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# Machine learning and spatial regression approaches to estimating willingness to pay for ecosystem services in Jakarta and Taoyuan

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ABSTRACT

Ecosystem services (ES) are essential to environmental sustainability and human well-being. Among them, hydrological ecosystem services (HES) play a critical role in flood mitigation, climate regulation, and water security. This study examines the socioeconomic drivers influencing individuals' willingness to pay (WTP) for HES in two contrasting urban settings: Jakarta in Indonesia and Taoyuan in Taiwan. We applied and compared three data-driven models (i.e., Logistic Regression, Geographically Weighted Logistic Regression, and Extreme Gradient Boosting) to assess both spatial and non-linear determinants of WTP. A total of 1006 respondents were surveyed using structured face-to-face interviews. Respondents were selected via purposive sampling to ensure representation of relevant sociodemographic and regional characteristics. Results show that WTP, expressed in 2024 USD per person per year, is lower in Jakarta (5.52 USD) compared to in Taoyuan (9.99 USD). Demographic and socio-economic variables, particularly gender and education, are key predictors of WTP, followed by support for environmental initiatives. The influence of these factors varies spatially, suggesting that effective ES protection policies should be tailored to local population characteristics. By integrating spatially explicit and data-driven approaches, Payment for Ecosystem Services (PES) policies can more effectively promote community participation and support sustainable ecosystem preservation, particularly for urban ES valuation across East and Southeast Asia.

## 1. Introduction

Nature is essential to human existence and quality of life, and it plays a critical role in providing food and feed, energy, medicines, genetic resources, and a wide range of materials that are vital for physical well-being and maintenance of cultural heritage (Brondizio et al., 2019). Ecosystem services (ES) are benefits derived from well-functioning natural ecosystems, including provision, regulation, cultural, and support services. Among these, hydrological ecosystem services (HES) supplied by river basins are considered essential, because they help to regulate climate impacts, mitigate floods, and support aquatic biodiversity (Jin et al., 2018; Sahle et al., 2019; Sun et al., 2017). Since 1970, trends in agricultural production, industrial development, population growth, and dietary changes have led to an increase in provisioning services, including food and material supply. However, these gains have come at the expense of regulating and supporting services, such as biodiversity and soil organic carbon loss, illustrating trade-offs that weaken ecosystem resilience to pests, pathogens and climate change.

Economic valuation of ES helps to compare natural capital with physical and human capital, thereby facilitating sustainable development and conservation planning (Yihang et al., 2019). However, assigning monetary value to ES remains challenging because most ES are non-marketed, intangible, and difficult to express in economic terms. These difficulties stem not only from their non-economic nature but also from the complex and interdependent relationship between humans and ecosystems, which defies simplistic, anthropocentric frameworks (Costanza, 2024). Additional barriers, such as limited data, funding, expertise, and regulatory or political constraints, further complicate efforts to assess ES, even within specific regions or sectors comprehensively (Thomasz et al., 2024). Payment for Ecosystem Services (PES) has

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emerged as an innovative environmental management approach that offers economic incentives to maintain or enhance ecosystem services (Costanza et al., 2014). PES requires an evaluation of ES in monetary terms, underscoring their importance compared to human-provided services (Costanza et al., 2014; Wunder et al., 2020). This approach addresses the financial needs of ecosystem management, especially where traditional funding for ecosystem conservation is lacking (Wegner, 2016). Socioeconomic factors such as income, education, and local knowledge influence the effectiveness of the PES program (Okiria et al., 2021), and willingness to pay (WTP) can strongly vary across countries (Neef and Sangkapitux, 2017). Although studies have shown that farmers are willing to contribute to climate adaptation through social capital initiatives (Petway et al., 2019; Saptutyningsih et al., 2020), the specific drivers influencing WTP, particularly in Southern Asia, remain poorly understood. The maximum amount individuals are prepared to contribute financially for maintaining or improving ecosystem services, serves as a key indicator of public support for PES schemes.

