variables not often included in prior meta-analyses. These include average income (coded into seven intervals), education level (broken into four categories), age (grouped by decade), and gender ratio. Missing data were replaced with population-level averages where appropriate. We also coded valuation method types: stated preference methods dominate (368 estimates), with contingent valuation (296) and choice experiments (72) being the most common. In addition to these methods, the authors of some studies also employed conjoint analysis and best-worst scaling to elicit preferences, though these methods were less frequently used than contingent valuation and choice experiments. The inclusion of these additional methods contributes to the diversity of the valuation approaches and further enriches the findings of this meta-analysis [53].

The independent variables are grouped into 13 categories: resource type, economic value type, valuation approach, elicitation format, payment vehicle, scope of nature, sample size, study year, publication year, survey method, seasonal classification, socioeconomic profile, and study quality. These moderator variables allow us to account for systematic differences in WTP estimates.

The dataset has an unbalanced panel structure. To account for hierarchical data and within-group correlation, we applied a mixed-effects modeling approach. Fixed effects capture average trends across observations, while random effects adjust for grouped structures such as study year and geographic region. These group-level variables—modeled as random effects—reflect unobserved heterogeneity and improve the estimation of fixed coefficients. Random effects were applied to regional groupings, classified as Gyungsang (113 estimates), Jeonra (73), Chungcheong (52), Gangwon (49), Seoul (39), Gyeonggi (30), Jeju (17), and nationwide studies (103). By accounting for region-level variation and survey timing, we reduced residual error and enhanced the generalizability of the results for benefit transfer applications.

4. Meta-Analysis Specification and Estimation Results

4.1. Empirical Specification

One of the key advantages of meta-analysis is its ability to mitigate researcher subjectivity by providing a systematic and statistical framework for synthesizing existing evidence [24,62]. While meta-analysis is widely applied across fields such as business, macroeconomics, and agricultural economics—particularly in studies on seasonal price fluctuations—its application in environmental valuation, especially concerning seasonal preferences, remains limited.

Most non-market valuation studies derive WTP estimates from surveys conducted during a single season, often ignoring the potential influence of seasonal variation [63]. As a result, these estimates may reflect only a partial snapshot rather than the comprehensive annual value of ecosystem services. This issue is particularly problematic in forest valuation, where public preferences and perceived benefits can vary markedly across seasons because of visual, experiential, and ecological differences.

To address this issue, we explicitly incorporated seasonal variation into the meta-regression model. Seasonal distinctions—such as spring freshness, summer greenery, autumn foliage, and winter snow cover—can shape individual perceptions and thus influence WTP. The timing of survey administration relative to these seasonal characteristics can result in systematic differences in valuation outcomes, underscoring the need to control for seasonality in environmental valuation.

In the log-linear meta-regression model, dummy variables were used to capture qualitative characteristics, including seasonal effects. These binary variables assume a value of 1 if a condition is met (e.g., surveys conducted in the autumn) and 0 otherwise. In a log-linear context, the percentage change in the dependent variable associated with the presence of a dummy variable is calculated as percentage change = $100\% \times \left(e^{\beta} - 1\right)$. While theoretical expectations regarding the direction of each variable's effect on WTP can guide model interpretation, these relationships may vary depending on context. Thus, coefficients may be positive, negative, or neutral [64].

To maintain sample size and avoid listwise deletion, missing values in socioeconomic variables (e.g., income and age) were imputed using variable means. This approach ensures there is a more completed and balanced dataset for statistical estimation. A comprehensive summary of the explanatory variables—including descriptive statistics, value ranges, and expected coefficient signs—is provided in Appendix A, Tables A1 and A2. To enhance the readability of the main text and avoid overloading the model description segment with technical detail, Appendix A, Table A2, is presented separately at the end of the manuscript. This placement allows readers to refer to the complete summary of descriptive statistics and expected signs of explanatory variables as needed.

4.2. Econometric Specification for Testing Seasonal Preferences and Their Effects

The structure of the data in the meta-analysis is inherently complex, as the selected WTP values are derived from different studies conducted at various times, at different geographical locations, and using diverse valuation formats. Controlling for heterogeneity and heteroscedasticity is crucial for ensuring validity, reliability, and credibility in benefit transfer [65,66]. To account for these variations, geographical location and time variables were incorporated as random effects in the mixed-effects model.

This empirical meta-regression model has a semi-log functional form, as specified in Equation (2), where the dependent variable (y_{it}) represents WTP values in Korean Won (KRW) for the estimated year. The semi-log functional form is widely used because it helps normalize the variation in WTP, which is presented on vastly different scales across primary studies. In the semi-log component, the coefficient measures the proportional change in the dependent variable, while in the log–log component, the coefficient of socioeconomic variables corresponds to elasticities, indicating the proportional change in the dependent variable in response to a proportional change in an explanatory variable [65,66].

This approach is frequently adopted in environmental economics and ecosystem services valuation studies because of its ability to address heteroscedasticity and the large-scale variations inherent in WTP estimates. The log transformation stabilizes the variance of the dependent variable and reduces the influence of extreme values (outliers), thereby enhancing the robustness of the results. Furthermore, this functional form allows for a more intuitive interpretation of the coefficients as percentage changes, facilitating a clearer understanding of the impact of different predictors on WTP [67,68].

The authors of several studies have utilized similar approaches to deal with WTP heterogeneity and distributional issues. For instance, Brander et al. (2024) [1] employed a semi-log model to standardize WTP estimates across diverse ecosystem services and regions. Groot et al. (2020) [2] applied the semi-log approach in valuing forest ecosystem services across multiple studies, while Newbold and Johnston (2020) [27] used the log-transformation to analyze WTP for water quality improvement. Additionally, Filho et al. (2021) adopted a semi-log model in their meta-analysis of ecosystem service valuations, demonstrating its effectiveness in managing heterogeneity and skewed data distributions [43].

The explanatory variables used in the model are categorized into four groups, as detailed in Appendix A, Table A1: (1) types of natural resources, (2) methodological characteristics of the studies, (3) seasonal variables, and (4) socioeconomic characteristics.

In the mixed-effects model, two R-squared measures were calculated, namely, marginal R-squared and conditional R-squared, both of which provide valuable insights into model fit. Marginal R-squared reflects the proportion of variance explained by the fixed effects alone. This value suggests that the fixed factors modeled in this study (such as seasonality, payment vehicle, and WTP methods) only explain the variance in WTP. They often exhibit significant unobserved variability due to factors like study design, regional differences, and other unmeasured factors. Conditional R-squared, on the other hand, includes both the fixed and random effects (study- and region-specific variability) and accounts for the total variance in WTP.

This higher value indicates that when unobserved heterogeneity is considered, the model provides a much stronger fit, highlighting the importance of incorporating both observed and unobserved factors in modeling WTP estimates. This difference in R-squared values underscores the need to consider both fixed and random effects in meta-regressions. While marginal R-squared captures the explanatory power of the model’s systematic components, conditional R-squared provides a more comprehensive understanding by accounting for study-specific and regional variations that significantly contribute to the variability in WTP estimates.

The estimated model is specified as follows:

$$y_{it} = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \delta_1 Season1 + \delta_2 Season2 + \delta_3 Season3 + \delta_4 Season4 + \varepsilon_{it} \quad (2)$$

where

- α is the constant term;
- β represents the vector of coefficients for the continuous or categorical explanatory variables;
- δ_1 through δ_4 are coefficients for the seasonal dummy variables, capturing the seasonal heterogeneity in WTP estimates;
- ε_{it} is the error term, assumed to be independently and identically distributed;
- i denotes the study identified, and t refers to the time dimension (if applicable).