WTP is a complex construct that is influenced by several interrelated factors and potentially nonlinear relationships (Davies et al., 2023; Heckenhahn and Drupp, 2022), as well as spatial interrelationships among ES and human activities (Zhang et al., 2023; Zhou et al., 2024). Despite widespread use of linear and parametric models in WTP estimation, several methodological gaps persist that limit their effectiveness in capturing the full complexity of human valuation for ecosystem services. Traditional models often assume linearity and homogeneity across space, overlooking complex interactions among socioeconomic, ecological, and perceptual variables (Schaafsma et al., 2012; Zhang et al., 2023). To address these gaps, spatial and machine-learning approaches have been proposed to capture both nonlinear and geographic variations in WTP, such as the Extreme Gradient Boosting (XGBoost) algorithm, allowing one to model nonlinear relationships, interactions, and heterogeneous effects often found in survey datasets (Liu et al., 2025; Lu et al., 2025) without strong parametric assumptions.

This study aimed to explore the factors influencing the WTP for water supply by residents in two Asian cities, Jakarta and Taoyuan, which differ markedly in socioeconomic and ecological conditions. Jakarta, the capital of Indonesia, faces complex challenges relating to pollution, water management, and rapid urbanization. These challenges lead to water quality degradation, biodiversity loss, flooding, consequently reducing the capacity to provide clean drinking water amid economic growth (Asdak et al., 2018; Costa et al., 2016; Lin et al., 2016; Remondi et al., 2016). In contrast, Taoyuan city has issues with water conservation and industrial waste, but benefits from stable forest areas despite a decline in agricultural land and inland waterways (Lin et al., 2024). Economically, Taoyuan is classified as a high-income city, whereas Jakarta falls into the upper-middle-income category (World Bank, 2024). Despite differing institutional and cultural attributes, Jakarta and Taoyuan maintain active trade, education, and immigration linkages (Maksum, 2023; Tng et al., 2021). These cross-border interactions promote information sharing, exposure to environmental norms, and mutual learning, which may shape public awareness, perceptions, and willingness to invest in PES initiatives (Chaikumbung, 2023; Rakotomahazo et al., 2023). To better understand the factors shaping WTP for HES, this study compares two rapidly urbanizing Asian cities with contrasting ecological and socioeconomic contexts. The findings provide evidence-based design that supports sustainable urban water management and regional ecosystem conservation.

## 2. Materials and methods

### 2.1. Study area

This study was conducted in two different locations: the Shimen Reservoir watershed in Taoyuan, Taiwan (Fig. 1A), and the Ciliwung Watershed in Jakarta, Indonesia (Fig. 1B), hereafter referred to as the Taoyuan and Jakarta areas. Both watersheds provide various environmental ecosystem services such as water supply, flood regulation, carbon sequestration, and habitat for biodiversity, all of which are critical to the nearby urban areas of Taoyuan and Jakarta. Jakarta, located on

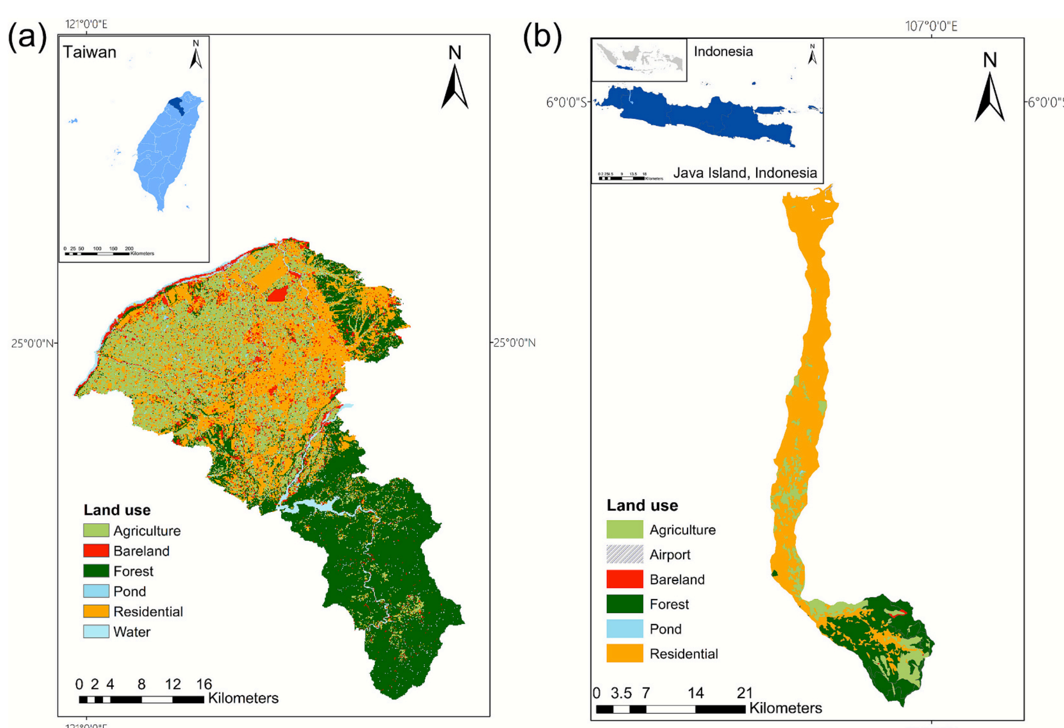


**Fig. 1.** Study areas of (a) Taoyuan in Taiwan and (b) Jakarta in Indonesia. Taoyuan, located in northern Taiwan, forms part of the Taipei–Keelung metropolitan region and is one of the island's most industrialized and densely populated cities, serving as a major logistics and technology hub. Jakarta is situated on the northwestern coast of Java, Indonesia's most populous and economically dominant island, hosting its largest metropolitan area.

Java Island, the most populous island in Indonesia, represents the country's largest metropolitan area. In contrast, Taoyuan, situated in northern Taiwan, is a rapidly urbanizing industrial hub with high population density and strategic proximity to Taipei. Taoyuan receives less rainfall than Jakarta, but Jakarta exhibits a much higher degree of urbanization and population density, with approximately eight times more people than Taoyuan (Table 1). Taoyuan also ranks higher institutionally, as reflected in indicators such as lower corruption, stronger democratic practices, and higher scores for indulgence and uncertainty avoidance.

### 2.2. Survey methods

#### 2.2.1. Questionnaire

A questionnaire was distributed via structured face-to-face interviews to 500 respondents in Taoyuan and 506 respondents in Jakarta. In-person interviews were chosen to enhance respondent engagement and comprehension, particularly in rural settings (Cernat et al., 2016). The survey was conducted using a voluntary participation approach, and only fully completed questionnaires were included in the analysis; therefore, a conventional response rate cannot be reported. Respondents were selected using purposive sampling, with neighborhoods chosen to cover a range of socioeconomic and environmental contexts, ensuring inclusion of both urban and peri-urban districts. We acknowledge that purposive sampling limits the representativeness of the sample and may not fully reflect the broader population, but it is appropriate for exploratory research aimed at identifying key drivers of WTP (Coyne, 1997; Etikan, 2016).

The questionnaire (see Supplementary Information S1) was designed to assess sociodemographic characteristics and PES perceptions, with a focus on understanding the factors influencing WTP for HES. Sociodemographic variables included gender, education, and income (Galati et al., 2023; Liu et al., 2023; Suryawan and Lee, 2023). PES perception variables included environmental attitude, PES awareness, degree of support, degree of approval, degree of understanding, environmental satisfaction, and distance to the nearest water treatment plant (Cheng et al., 2021; Galati et al., 2023; Liu et al., 2023; Qin et al., 2025). Distance refers to the straight-line distance from the central city of the respondent to the nearest clean water treatment plant, most of which are located upstream. The survey used a 5-point Likert scale, with a possibility that majority of the respondents selected the neutral midpoint, which potentially indicates a lack of interest or a strong, genuine neutral opinion (Mumu et al., 2022; Pascual et al., 2010; Sturgis et al., 2012).