To analyze the data, we employed a robust mixed-effects model, which integrates both fixed and random effects to accommodate unbalanced panel data. This approach is advantageous because it eliminates the complex decision-making process associated with choosing between purely fixed-effects and random-effects models. Given that there are multiple observations for certain studies in the dataset, a panel data structure is well suited for estimation. The mixed-effects analysis was conducted using R software (R-4.5.1), specifically using the *lme4* (1.1-32) and *robustlmm* packages (3.2-3) [59,60]. Additionally, pooled ordinary least squares (POLS) and weighted least squares (WLS) models were included to ensure robustness. To test the validity of the hypotheses, we estimated the model and conducted an F-test on the seasonal dummy variables using unrestricted and restricted models. In particular, to avoid multicollinearity caused by the dummy variable trap, one of the four seasonal dummies was omitted from the estimation model. The null hypothesis was formulated as follows:

$$H_0 : dum1 = 0, dum2 = 0, dum3 = 0, dum4 = 0 \quad (3)$$

This implies that all four seasons have the same WTP and that seasonal preferences do not significantly influence WTP values. The alternative hypothesis is

$$H_1 : \text{ dum } 1 \ddagger 0, \text{ dum } 2 \ddagger 0, \text{ dum } 3 \ddagger 0, \text{ dum } 4 \ddagger 0$$

If the seasonal dummy variables are statistically significant, the null hypothesis is rejected, indicating that If the seas WTP varies across seasons. The null hypothesis is rejected when the F-statistic exceeds the critical value of the F-distribution at a predetermined significance level (e.g., 0.05 or 0.01). Since the F-statistic is a monotonic function of the likelihood ratio statistic, the F-test serves as a likelihood ratio test.

Given the well-established nature of the F-statistic and the log-transformation, these specific formulae are not presented here in order to avoid redundancy. Instead, this research focuses on the interpretation of the results in the context of the data. The key takeaway from the F-test is that the inclusion of seasonal variables significantly improved the model's fit, supporting the hypothesis that WTP varies across seasons.

5. Results

5.1. Descriptive Results

The metadata for this study spans the period from 1999 to 2022. In terms of geographic distribution, the dataset includes 113 cases (23.7%) from Gyeongsang-do, 102 cases (21.4%) from Seoul, 74 cases (15.5%) from Jeonra Province, 52 cases (10.9%) from Gyeonggi Province, 49 cases (10.3%) from Jeju Province, 30 cases (6.3%) from Gangwon Province, 17 cases (3.6%) from Chungcheong Province, and 39 cases (8.2%) from other regions. The average reported income is approximately KRW 3.3 million, while the average education level falls between high school and college. The mean age of the respondents is in the early 40s, with men and women averaging 50.69 and 49.7 years of age, respectively. In terms of seasonal distribution, the dataset includes 151 cases (24.1%) from spring, 201 cases (32.1%) from summer, 212 cases (33.9%) from autumn, and 62 cases (9.9%) from winter.

5.2. Meta-Regression Estimation and Results

Table 3 presents the estimation results across different model specifications. The first column reports the results from the POLS model and the WLS estimates, and the next column (ME) provides results from the robust mixed-effects model and weighted robust mixed-effects model. All the specifications include the same moderators. The parameter estimates in the panel measure the average WTP (in KRW) for each observation. The coefficients of the moderators (independent variables) capture the variations in WTP, and the study characteristics illustrate how WTP estimates change depending on methodological approaches and sample characteristics. To address the key concerns raised by Nelson et al. (2009) [47] regarding meta-analysis, our model accounts for (1) sample heterogeneity through the use of binary dummy variables and random effects, (2) heteroskedasticity by prioritizing the collection of primary data on variance and sample sizes, and (3) the non-independence of primary estimates by employing panel data methods and other econometric techniques to handle correlated data [69]. This research incorporates these considerations to enhance the robustness of the analysis.

Among the four models in Table 3, the robust mixed-effects specification offers the best overall fit. Using Nakagawa & Schielzeth's framework, its conditional R^2 is 0.59, exceeding the OLS ($R^2 = 0.34$) and WLS ($R^2 = 0.43$) benchmarks. These results indicate that the robust mixed-effects model explains a larger share of variance in WTP than conventional meta-analytic specifications [39]. Consistent with model diagnostics, the residual plots show no systematic patterns, and the VIFs indicate no critical multicollinearity among moderators.

Focusing on the robust mixed-effects specifications, Table 3 reports the results for the unrestricted model exploring seasonal preferences. The adjusted model explains approximately 29% (R^2m) to 59% (R^2c) of the variation in WTP estimates, serving as an indicator of model goodness of fit. Here, R^2m concerns the explanation of just fixed effects, while R^2c is the full model. In this case, the R squared values are similar between models, and, most importantly, R^2c is only slightly different from R^2m, indicating that including random effects does not improve accuracy. Thus, the estimated models account for a substantial proportion of the observed variability in mean WTP values. It is essential to interpret the signs of the estimated coefficients, as these indicate positive or negative relationships between explanatory variables and WTP. Variables were retained in the model based on their expected direction, regardless of their statistical significance at the 0.05 or 0.1 level.

The fixed-effects component of the model captures the mean effects of each variable, like a standard regression framework, while the random-effects component models heteroskedasticity. The variance and standard deviation estimate of the random intercepts provide insights into the extent to which WTP varies across years and geographic locations. For instance, the standard deviation of the year-specific random intercept suggests that WTP for forest resources fluctuates around the mean intercept of 6.42% WTP by approximately 0.73% WTP (random effects: time (Intercept) 0.55 (variance), 0.73 (Std. Dev.); id (Intercept) 0.06 (variance), 0.99 (Std. Dev.); Residual 0.98 (variance), 0.99 (Std. Dev.) [45].

Table 3. Estimation results from pooled and weighted OLS and mixed-effects and weighted mixed-effects models (unrestricted).

	Ordinary Least Squares (OLS)				**Mixed Effects (MEs)**			
	Pooled OLS (POLS)		**Weighted OLS (WOLS)**		**Robust MEs (RMEs)**		**Weighted RMEs (WRMEs)**	
Coefficients	**Estimate**	**t-Value**	**Estimate**	**t-Value**	**Estimate**	**t-Value**	**Estimate**	**t-Value**
Intercept	5.90	15.20 ***	5.87	15.55 ***	6.44	15.86 ***	6.63	15.25 ***
A. Types of items								
River	0.37	0.16	0.53	0.21	−0.53	−0.32	−0.11	−0.07
Sea	−0.17	−0.39	0.01	0.02	−0.68	−2.05 *	−0.67	−2.16 *
Animals	−0.26	−0.17	−0.43	−0.25	1.35	1.27	1.05	0.93
National Parks	0.28	1.44	0.28	1.31	−0.33	−1.33	−0.41	−1.68
Provincial Parks	1.22	3.24 **	1.23	2.88 **	0.79	2.56 *	1.01	3.01 **
B. Instruments								
Use and Non-Use Value	2.96	1.87 *	3.45	2.53 *	1.81	1.47	2.58	2.41 *
Unit: per Person	2.13	4.63 ***	1.46	2.93 **	2.13	6.02 ***	1.59	4.17 ***
Unit: per Household	2.66	5.50 ***	2.42	4.63 ***	2.71	7.09 ***	2.44	5.95 ***
CVM	−0.70	−2.82 **	−0.59	−2.11 *	−0.88	−4.33 ***	−0.85	−3.90 ***
CE	−0.60	−2.00 *	−0.66	−2.03 *	−0.94	−3.65 ***	−0.95	−3.63 ***
Single-Bounded	0.55	2.17 *	0.30	1.14	0.44	2.23 *	0.36	1.82 *
Double-Bounded	0.28	1.06	0.19	0.76	0.49	2.30 *	0.68	3.39 **
National vs. Local	2.62	9.54 ***	2.66	9.82 ***	1.51	4.43 ***	1.21	2.77 **
Number of Samples	0.00	−1.29	−0.00	−2.05 *	−0.00	−0.95	−0.00	−0.20
Payment of Tax	−0.56	−2.67 **	−0.76	−3.56 ***	−0.66	−4.11 ***	−0.85	−5.24 ***
Face to Face	0.92	2.57 *	1.45	4.08 ***	0.94	2.99 **	1.00	3.23 **
Academic Journals	0.07	0.32	0.42	1.85 *	0.06	0.34	0.15	0.87
C. Seasons								
Summer	0.00	0.02	−0.24	−1.33	−0.18	−1.16	−0.10	−0.65
Fall	0.46	2.81 **	0.35	2.05 *	0.67	5.17 ***	0.71	5.38 ***
Winter	−1.44	−5.66 ***	−1.66	−6.26 ***	−0.65	−2.69 *	−0.64	−2.60 *
Model Fit Criteria	Multiple R^2: 0.34 Adjusted R^2: 0.31		Multiple R^2: 0.43 Adjusted R^2: 0.39		Conditional R^2: 0.59 Marginal R^2: 0.29		Conditional R^2: 0.08 Marginal R^2: 0.03	

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Marginal R^2 (R^2m): the proportion of variance explained only by the fixed effects in the model. Conditional R^2 (R^2c): the proportion of variance explained by both the fixed and random effects in the model.