**Table 1**
Characteristics of Taoyuan and Jakarta.

| Characteristics | Study area<br>Taoyuan | Jakarta |
|---|---|---|
| Cover area (km$^2$) | 1196.52 | 387 |
| Coordinate location | 24°35′ N–24°6′ N and 120 °59′ E– 121°28′ E | 6°1′–7°1′ S and 106°42′–106°55′ E |
| Dominant land use | 37 % Forest, 28.5 % Building, 23 % Agriculture | 80 % Building |
| Annual rainfall (mm) | 1,114–1,202 | 2,862–4,458 |
| Population (million people) | 2.270 | 19.28 |
| Population density (people/km$^2$) | 1,916 | 9,503 |
| Number of households | 903,481 | 4,921,187 |
| Minimum wage (in USD PPP) | 1,989.14 | 1,064.57 |
| Income per capita per year (in USD PPP) | 63,218 | 21,170 |
| Problem identified | Water Pollution, Reservoir Sedimentation, Water Scarcity | Flood, Sedimentation, Water Quality, Chemical Pollution |
| Institutional index | | |
| Corruption index[a] | 34 | 67 |
| Democracy index[b] | 6.50 | 8.90 |
| Number of respondents | 500 | 506 |
| Survey period | June 1–30, 2024 | April 11–29, 2023 |

[a]Value scale from 0 (highly corrupt) to 100 (very clean). [b]Based on index by the Economist Intelligence Unit (2006–2024), ranges from 0 to 10 (most democratic).

The WTP for HES was assessed using the Contingent Valuation Method (CVM), a widely used approach for valuing non-marketable resources, such as environmental preservation (Mauri et al., 2022; O'Connor et al., 2020) and benefit-cost assessments (Carson, 2012). CVM is a method for estimating the economic value individuals assign to environmental resources, capturing both use values, associated with actual or potential use of the resource, and non-use values, such as existence, option, or bequest values, which are not related to direct use. Despite ongoing debates about its reliability and potential biases, CVM remains a valuable tool for informing policy decisions and expanding the range of impacts considered in benefit-cost analyses (O'Connor et al., 2020). Its continued use is often attributed to its simplicity, directness, and ease of comprehension.

We created a hypothetical market linking payment to maintenance of hydrological ecosystem services. Before eliciting WTP, respondents received a scenario about a watershed management program to improve water resource stability. It explained funds would support actions like protecting catchments, reducing pollution, maintaining vegetation, enhancing water retention, and monitoring to ensure reliable water supply. Respondents were told that without these measures, water shortages, flooding, and water quality could worsen. To elicit WTP, we employed a payment card format, which allows respondents to select their preferred contribution from a predefined set of monetary intervals. This format was chosen instead of discrete values because these are more easily understood by respondents (Peng et al., 2020; Schlereth et al., 2012). The bid amounts ranged based on average water bills: Taoyuan (NTD 100) and Jakarta (Rp. 30,000). Payment intervals were: Taoyuan: NT$0, NT$1–100, NT$101–200, NT$201–300, NT$301–400. Jakarta: Rp0, ≤Rp30,000, Rp30,000–40,000, Rp40,000–50,000, Rp50,000–60,000. The questionnaire included CVM questions on ecosystem functions about the maximum annual amount they would be willing to contribute to support the proposed watershed management program and maintain hydrological ecosystem functions. It was pretested with 40 Indonesians and revised accordingly. Interviewers received training to ensure data consistency across diverse sociodemographic respondents.

### 2.3. Data analysis

#### 2.3.1. Preprocessing

Most WTP studies address how to handle protest responses. Although past studies have often focused on whether to include or exclude protestors, this is not the primary concern of our main analysis. Protest responses have been shown to be systematically related to explanatory variables and WTP outcomes, implying that their exclusion could introduce sample-selection bias and misrepresent the true distribution of preferences (Meyerhoff and Liebe, 2006; Velasco et al., 2024). Protest beliefs significantly influence both the decision to report WTP and the amount stated, making their removal problematic without further adjustments (Meyerhoff and Liebe, 2006). Moreover, protestors often differ systematically in their socio-demographic characteristics and underlying preferences, which can further cause bias in WTP estimates if their responses are excluded (Grammatikopoulou and Olsen, 2013). Standard procedures that assume that protest responses are random have also been challenged, with evidence suggesting that such exclusions may distort valuation outcomes (Lo and Jim, 2015). Based on these considerations, we retained protest responses in our main analysis to ensure a more representative and unbiased estimation of WTP. Nonetheless, for completeness, we also conducted a robustness check by excluding protest responses, and the results are presented in the supplementary materials (see Supplementary Information S4). Protesters were identified as respondents who reported zero WTP along with explicit protest-related reasons (e.g., do not trust in government) or refusal arguments (i.e., no money). This approach allows us to focus the main discussion on the substantive findings, while transparently addressing the potential biases related to protest responses. Differences in the population statistics (e.g., age, gender, education, and family size) between the two areas were analyzed using Wilcoxon rank-sum test due to the ordinal nature of the data and their non-normal distribution.