Based on the meta-data compiled for forest ecosystem services [70] and the robust mixed-effects model applied, seasonal preferences significantly influence WTP. Specifically, WTP is negative in the summer and winter but positive in the autumn, indicating a clear preference for autumn among Koreans [71]. This finding aligns with observed patterns of more forest and mountain visits during the autumn. Additionally, natural resources such as rivers and oceans exhibit a negative association with WTP for forests, suggesting a substitution effect, particularly during summer vacations when individuals choose between visiting mountains, rivers, or coastal areas. Provincial parks emerge as a statistically significant variable with a positive WTP, indicating their distinct appeal and value to consumers. This finding underscores the importance of location-specific and seasonal considerations in environmental valuation [72].

Regarding the unit of payment in non-market valuation methodologies [73], the results indicate positive WTP when the unit of payment is per person or household, while negative WTP can be observed when using stated preference methods such as CV and CE. Additionally, WTP is negatively associated with tax-based payment instruments [74,75], whereas it is positively associated with payment instruments linked to national resources rather than local forest resources. Moreover, face-to-face survey methodologies yield a positive WTP, suggesting their effectiveness in eliciting higher valuation responses.

Although they were found to be statistically insignificant, several other patterns emerged: WTP is positive when both use and non-use value are considered simultaneously as well as when a single- and double-bounded format is used. Conversely, WTP decreases with larger sample sizes, potentially indicating that larger samples reduce bias and provide more precise WTP estimates reflecting broader population attitudes. Additionally, studies published in academic journals using non-market valuation approaches report higher WTP values [24].

The constant term in the model is positive and statistically significant at the 1% level, reinforcing the conclusion that the respondents were generally willing to pay for forest resources. Regarding sample size adjustments to account for heterogeneity and heteroscedasticity [42,47,63], we adopted an alternative weighting method, using sample sizes instead of inverse variances owing to the limited primary study information. The practical implication of this approach is that larger sample sizes tend to yield lower WTP estimates, reflecting more precise valuations that mitigate bias.

More specifically, the estimated coefficient for the dummy variable ‘payment vehicle’ in the model in Table 3 indicates that WTP is, on average, 66% lower relative to other payment methods when income tax is used as the payment vehicle. Furthermore, WTP is approximately 88–94% (ceteris paribus) lower, relative to other revealed-preference approaches, when using contingent valuation and choice experiment methods. This finding aligns with prior research indicating that dichotomous choice formats yield significantly lower WTP estimates than other elicitation techniques, such as iterative bidding procedures. Survey methodology also plays a crucial role in determining WTP. Face-to-face survey methods significantly increase WTP estimates, likely because of their ability to enhance respondent reliability and improve response rates [56,73].

In addition to these methodological factors, the robust mixed-effects model reveals significant seasonal variations in WTP. The seasonal dummy coefficients are statistically significant at the 0.01 and 0.05 levels. Specifically, the coefficients for summer (−0.18), fall (0.67), and winter (−0.65) suggest that WTP is 18% and 65% lower in the summer and winter, respectively, and 67% higher in the fall. These findings indicate that autumn is the most preferred season for forest-related activities, followed by summer and winter, for which there were significantly lower WTP estimates. To ensure these results were robust, we attempted to incorporate socioeconomic variables (e.g., income, education, and age) and methodological controls into our models, isolating the effects of seasonality from other potential confounders. Nevertheless, the estimated effects of those variables were statistically insignificant across model specifications.

5.3. Testing Seasonal Variation Using the F-Test

As illustrated in Tables 3 and A3, the above observations allowed us to conduct an F-test to assess the significance and influence of seasonal variation with respect to the regression, independently of other variables. An F-test is a statistical test in which the test statistic follows an F-distribution under the null hypothesis [64]. Based on the RME in Table 3, the F-value was calculated as follows:

$$F = \frac{(Restricted\ part)}{(Unrestricted\ part)} = \frac{(811.16 - 776.32)/3}{(776.32/476 - 23 - 1)} = 6.76 \tag{4}$$

where SSR_r is 811.16 (please see Appendix A, Table A3); SSR_{ur} is 776.32; q is 3; n is 476; and k is 23. The resulting F-statistic follows an $F_{3,476}$ distribution. The restricted (SSR_r) values are provided in Appendix A, Table A3.

Based on the F-distribution table, the critical value for $F_{3,476}$ at the 5% significance level is 2.60. Since the computed F-statistic (6.76) exceeds this critical value, the null hypothesis (H_0) can be rejected. This indicates that at least one of the seasonal dummy variables differs from zero and that the alternative hypothesis (H_1) is jointly statistically significant at the 5% level. These findings confirm that seasonal variables are critically important factors in ecosystem service valuation. Ignoring seasonal variations in WTP could lead to biased estimates, potentially overestimating or underestimating the true WTP. Therefore, WTP estimates must be adjusted to account for seasonal variation.

5.4. Seasonal WTP Distributions

To illustrate the distribution of WTP across seasons, coefficients and standard errors from the previous model in Table 3 were used to simulate approximately 1,000,000 draws. Figure A1 presents the resulting distributions, with WTP expressed as percentage changes relative to the spring (baseline). Autumn shows the highest WTP (+67%), while the values for summer (−18%) and winter (−65%) are negative. Autumn also exhibits the least variability, whereas winter displays the greatest, indicating more diverse preferences. The seasonal WTP distributions indicate that autumn has the highest WTP (0.67), followed by summer (−0.18) and winter (−0.65), which show negative WTP, reflecting a preference for autumn and a lower WTP for summer and winter. Autumn also has the most consistent preferences (that is, the least variability), while winter shows the greatest variability, indicating diverse opinions. These findings suggest that forest policies and pricing strategies should emphasize attributes aligned with autumn preferences, while improvements or incentives may be needed to enhance the appeal of summer and winter [74].

According to the result of the simulation shown in Figure A1, the seasonal pattern is consistent between the RME and WLS models across specifications: WTP is highest in autumn and lowest in the winter, with summer not differing significantly from spring in this regard. The robust mixed-effects model implies a larger autumn premium (+83.7%, 95% confidence interval: +42.9% to +136.1%) and a moderate winter discount (−51.8%, 95% confidence interval: −69.8% to −23.2%), whereas the WLS model suggests a smaller autumn premium (+49.2%, 95% confidence interval: +6.3% to +109.4%) but a much stronger winter discount (−80.7%, 95% confidence interval: −88.5% to −67.6%). Summer effects are statistically indistinguishable from zero in both models.

5.5. Results of Experimental Estimation Using Robust Mixed-Effects Model

We applied the RME results in Table 3 to three experimental questions relevant to non-market valuation. The first hypothesis examines how the stated preference method affects WTP compared to other methodologies. The second hypothesis introduces an interaction effect assumption by incorporating season with the stated preference framework. The third hypothesis focuses on the use of taxes as a payment instrument within the stated preference method. The results, presented in Table 4, are as follows: In experimental test 1, the estimation results for the CVCE variable, analyzed using both the choice experiment and contingent valuation methodologies, show a statistically significant negative WTP. This finding suggests that these methodologies result in lower WTP values compared to alternative approaches. In experimental test 2, the analysis of interaction effects on seasonal dummies showed that the impact of key explanatory variables on WTP varied significantly by season, emphasizing the moderating role of seasonal context in stated preference responses. In experimental test 3, which examined the use of taxes as a payment instrument within the stated preference method (CVCETAX), the results are statistically significantly lower WTP values. Overall, these three experiments provide valuable insights.

Table 4. Experimental model estimates testing stated-preference and interaction effects.

Experimental Test 1			**Experimental Test 2**			**Experimental Test 3**		
Variables	**Estimate**	**t-Value**	**Variables**	**Estimate**	**t-Value**	**Variables**	**Estimate**	**t-Value**
Intercept	6.45	16.15 ***	Intercept	6.44	15.86 ***	Intercept	6.55	15.20 ***
River	−0.57	−0.35	River	−0.53	−0.32	River	−0.55	−0.34
Sea	−0.67	−2.05 **	Sea	−0.68	−2.05 **	Sea	−0.68	−2.08 **
Animals	1.36	1.28	Animal	1.35	1.27	Animals	1.37	1.29
Provincial Parks	0.80	2.61 ***	Provincial Parks	0.79	2.56 **	Provincial Parks	0.79	2.56 ***
Use and Non-Use Value	1.83	1.49	Use and Non-Use Value	1.81	1.47	Use and Non-Use Value	1.80	1.46
Unit: per Household	2.72	7.13 ***	Unit: per Household	2.71	7.09 ***	Unit: per Household	2.66	6.93 ***
Unit: per Person	2.15	6.08 ***	Unit: per Person	2.13	6.02 ***	Unit: per Person	2.08	5.82 ***
Single-Bounded	0.46	2.36 **	CE	−0.94	−3.65 ***	CE	−0.98	−3.66 ***
Double-Bounded	0.50	2.42 **	CVM	−0.88	−4.33 ***	CVM	−0.93	−4.22 ***
Payment of Tax	−0.65	−4.08 ***	Single bound	0.29	1.56 **	Single-Bounded	0.45	2.24 **
National vs. Local	1.51	4.48 ***	Double bound	0.37	1.80 *	Double-Bounded	0.48	2.29 **
Number of Samples	−0.00	−1.12	Payment of Tax	−0.66	−4.11 ***	Payment of Tax	−1.00	−2.04 **
Academic Journals	0.05	0.32	National vs. Local	1.51	4.43 ***	National vs. Local	1.51	4.36 ***
Face to Face	0.92	2.96 **	Number of Samples	−0.00	−0.95	Number of Samples	−0.00	−0.99
Summer	−0.18	−1.17	Academic Journals	0.06	0.34	Academic Journals	0.07	0.43
Fall	0.67	5.18 ***	Face to Face	0.94	2.99 ***	Face to Face	0.92	2.92 ***
Winter	−0.67	−2.92 ***	Summer	−0.18	−1.16	Summer	−0.20	−1.28

Table 4. *Cont.*

Experimental Test 1			Experimental Test 2			Experimental Test 3		
Variables	**Estimate**	**t-Value**	**Variables**	**Estimate**	**t-Value**	**Variables**	**Estimate**	**t-Value**
National Parks	−0.32	−1.31	Fall	0.67	5.17 ***	Fall	0.65	4.69 ***
-	-	-	Winter	−0.65	−2.69 ***	Winter	−0.66	−2.73 ***
			National Parks	−0.33	−1.33	National Parks	−0.31	−1.26
Experimental and interaction variables								
CVCE	−0.89	−4.52 ***	Summer: Use Value	−0.96	−4.84 ***	CVCETAX	−0.76	4.89 ***
			Face to Face: Fall	4.05	8.29 ***			
			Unit for People: Summer	1.15	4.36 ***			
			Face to Face: Summer	1.77	2.12 **			
			National vs. Local: Fall	1.36	3.31 ***			
Model Fit Criteria	Conditional R^2: 0.59 Marginal R^2: 0.29		Conditional R^2: 0.65 Marginal R^2: 0.53			Conditional R^2: 0.59 Marginal R^2: 0.28		

Notes: *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

6. Conclusions and Discussion

Despite the growing body of research on ecosystem service valuation, seasonal preference remains one of the most overlooked dimensions in non-market valuation studies. Most existing studies rely on data collected during a single season—typically spring or summer—thereby omitting the full temporal spectrum of benefits that forest ecosystems provide. This oversight results in biased estimates that either over- or undervalue environmental resources, depending on when and how the data are collected [27,29,39,55].

This study addresses this critical gap by statistically validating the influence of seasonal variation on WTP for forest ecosystem services. Using a meta-dataset of 476 estimates from 90 studies in Korea and applying pooled, weighted, and robust mixed-effects (RME) models, we found consistent evidence of significant seasonal fluctuations. The RME specification, which better accounts for study-level heterogeneity, confirmed that autumn generates the highest WTP premiums, whereas winter is associated with sharp reductions. These results underscore the importance of modeling temporal dynamics when synthesizing non-market values [25,45,61].

However, it is important to recognize the heterogeneity inherent in the studies included in the meta-analysis. Different research designs, survey methods, sample sizes, and regional contexts introduce variability in WTP estimates [36,37,47,49]. For example, variations in payment vehicles, elicitation formats, and survey timing can lead to discrepancies between studies. While we accounted for some of this variation using random effects, the fact that such differences may affect the comparability of the results remains a limitation [24,25]. Consequently, this finding should be interpreted with caution. The seasonal effects observed here represent general trends rather than precise, universally applicable values. Socioeconomic factors, though determined not significant herein, could be explored in the future.

In this analysis, winter showed the most significant decrease in WTP (65% reduction), which seems to suggest that people appreciate forests less in the winter because of the colder weather and limitations regarding outdoor activities [10,32,55]. However, upon further consideration, it becomes clear that this decrease in WTP is likely influenced by more complex factors. In many regions, winter is characterized by lower visibility of forests' esthetic value, as leafless trees and sparse vegetation can make forests appear less appealing. Additionally, people may have different recreational preferences during the winter, such as engaging in snow-related activities (e.g., skiing and snowboarding) instead of typical forest-based recreation. Furthermore, in the winter, the emotional and psychological benefits provided by forests may be less emphasized owing to seasonal affective disorders or the general tendency for people to focus on indoor activities during colder months [11,12]. Therefore, the seasonal variation in WTP is likely due to multiple interacting factors, such as perceived esthetic value, recreational availability [23,29], and psychological experiences related to the season, not simply a reduction in attention to forests [22,23,55].

The findings reveal that seasonal variation is not a marginal factor but a core determinant of preference heterogeneity, with WTP increasing by up to 67% in the autumn and decreasing by 65% in the winter. Autumn emerged as the most preferred season, confirming that people assign distinct value to seasonal experiences. These results not only align with but also extend those of prior studies [29,32] by offering empirical evidence, obtained using advanced statistical tools, across a broader national dataset. Furthermore, this experimental analysis underscores a persistent issue in stated preference methods: the tendency to generate lower WTP estimates relative to other approaches [3,74,75]. By integrating both seasonal variation and methodological testing, this study provides a more realistic and behaviorally grounded framework for environmental valuation [3,61].

This research challenges the prevailing assumptions in non-market valuation, where temporally static models dominate despite the dynamic nature of both ecosystems and human preferences. We propose that failing to account for seasonal dynamics contributes to the systematic mispricing of environmental assets, ultimately distorting policy priorities and resource allocation [57,65,66,69]. Recognizing the intrinsic temporal variability of ecosystem services is not only a methodological refinement but also a necessity for designing equitable, accurate, and sustainable forest management policies. Integrating seasonal variation into valuation practices can lead to more precise benefit estimations, better-informed policy design, and greater societal welfare [20,21,26,58,76–78].

From a practical perspective, the findings provide several directions for policymakers [79–81]. First, season-sensitive pricing strategies could be introduced, such as differentiated entrance fees across peak and off-peak seasons, to stabilize revenues and manage visitor flow more efficiently [13,55]. Second, restoration and conservation campaigns may be strategically timed to coincide with seasons during which public willingness to pay is higher (e.g., autumn), thereby maximizing funding potential, while winter campaigns may require stronger awareness-building measures. Third, marketing and communication strategies should emphasize the distinct seasonal benefits of forests—for instance, cooling and shade in the summer and esthetic landscapes in the autumn—to strengthen public engagement [9,10,13]. Finally, incorporating seasonal adjustment factors into cost–benefit analyses and benefit transfer practices can reduce systematic bias and support more equitable and sustainable forest policy decisions [36,38,69].

Methodologically, this study reinforces the value of robust mixed-effects and meta-regression frameworks for synthesizing heterogeneous datasets [45,49,61]. Researchers should continue to refine meta-analytic approaches by integrating geospatial validity [14], testing for publication bias [47], and adopting Bayesian hierarchical models [50,51]. Beyond national contexts, comparative meta-analyses across climatic zones would illuminate how seasonal valuation patterns differ globally, thus providing a foundation for international forest governance and climate adaptation strategies [7,26,40].