#### 2.3.2. Calculation of willingness to pay

The WTP of respondents in each study area was calculated using Eq. (1), following Ndebele and Forgie (2017):

$$E(WTP) = \sum\nolimits_{i=1}^{n} b_i P_i \tag{1}$$

where $b_i$ represents the median bid value of the respondents' WTP intention for ES, $P_i$ represents the probability of respondents choosing the bid value, $i$ is the respondent, and $n$ is the sample size. $P_i$ was computed as the proportion of the respondents selecting bid $b_i$ within the sample, following standard payment card procedures (Peng et al., 2020). All monetary values, such as the WTP value and income, were converted from the local currencies of Indonesia (Rupiah) and Taiwan (NTD) to the USD Purchasing Power Parities (PPP), that is, the ratio of the price of a market basket at one location divided by the price of the basket of goods at a different location, to correct for differences in living costs (Majumder and Ray, 2020). USD PPP conversion rates for 2024 were obtained from the International Monetary Fund (IMF) database and used in this study. The WTP was normalized by average income to assess the monetary value that residents are willing to pay for HES conservation in USD per year per person.

#### 2.3.3. Regression analysis

To analyze the factors controlling the WTP for HES, we applied three machine learning models: the Logistic Regression (LR), the Geographically Weighted Logistic Regression (GWLR), and extreme gradient boosting (XGBoost).

First, we used a logistic regression model to examine how socioeconomic factors and perceptions of PES influence WTP. WTP was categorized as a binary variable, distinguishing between those who are not willing to pay and those who are willing to pay a certain amount of money for ES. Using the log odds of WTP as the dependent variable, we analyzed the impact of socioeconomic factors and PES perceptions ($X_i$) using the following regression model (Khan and Zhao, 2019; Norton and Dowd, 2018).

$$\Pr(WTP = 1) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_{10} X_{10} + \in \tag{2}$$

The main predictors were gender, education, income, environmental attitude, PES awareness, support degree, approval degree, environmental satisfaction, distance, water source importance, city code, and income_city_interaction.

Additionally, we applied a geographically weighted LR to determine whether spatial explicit variables affect the WTP for HES. GWLR extends traditional logistic regression by allowing parameters to vary across geographic space, capturing local variations and direction of associations (Brunsdon et al., 1996; Nkeki and Asikhia, 2019; Wheeler and Páez, 2010). In GWLR, the probability $p_i$ that individual i is willing to pay was modelled using a logarithmic function by considering the coefficient of each variable $X_{ik}$ to vary spatially, where $\beta_0$ represent global coefficients, $(u_i, v_i)$ is the spatial coordinates of observation i, and $\beta_k(u_i, v_i)$ are locally estimated coefficients (Eq. (3)).

$$log\left(\frac{p_i}{1 - p_i}\right) = \beta_0(u_i, v_i) + \sum\nolimits_{k=1}^{K} \beta_k(u_i, v_i) X_{ik} \tag{3}$$

We used the bisquare kernel function to weight observations based on their proximity to each focal location, following Brunsdon et al. (1996) and (Fotheringham and Oshan (2016). The adaptive bandwidth $b$ was selected through cross-validation to optimize model fit:

$$w_{ij} = \left(1 - \left(\frac{d_{ij}}{b_i}\right)^2\right)^2 \; for\ d_{ij} < b_{ij};\ otherwise\ w_{ij} = 0 \tag{4}$$

where $d_{ij}$ is the distance between observation $j$ and focal location $i$, and $w_{ij}$ is the weight used to estimate the local coefficients $\beta_k(u_i, v_i)$ at location $i$ (Eq. (5). A focal location is the specific spatial point at which local regression coefficients are computed, with nearby observations contributing more strongly to the estimation according to their distance.