In conclusion, recognizing the intrinsic temporal variability of ecosystem services is not merely a methodological refinement but a fundamental requirement for designing accurate, equitable, and sustainable forest management policies. Integrating seasonality into valuation practice will improve benefit estimation, guide cost–benefit analysis, and ultimately enhance societal welfare. Looking ahead, in future research, we intend to expand this research through international collaboration to analyze seasonal consumption patterns in diverse climatic and cultural contexts, aiming to build a globally relevant valuation framework that captures the full spectrum of ecosystem service benefits across time and space.

Author Contributions: C.J.: Conceptualization, methodology, formal analysis, investigation, data curation, writing—original draft, writing—review and editing, and project administration. D.C.: Conceptualization, methodology, writing—Review and Proofreading, and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding. The publication fee for this article is supported by the National Institute of Forest Science.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Structure and coding framework of the meta-database (1999–2022).

Category			**Value**	**Descriptions**
WTP	**WTP Estimated**		**KRW**	**WTP Estimated (KRW (Korean Won))**
Type of natural resource	Mountain (forests)		0, 1	1 if mountain and 0 otherwise
	Sea		0, 1	1 if sea and 0 otherwise
	River (freshwater wetland)		0, 1	1 if river/freshwater wetland and 0 otherwise
	Stream		0, 1	1 if stream and 0 otherwise
	Park	National Park	0, 1	1 if national park and 0 otherwise
		Provincial Park	0, 1	1 if provincial park and 0 otherwise
		Local facilities	0, 1	1 if local level and 0 otherwise
		Others (local park)	0, 1	1 if others and 0 otherwise
	Tidal flat		0, 1	1 if tidal flat and 0 otherwise
	Animal		0, 1	1 if animal and 0 otherwise
	Other [a]		0, 1	1 if other and 0 otherwise
Type of economic value (value type)	Use value		0, 1	1 if the use value is included and 0 otherwise
	Non-use value		0, 1	1 if non-use value is included and 0 otherwise
	Use and non-use value		0, 1	1 if both use and non-use value are included and 0 otherwise
Payment unit of WTP	Unit on people		0, 1	1 if payment unit is per person and 0 otherwise
	Unit on household		0, 1	1 if payment unit is per household and 0 otherwise
	Others		0, 1	1 if payment unit is ‘other’ and 0 otherwise
Stated or Revealed preference	Stated preference [b]		0, 1	1 if SP and 0 otherwise (RP)
	Contingent valuation		0, 1	1 if contingent valuation and 0 otherwise
	Choice experiment		0, 1	1 if choice experiment and 0 otherwise
	Others		0, 1	1 if other methods were applied and 0 otherwise

Table A1. *Cont.*

Category			Value	Descriptions
WTP	**WTP Estimated**		**KRW**	**WTP Estimated (KRW (Korean Won))**
Elicitation formats	Single-bounded		0, 1	1 if single-bounded and 0 otherwise
	Double-bounded		0, 1	1 if double-bounded and 0 otherwise
	Others		0, 1	1 if other formats were applied and 0 otherwise
Scope of nature	National vs. local		0, 1	1 if national and 0 otherwise
Research site location	Seoul		0, 1	1 if the site is Seoul and 0 otherwise
	Gyeonggi		0, 1	1 if the site is Gyeonggi and 0 otherwise
	Gangwon		0, 1	1 if the site is Gangwon and 0 otherwise
	Chungcheong		0, 1	1 if the site is Chungcheong and 0 otherwise
	Jeonra		0, 1	1 if the site is Jeonra and 0 otherwise
	Kyungsang		0, 1	1 if the site is Kyungsang and 0 otherwise
	JeJu		0, 1	1 if the site is JeJu and 0 otherwise
Total sample	Number of samples		Number	The sample size
Year	Year estimated		Number	The year in which the survey was conducted
	Year published		Number	The year in which the paper was published
Quality of articles (studies) and data characteristics	Ph.D. thesis report		0, 1	1 if WTP is from a Ph.D. thesis and 0 otherwise
	Natural science journal		0, 1	1 if WTP is from a natural science journal and 0 otherwise
	Economic journal		0, 1	1 if WTP is from an economic journal and 0 otherwise
	Academic paper		0, 1	1 if WTP is from an academic paper and 0 otherwise
	Number of authors		0, 1	1 if the author is in the paper is one and 0 otherwise
	Replications		0, 1	1 if WTP is replicated and 0 otherwise
Payment vehicle	Tax		0, 1	1 if tax is applied and 0 otherwise
Survey methods	Face to face		0, 1	1 if face-to-face is applied and 0 otherwise
Four seasons	Spring		0, 1	1 if survey was conducted in spring and 0 otherwise
	Summer		0, 1	1 if survey was conducted in summer and 0 otherwise
	Fall		0, 1	1 if survey was conducted in fall and 0 otherwise
	Winter		0, 1	1 if survey was conducted in winter and 0 otherwise
Socioeconomic	Household monthly income		Number	(a) under KRW 1 million; (b) more than KRW 1 million~less than KRW 2 million; (c) more than KRW 2 million~less than KRW 3 million; (d) more than KRW 3 million~less than KRW 4 million; (e) more than KRW 4 million~less than KRW 5 million; (f) more than KRW 5 million~less than KRW 6 million; (g) more than KRW 7 million
	Education		Number	(a) under middle school; (b) high-school level; (c) undergraduate level; (d) postgraduate level
	Age		Number	(a) under 20; (b) 30s; (c) 40s; (d) 50s; (e) 60s; (f) over 70
	Gender	Male	Number	Percentage of male respondents
		Female	Number	Percentage of female respondents

Notes: This table outlines the variable names, value coding, and brief descriptions of the 476 WTP estimates included in the meta-analysis, categorized by natural resource type, valuation method, socioeconomic attributes, seasonal classification, and study characteristics. [a] Hereafter, the data included in 'other' for each category are those that are not included in the significant items for each category. These 'other' data were not included in the final model, but an estimate was obtained. [b] Here, the dummy variables are separated to distinguish between the stated and revealed preference methods, and only one of the two variables was used in the final model. Because stated preference involves contingent valuation and choice experiments, the use of both variables in the same model raises a multicollinearity problem. The results presented in the table are based on stated preference studies (contingent valuation and choice experiments), which constitute the majority of the dataset.

Table A2. Summary statistics and expected signs of explanatory variables.

Variables			Mean	Std. Dev.	Min.	Max.	Expected Sign
Willingness to pay	WTP (KRW Korean Won)		26,951.9	48,679.5	0.1	316,248.0	
Region	Id		4.34	2.380	1	8	N
Year	Time		2006.71	5.743	1991	2020	+ or N
Type of natural resources	River		0.00	0.046	0	1	+
	Sea		0.03	0.169	0	1	+
	Stream		0.00	0.046	0	1	+
	Parks	Park	0.38	0.486	0	1	+
		National park	0.42	0.495	0	1	+ or N
		Provincial park	0.04	0.206	0	1	+ or N
		Local park	0.25	0.435	0	1	+ or N
		Local facilities	0.03	0.175	0	1	+
	Tidal flats		0.00	0.046	0	1	+
	Animals		0.00	0.065	0	1	+
	Other		0.01	0.120	0	1	+
Type of values	Use value		0.49	0.500	0	1	+
	Non-use value		0.51	0.500	0	1	+
	Use and non-use value		0.00	0.046	0	1	+
Payment unit of WTP	Unit: per person		0.61	0.489	0	1	−
	Unit: per household		0.33	0.471	0	1	+
	Unit: other		0.06	0.239	0	1	+
Methodology	Stated preference		0.77	0.419	0	1	−
Stated preference or revealed preference	Contingent valuation		0.62	0.485	0	1	−
	Choice experiment		0.15	0.359	0	1	−
	Other methods		0.23	0.419	0	1	+
Elicitation formats	Closed		0.47	0.500	0	1	−
	Single-bounded		0.18	0.364	0.0	1.0	+
	Double-bounded		0.12	0.302	0.0	1.0	−
	Others		0.20	0.386	0.0	1.0	−
Scope of nature	National vs. local		0.22	0.412	0	1	+
Total sample	Number of samples		749.13	999.266	26	8457	−
Years	Year published		2008.43	5.728	1999	2022	− or N
Quality of articles	Ph.D. thesis report		0.04	0.186	0	1	−
	Natural science journal		0.27	0.443	0	1	+
	Economics journal		0.22	0.416	0	1	−
	Academic journal		0.85	0.357	0	1	−
	Number of authors		0.31	0.462	0	1	N
	Replications		0.59	0.493	0	1	− or N
Payment vehicle	Tax		0.42	0.4829	0.0	1.0	−
Survey method	Face to face		0.91	0.284	0	1	−

Table A2. *Cont.*

Variables			Mean	Std. Dev.	Min.	Max.	Expected Sign
Four seasons	Spring		0.32	0.466	0	1	N
	Summer		0.42	0.494	0	1	N
	Autumn		0.45	0.498	0	1	N
	Winter		0.13	0.337	0	1	N
Socioeconomic variables	Income		3.33	2.006	1.00	23.00	+ or N
	Education		2.78	0.200	2.00	4.00	+ or N
	Age		3.07	0.477	1.00	5.00	N
	Gender	Male	50.69	5.734	28.00	88.10	N
		Female	49.71	5.775	11.90	72.00	− or N

Notes: KRW 1291.95 is equal to USD 1 (2022) [80]. The positive (+) sign shows the same direction between dependent and independent variables; negative (−) is the opposite; N = neutral.

Table A3. Estimation results from the restricted robust mixed-effects model.

Random Effects	Groups	Name	Variance	Std. Dev.	
	Time	Intercept	1.00	1.00	
	Id	Intercept	0.15	0.38	
	Residual	1.7077	1.31		
Number of observations	476	Groups:	Time (28)	id	8
			Fixed effects		
	Estimate	Std. error	df	t-value	Pr (>∣t∣)
Intercept	6.18 ***	0.50	127.80	12.40	0.00
River	−1.24	2.07	450.40	−0.60	0.55
Sea	−0.71.	0.42	445.00	−1.71	0.09
Animals	1.77	1.35	432.10	1.32	0.19
Provincial parks	0.95 *	0.38	428.60	2.48	0.01
Use and non-use value	1.11	1.53	421.90	0.72	0.47
Unit: per household	3.15 ***	0.47	451.40	6.72	0.00
Unit: per person	2.68 ***	0.44	456.30	6.08	0.00
CVM	−0.99 ***	0.26	449.70	−3.89	0.00
CE	−1.43 ***	0.32	450.60	−4.45	0.00
Single-bounded	0.50 *	0.25	455.60	1.97	0.05
Double-bounded	0.20	0.26	453.00	0.77	0.44
Nation vs. local	1.35 *	0.48	5.18	2.82	0.04
Number of samples	0.00	0.00	438.20	0.96	0.34
Academic journals	0.14	0.20	438.70	0.69	0.49
Payment of tax	−0.55 **	0.20	456.80	−2.74	0.01
Face to face	0.63	0.38	433.90	1.66	0.10
National parks	−0.25	0.30	451.50	−0.84	0.40

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

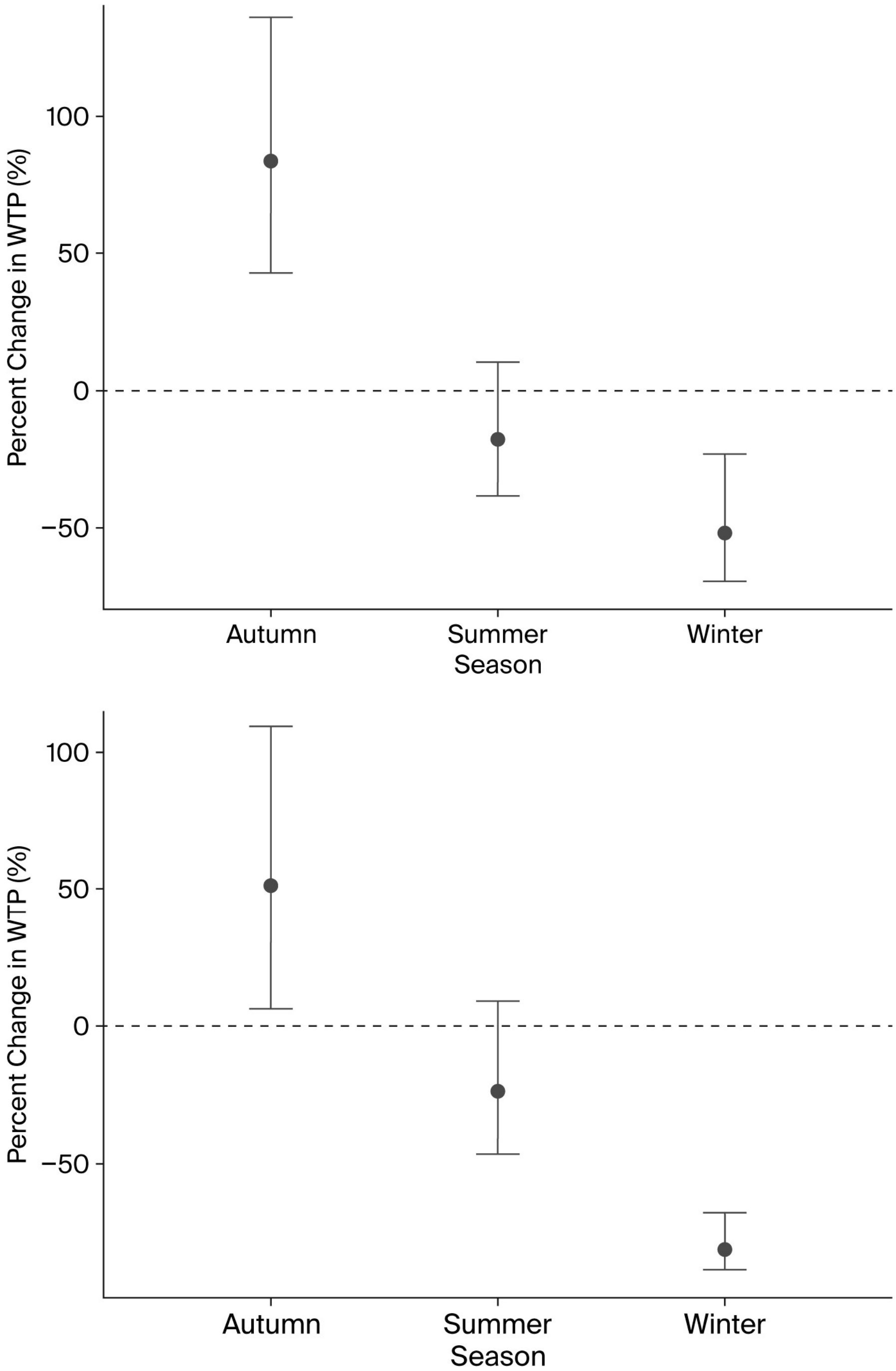

Figure A1. Simulated seasonal WTP distribution based on the RME (first) and WLS (second) models. Note: Points show percent change in WTP relative to spring; error bars denote 95% critical intervals. Other moderators are held constant. The distributions of the pooled OLS and weighted OLS models are similar.

References

1. Brander, L.M.; Groot, R.; Schägner, J.P.; Guisado-Goñi, V.; Hoff, V.V.; Solomonides, S.; McVittie, A.; Eppink, F.; Sposato, M.; Do, L.; et al. Economic values for ecosystem services: A global synthesis and way forward. *Ecosyst. Serv.* **2024**, *66*, 101606. [CrossRef]
2. Groot, R.D.; Brander, L.; Solomonides, S. *Update of Global Ecosystem Service Valuation Database (ESVD)*; Report; Department for Environment, Food and Rural Affairs: Defra, UK, 2020. Available online: https://www.esvd.org/ (accessed on 20 March 2023).
3. Liu, P.; Bi, X.; Luo, Q.; Whitehead, J.C. Effects of policy consequentiality and payment vehicle on contingent valuation: Structural estimates on preference misrepresentation. *J. Environ. Econ. Manag.* **2020**, *103*, 102350. [CrossRef]
4. Millennium Ecosystem Assessment (MA). *Ecosystems and Human Wellbeing Biodiversity Synthesis*; World Resources Institute: Washington, DC, USA, 2005.