$$\beta_k(u_i, v_i) = argmax_\beta \sum\nolimits_{j=1}^{n} w_{ij} \left[ y_j log\left(p_j\right) + \left(1 - y_j\right) log\left(1 - p_j\right) \right] \tag{5}$$

We searched for the best bandwidth through an iterative grid search process, testing multiple bandwidth values ranging from 100 to 1000 in increments of 100. Each bandwidth was evaluated using the Area Under the Curve (AUC) and Pseudo $R^2$ as complementary metrics to assess goodness-of-fit, but the optimal bandwidth was chosen as the one that minimized cross-validation error. The final selected bandwidth value (700) represents the optimal balance between model complexity and predictive performance. We used the GWmodel R package (Gollini et al., 2015; Lu et al., 2014).

We employed XGBoost to account for potential complex and nonlinear relationships between WTP and its controlling factors (Chen and Guestrin, 2016). In the XGBoost model, the prediction is constructed as an ensemble of decision trees. Each tree consists of branches that split the data based on predictor variables, and leaves, which are the terminal nodes of the tree, assign a prediction to all observations in that leaf. The leaf weights ($w_j$) represent the contribution of each leaf to the predicted probability of being willing to pay. During training, the tree structures and leaf weights are optimized to minimize the log loss, while a regularization term penalizes trees with too many leaves or overly large leaf weights to reduce overfitting (Chen and Guestrin, 2016). The learning objective for binary classification was defined as follows:

$$L(\phi) = \sum\nolimits_{i=1}^{n} l(y_i, \hat{y}_i) + \sum\nolimits_{t=1}^{T} \Omega(f_t) L(\phi) \tag{6}$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum\nolimits_{j=1}^{T} w_j^2 \tag{7}$$

where $l(y_i, \hat{y}_i)$ is a differentiable convex loss function (log loss for binary classification), and $\Omega(ft)$ is a regularization term penalizing model complexity. T is the number of leaves in the tree, $w_j$ are the leaf weights, $\gamma$ controls the number of leaves, and $\lambda$ is the L2 regularization term. At each boosting iteration, a new tree $f_t$ is added to minimize the objective loss function. This model was calibrated using a hyperparameter search via grid search and 5-fold cross-validation, with AUC as the evaluation criterion. The hyperparameters explored included tree depth (max_depth), learning rate (eta), subsampling ratio (subsample), column sampling ratio per tree (colsample_bytree), minimum child weight (min_child_weight), and regularization parameters (gamma, lambda, and alpha) to find the best combination. A random seed was established for consistent replication of results, following standard practices in machine learning to control for stochasticity and enhance reproducibility (Semmelrock et al., 2025), with the best model selected based on the highest AUC value during cross-validation. The XGBoost model was trained using the XGBoost package in R (Chen and Guestrin, 2016). The final selected hyperparameters were: max_depth: 4; eta: 0.09; subsample: 0.5; colsample_bytree: 0.5; min_child_weight: 2; gamma: 0.05; lambda: 0; alpha: 0.25; nrounds: 100.

### 2.4. Model evaluation

#### 2.4.1. Data split

The dataset was randomly divided into three subsets: a calibration set (70 %), a validation set (20 %), and a test set (10 %). The test set was reserved exclusively for evaluating model performance. Prior to analysis, all subset underwent coordinate transformation into EPSG:3857 projections to facilitate GWLR analysis. Model calibration was performed using the combined calibration and validation set, whereas the test set was used solely for independent model evaluation of all three models.

#### 2.4.2. Model performance

We used the Area Under the Receiver Operating Characteristic (ROC) Curve (AUC), Root Mean Square Error (RMSE), and McFadden Pseudo-$R^2$ to evaluate the performance of the three models. The independent test set was used to produce the evaluation metrices for all three model approaches. The AUC was calculated using *pROC* package in R (Robin et al., 2011), which plots the true positive rate against the false positive rate at each threshold setting. An AUC value of 0.5 indicates no discrimination power (i.e., random performance), values between 0.7 and 0.8 are considered acceptable, values between 0.8 and 0.9 indicate strong predictive performance, and values exceeding 0.9 are regarded as very strong predictive performance (Mandrekar, 2010). RMSE was used to quantify the average difference between observed and predicted values, with lower RMSE indicating higher model accuracy. The McFadden Pseudo-$R^2$ was used as a measure of model fit, comparing the log-likelihood of the fitted model to that of a null model with only an intercept. Higher values indicate better fit, though they should not be interpreted as the proportion of variance explained.