5. Pisani, D.; Pettinelli, E.; Mariani, M.; Leone, A. Forest biomass estimates and global carbon stock distribution. *Environ. Res. Lett.* **2022**, *17*, 045001.
6. TEEB. The Economics of Ecosystems and Biodiversity (TEEB) Initiative. *United Nations Environment Programme.* 2023. Available online: https://www.cbd.int/incentives/teeb?utm_source=chatgpt.com (accessed on 19 November 2023).
7. Dominati, E.; Mackay, A.; Dodd, M. Seasonal variation of ecosystem services: A framework for measurement. *Ecolo. Indic.* **2021**, *120*, 106895.
8. IPBES. *Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*; Brondizio, E.S., Settele, J., Díaz, S., Ngo, H.T., Eds.; IPBES Secretariat: Bonn, Germany, 2019; 1148p. [CrossRef]
9. Soga, M.; Gaston, K.J. Towards a unified understanding of human–nature interactions. *Nat. Sustain.* **2022**, *5*, 374–383. [CrossRef]
10. Buckley, R. Nature tourism and mental health: Parks, happiness, and causation. *J. Sustain. Tour.* **2020**, *28*, 1409–1424. [CrossRef]
11. Fuller, R.A.; Irvine, K.N.; Devine-Wright, P.; Warren, P.H.; Gaston, K.J. Psychological benefits of greenspace increase with biodiversity. *Biol Lett.* **2007**, *3*, 390–394. [CrossRef] [PubMed] [PubMed Central]
12. Gregory, N.; Bratman, C.B.; Anderson, M.G.; Berman, B.C.; Sjerp, D.V.; Jon, F.; Carl, F.; Howard, F.; James, J.G.; Gretchen, C.D. Nature and mental health: An ecosystem service perspective. *Sci. Adv.* **2019**, *5*, eaax0903. [CrossRef]
13. Buckley, R.; Brough, P.; Hague, L.; Chauvenet, A.; Fleming, C.; Roche, E.; Sofija, E.; Harris, N. Economic values of protected areas via visitor mental health. *Nat. Commun.* **2019**, *10*, 5706. [CrossRef]
14. Johnston, R.; Besedin, E.Y.; Stapler, R. Enhanced geospatial validity for meta-analysis and environmental benefit transfer: An application to water quality improvements. *Environ. Resour. Econ.* **2017**, *68*, 343–375. [CrossRef]
15. Korea Forest Services (KFS). *Statistical Yearbook of Forestry 2023*; KFS: Daejeon, Republic of Korea, 2023; ISBN 11-1400000-000001-10.
16. Yoo, S.H.; Kwak, S.J.; Lee, J.S. Using a choice experiment to measure the environmental effects of urban parks in Seoul. *Lands. Urban Plan.* **2014**, *123*, 134–143. [CrossRef]
17. Yu, Z.; Ning, Z.; Chang, W.; Chang, S.; Yang, H. Optimal harvest decisions for the management of carbon sequestration forests under price uncertainty and risk preferences. *For. Policy. Econ.* **2023**, *151*, 102957. [CrossRef]
18. Yu, Z.; Ning, Z.; Zhang, H.; Yang, H.; Chang, S. A generalized Faustmann model with multiple carbon pools. *For. Policy. Econ.* **2024**, *169*, 103363. [CrossRef]
19. Sohn, J.; Lee, W.K.; Kim, S.; Kwak, D.A. Economic valuation of forest ecosystem services in South Korea. *For. Sci. Technol.* **2016**, *12*, 183–191.
20. Kim, H.N.; Lee, S.Y. Economic value of forest recreation across seasons: A comparison using CVM and TCM. *Korean J. Agric. Econ.* **2018**, *59*, 45–67.
21. Oh, H.; Lee, J. Seasonal variations in forest visitation and WTP for forest healing programs. *For. Policy Econ.* **2020**, *118*, 102252.
22. Korea Tourism Organization (KTO). *Annual Domestic Tourism Statistics Report 2022*; KTO: Seoul, Republic of Korea, 2022; Available online: https://kto.visitkorea.or.kr (accessed on 18 August 2023).
23. Lee, H.J.; Han, K.S. Four-season tourism patterns in national parks: Empirical evidence from Korea. *J. Tour. Sci.* **2019**, *43*, 95–112. [CrossRef]
24. Stanley, T.D.; Doucouliagos, H. *Meta-Regression Analysis in Economics and Business (Routledge Advances in Research Methods)*; Routledge: London, UK; New York, NY, USA, 2012.
25. Havranek, T.; Stanley, T.D.; Doucouliagos, H.; Bom, P.; Geyer-Llingeberg, J.; Iwasaki, I.; Reed, W.R.; Rost, W. Reporting guidelines for meta-analysis in economics. *J. Econ. Surv.* **2020**, *34*, 469–475. [CrossRef]
26. Taye, F.A.; Folkersen, M.V.; Fleming, C.M.; Buckwell, A.; Mackey, B.; Diwakar, K.C.; Le, D.; Hasan, S.; Ange, C.S. The economic values of global forest ecosystem services: A meta-analysis. *Ecolo. Econ.* **2021**, *189*, 107145. [CrossRef]
27. Newbold, S.C.; Johnston, R.J. Benefits transfer with limited temporal data: Causes and corrections for bias. *Environ. Resour. Econ.* **2017**, *67*, 317–338.
28. Kim, H.N.; Ahn, S.E. *Economic Valuation for Improving Water Quality Using Meta-Regression Analysis*; The Environment Forum, Korea Environment Institute: Sejong, Republic of Korea, 2018; Volume 22, ISSN 2287-3414.
29. Kim, J.; Park, H. Valuing recreational ecosystem services with seasonal variation: A meta-analysis. *For. Policy Econ.* **2023**, *152*, 102957.
30. Ali, A.; Shedayi, A.A. Willingness to pay as an economic instrument for managing nature-based tourism in Gilgit-Baltistan, Pakistan. *Environ. Dev. Sustain.* **2023**, *27*, 1–20. [CrossRef]
31. Ansari, A.; Mahmood, S.; Khan, K.I.; Asghar, F. Fostering green creativity through environmental values: The role of intrinsic motivation, environmental identity and green HR practices. *Pak. J. Commer. Soc. Sci.* **2023**, *17*, 370–389. [CrossRef]
32. Bartczak, A.; Lindhjem, H.; Navrud, S.; Zandersen, M.; Żylicz, T. Valuing forest recreation on the national level in a transition economy: The case of Poland. *For. Policy. Econ.* **2012**, *20*, 81–89. [CrossRef]
33. Shrestha, R.K.; Loomis, J.B. Testing a meta-analysis model for benefit transfer in international outdoor recreation. *Eco. Econ.* **2001**, *39*, 195–206. [CrossRef]