#### 2.4.3. Impact of drivers on WTP

Impacts of socioeconomic factors and ES perception on the WTP were analyzed using Feature Importance and Accumulated Local Effect (ALE) Plots. Feature importance was assessed by measuring the change in model error resulting from random permutation of individual variables while keeping all other variables constant. This approach quantifies each variable's contribution to the overall model performance. For LR and XGBoost models, error was measured using Cross-Entropy loss, whereas for GWLR, the RMSE on the validation set was used. To address potential correlations among explanatory variables, unbiased ALE plots were generated to evaluate how changes in these factors affected the predicted WTP (Molnar et al., 2024). These ALE plots estimate how the average predicted WTP changes with each feature, while accounting for the marginal effects of other features (Gkolemis et al., 2022). This model-agnostic approach allows for transparent interpretation of variable effects, particularly in complex models (Okoli, 2023). Error bars on the ALE plots represent variability across multiple permutations, offering a robust estimate of uncertainty. Both feature importance and ALE plots were derived using the DALEX package in R (Biecek, 2018).

## 3. Results

### 3.1. Population description and willingness to pay

This study involved a total of 1,006 respondents—500 from Taoyuan and 506 from Jakarta. Significant differences were observed between the two populations in terms of gender, age, education level, and household size ($p < 0.001$, Table 2). Respondents in Taoyuan were, on average, 5 to 10 years older than those in Jakarta, and the education level was generally higher in Taoyuan. The sex distribution of respondents roughly reflected the population in each city: male respondents accounted for 48 % in Jakarta and 41 % in Taoyuan, while female respondents made up 52 % and 59 %, respectively. Although the distributions differ between the two cities, the sample captures the general gender composition of the respective populations. The average number of household members was 3.7 in Jakarta and 3.3 in Taoyuan. Most Jakarta respondents reported a monthly income between 844 and 1,054 USD, while the majority in Taoyuan earned between 1,716 and 2,394 USD.

Regarding the perception of PES, respondents in Taoyuan expressed

**Table 2**
Socioeconomic characteristics of our survey and regional database.

| Variable | Category | | Sample data | | | | Regional data | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Jakarta | | Taoyuan | | Jakarta[1)] | | Taoyuan[2)] | |
| | | | N | % | N | % | N | % | N | % |
| Total sample/Total population | | | 506 | | 500 | | 19,310,020 | | 2,272,000 | |
| Gender | Male | | 244 | 48.2 | 203 | 40.6 | 9,788,619 | 50.7 | 1,125,000 | 49.5 |
| | Female | | 262 | 51.8 | 297 | 59.4 | 9,521,401 | 49.3 | 1,147,000 | 50.5 |
| Age group | 20–30 | | 284 | 56.1 | 119 | 23.8 | 3,206,841 | 16.6 | 300,978 | 13.2 |
| | 31–40 | | 94 | 18.6 | 203 | 40.6 | 3,219,544 | 16.7 | 344,995 | 15.2 |
| | 41–50 | | 80 | 15.8 | 146 | 29.2 | 2,908,646 | 15.1 | 399,314 | 17.6 |
| | 51–60 | | 37 | 7.3 | 25 | 5.0 | 2,134,536 | 11.1 | 336,971 | 14.8 |
| | >60 | | 11 | 2.2 | 7 | 1.4 | 1,728,742 | 9.0 | 504,283 | 22.2 |
| Education | High school | | 323 | 63.8 | 101 | 20.2 | 9,337,675 | 48.4 | 444,827 | 19.6 |
| | Bachelor | | 156 | 30.8 | 339 | 67.8 | 1,806,219 | 9.4 | 494,804 | 21.8 |
| | Graduate degree | | 27 | 5.3 | 60 | 12.0 | 163,375 | 0.8 | 125,828 | 5.5 |
| Family member | Average family member | | 3.7 | | 3.3 | | 3.8 | | 2.5 | |
| Income | Jakarta | Taoyuan | | | | | | | | |
| | < USD 422 | < USD 1715 | 140 | 27.7 | 79 | 15.8 | | | | |
| | USD 423 – USD 632 | USD 1716 – USD 2394 | 155 | 22.7 | 140 | 28 | | | | |
| | USD 633 – USD 843 | USD 2395 – USD 3073 | 8 | 1.6 | 168 | 33.6 | | | | |
| | USD 844 – USD 1054 | USD 3074 – USD 3753 | 145 | 28.7 | 71 | 14.2 | | | | |
| | > USD 1054 | > USD 3753 | 98 | 19.4 | 42 | 8.4 | | | | |
| Occupation | Employee | | 395 | 79 | 203 | 40.12 | | | | |
| | Entrepreneur | | 19 | 3.8 | 117 | 23.12 | | | | |
| | Farmer | | 6 | 1.2 | 0 | 0 | | | | |
| | Housewife | | 32 | 6.4 | 53 | 10.47 | | | | |
| | Retiree | | 8 | 1.6 | 11 | 2.17 | | | | |
| | Student | | 40 | 8 | 122 | 24.11 | | | | |
| GDP per capita | Income per capita (in USD PPP) | | | | | | 21,170 | | 63,218 | |