34. Park, C.H. Estimating the Value of Natural Tourism Resources in Considering the Seasonal. Master's Thesis, Dong-Myung University, Busan, Republic of Korea, 2010.
35. Bergh, V.B.; Button, K.J. Meta-analysis of environmental issues in regional, urban and transport economics. *Urban. Stud.* **1997**, *34*, 927–944. [CrossRef]
36. Boutwell, J.L.; Westra, J.V. Benefit transfer: A review of methodologies and challenges. *Resources* **2013**, *2*, 517–527. [CrossRef]
37. Carson, R.T.; Louviere, J.J.; Rose, J.; Swait, J. Frontiers in Modeling Discrete Choice Experiments: A Benefit Transfer Perspective. In *Benefit Transfer of Environmental and Resource Values: A Guide for Researchers and Practitioners*; Johnston, R.J., Rolfe, J., Rosenberger, R., Brouwer, R., Eds.; Springer: Dordrecht, The Netherlands, 2015.
38. Rosenberger, R.S.; Loomis, J.B. *Benefits Transfer of Outdoor Recreation Use Values*; General Technical Report RMRS-GTR-72; Rocky Mountain Research Station, U.S.D.A. Forest Service: Fort Collins, CO, USA, 2001.
39. Lee, D.; Choi, S. Temporal heterogeneity in ecosystem service valuation: A mixed-effects approach. *For. Policy Econ.* **2024**, *153*, 103363.
40. Grammatikopoulou, I.; Vačkářová, D. The value of forest ecosystem services: A meta-analysis at the European scale and application to national ecosystem accounting. *Ecosyst. Serv.* **2021**, *48*, 101262. [CrossRef]
41. Newbold, S.C.; Johnston, R.J. Valuing non-market valuation studies using meta-analysis: A demonstration using estimates of willingness to pay for water quality improvements. *J. Environ. Econ. Manag.* **2020**, *104*, 102379. [CrossRef]
42. Roldan, D.; Sarmiento, J.P.; Rldan-arauz, F. Economic valuation meta-analysis of freshwater improvement in developed and developing countries. Are they different? *J. Wat. Health* **2021**, *19*, 736–749. [CrossRef]
43. Filho, L.M.; Roebeling, P.; Bastos, M.I.; Rodrigues, W.; Ometto, G. A global meta-analysis for estimating local environmental service value functions. *Environments* **2021**, *8*, 76. [CrossRef]
44. Giergiczny, M.; Valasiuk, S.; Salvo, M.D.; Signorello, G. Value of forest recreation. Meta-analyses of the European valuation studies. *Econ. Environ.* **2014**, *4*, 76–83.
45. Zandersen, M.; Tol, R.S.J. A meta-analysis of forest recreation values in Europe. *J. For. Econ.* **2009**, *15*, 109–130. [CrossRef]
46. Greene, W.H. *Econometric Analysis*, 7th ed.; Pearson: Boston, MA, USA, 2012.
47. Nelson, P.N.; Kennedy, P.E. The use (and Abuse) of meta-analysis in environmental and natural resource economics: An assessment. *Environ. Resour. Econ.* **2009**, *42*, 345–377. [CrossRef]
48. EFTEC. *Valuing Environmental Impacts: Practical Guidelines for the Use of Value Transfer in Policy and Project Appraisal*; Department of Environment, Food and Rural Affairs: London, UK, 2009.
49. Boyle, K.J.; Wooldridge, J.M. Understanding error structures and exploiting panel data in meta-analytic benefit transfers. *Environ. Resour. Econ.* **2018**, *69*, 609–635. [CrossRef]
50. Chen, D.G.; Peace, K.E. *Applied Meta-Analysis with R*; CRC Press: Boca Raton, FL, USA, 2013.
51. Chen, M.H.; Ibrahim, J.G.; Sinha, D. *Bayesian Survival Analysis*; Springer: New York, NY, USA, 2013.
52. Nelson, J.P.; Boyle, K.J.; Johnston, R.J. The economics of non-market valuation: Looking back and looking ahead. *Annu. Rev. Resour. Econ.* **2019**, *1*, 547–566.
53. Aizaki, H.; Nakatani, T.; Sato, K. *Stated Preference Methods Using R*; CRC Press: Boca Raton, FL, USA, 2015.
54. Ayala, A.D.; Mariel, P.; Meyerhoff, J. Transferring landscape values using discrete choice experiments: Is meta-analysis an option? *Econ. Agrar. Recur. Nat.* **2014**, *14*, 103–128.
55. Buckley, R.; Brough, P.; Westaway, D. Forest recreation and nature tourism benefits vary strongly across seasons. *Nat. Sustain.* **2022**, *5*, 15–23.
56. Tietenberg, T.; Lewis, L. *Environmental and Natural Resource Economics*, 11th ed.; Taylor and Francis: New York, NY, USA; London, UK, 2018.
57. Boyle, K.J.; Kotchen, M.J.; Smith, V.K. The role of economics in ecosystem valuation. *Ann. Rev. Resour. Econ.* **2018**, *10*, 147–165.
58. Hjerpe, E.; Hussain, A.; Phillips, S. Valuing type and scope of ecosystem conservation: A meta-analysis. *J. For. Econ.* **2015**, *21*, 32–50. [CrossRef]
59. Koller, M. Robustlmm: An R package for robust estimation of linear mixed-effects models. *J. Statis. Softw.* **2016**, *75*, 1–24. [CrossRef]
60. Brown, V.A. An introduction to linear mixed-effects modelling in R. *Adv. Methods Pract. Psychol. Sci.* **2021**, *4*, 1–19.
61. Johnston, R.J.; Bauer, D.M. Using Meta-analysis for large-scale environmental service valuation: Progress, prospects, and challenges. *Agric. Resour. Econ. Rev.* **2020**, *49*, 23–63. [CrossRef]
62. Stanley, T.D.; Jarrell, S.B. Meta-regression analysis: A quantitative method of literature surveys. *J. Econ. Surv.* **1989**, *3*, 161–170. [CrossRef]
63. Smetana, K.; Mesltrom, R.T.; Malone, T. A meta-regression analysis of consumer willingness to pay for aquaculture products. *J. Agric. Appl. Econ.* **2022**, *54*, 480–495. [CrossRef]
64. Wooldridge, J.M. *Introductory Econometrics: A Modern Approach*, 5th ed.; Cengage Learning: Boston, MA, USA, 2012.

65. Bateman, I.J.; Harwood, A.R.; Mace, G.M.; Watson, R.T.; Abson, D.J.; Termansen, M. Economic analysis for ecosystem service assessments. *Environ. Resour. Econ.* **2011**, *48*, 177–218. [CrossRef]
66. Hensher, D.A.; Rose, J.M.; Greene, W.H. *Applied Choice Analysis: A Primer*; Cambridge University Press: Cambridge, UK, 2005.
67. Boyle, K.J.; Kotchen, M.J.; Smith, V.K. The role of benefit-cost analysis in environmental policy debates. *Annu. Rev. Resour. Econ.* **2018**, *10*, 77–92.
68. Glass, G.V. Primary, secondary, and meta-analysis of research. *Am. Educ. Res. Assoc.* **1976**, *5*, 3–8.
69. Johnston, R.J.; Rolfe, J.; Rosenberger, R.; Brouwer, R. *Benefit Transfer of Environmental and Resource Values: A Guide for Researchers and Practitioners*; Springer: Dordrecht, The Netherlands, 2020.
70. Krieger, D.J. *The Economic Values of Forest Ecosystem Services: A Review*; The Wilderness Society: Washington, DC, USA, 2001.
71. Korea Environment Institute (KEI). Environmental Valuation Database in Korea (EVIS). 2022. Available online: http://evis.kei.re.kr (accessed on 25 August 2022).
72. McFadden, D.; Train, K. *Contingent Valuation of Environmental Goods: A Comprehensive Critique*; McFadden, D., Train, K., Eds.; Edward Elgar Pub: Northampton, MA, USA, 2017.
73. Nelson, J.P. Fixed-effect versus random-effects meta-analysis in economics: A study of pass-through rates for alcohol beverage excise taxes. *Adv. Econ. Bus.* **2020**, *9*, 23–41. [CrossRef]
74. Hafele, J.; Adamowicz, W.; Boxall, P. Compensating for loss in forest access: A choice experiment study of recreation in Alberta. *For. Policy Econ.* **2016**, *71*, 79–89.
75. Bateman, I.J.; Cole, M.A.; Georgiou, S.; Hadley, D.J. Comparing contingent valuation and contingent ranking: A case study considering the benefits of urban river water quality improvements. *J. Environ. Manag.* **2006**, *79*, 221–231. [CrossRef]
76. Pearce, D.W. *Economic Values and the Natural World*; The MIT Press: Cambridge, MA, USA, 1993.
77. RISS. Research Information Sharing Service (RISS) Database. 2023. Available online: https://www.riss.kr (accessed on 17 May 2023).
78. Newbold, T.; Johnston, E.A. Estimating the value of water quality improvements: A meta-analysis of contingent valuation and choice experiments. *J. Environ. Econ. Manag.* **2020**, *103*, 102350.
79. Filho, L.; Bi, X.; Luo, Q.; Whitehead, J.C. Estimation of local environmental services across 12 biomes. *Ecol. Indic.* **2021**, *120*, 106895.
80. Ali, K.; Amir, M.; Malik, M.S. Strategic motives, proactive environmental strategies and corporate performance: Role of business model innovation and competitive intensity. *Pakistan. J. Commer. Soc. Sci.* **2023**, *17*, 348–369. [CrossRef]
81. Bank of Korea. Economic Statistics System (ECOS). 2024. Available online: https://ecos.bok.or.kr (accessed on 12 March 2024).