[1)]Data retrieved from the Central Statistical Bureau of Indonesia (2021); [2)]Data retrieved from the Taoyuan Government Website (2021).

higher levels of environmental attitude, support, and environmental satisfaction compared to those in Jakarta (see Supplementary Information S2). Conversely, a greater proportion of Jakarta respondents reported higher levels of PES awareness and approval. However, actual understanding of PES was higher among Taoyuan respondents. This contrast between awareness and understanding suggests a dissonance: superficial awareness does not necessarily translate into deep comprehension. In both areas, the majority of respondents believed that residents should take responsibility for maintaining watershed functions—this view was particularly strong in Jakarta. In contrast, Taoyuan respondents more often believed that watershed users such as farmers and fishers should bear the associated costs (Supplementary Information S3). Among respondents reporting zero WTP, common motivations included the perception that others should cover the costs and, in some cases, distrust in government management.

WTP was significantly lower in Jakarta (5.53 USD/year) than in Taoyuan (9.99 USD/year) (Fig. 2A). However, relative to household income, Jakarta residents were willing to pay a higher share (0.069 %) compared to those in Taoyuan (0.034 %) (Fig. 2B). Annual WTP ranged from 0.07 to 7.24 USD in Taoyuan and from less than 1 to 6.3 USD in Jakarta. When protest responses were excluded (74 in Jakarta and 26 in Taoyuan), the overall pattern remained consistent: average WTP slightly decreased in both locations—Jakarta (4.27 USD/year) and Taoyuan (9.47 USD/year)—which represent 0.059 % and 0.033 % of the average household income, respectively (Supplementary Information S4). The similarity in both absolute and income-adjusted WTP across datasets shows that including or excluding protest responses does not significantly impact the main findings, confirming the robustness of the results.

### *3.2. Factors controlling willingness to pay*

Feature importance analysis identified gender, degree of understanding, and education as key factors influencing WTP (Fig. 3). Logistic regression further confirmed the significance of gender, education, degree of understanding, and income (Table 3). Interestingly, income had a differing impact between the two cities, suggesting that demographic and socioeconomic factors are critical drivers of WTP in both locations. When incorporating spatial interactions through GWLR, geographic location (Jakarta vs. Taoyuan) emerged as a driver with an effect comparable to education, understanding, gender, and support (Table 3). This indicates that although the key drivers remain consistent, their influence can vary across regions. Notably, income and distance to water sources had a relatively minor impact. In contrast to linear models, the XGBoost model captured more complex, non-linear relationships and identified education, understanding, support, and distance as influential factors. Environmental attitude, environmental satisfaction, and PES awareness were found to have moderate to low importance across all three models, implying that core demographic and geographic characteristics played a more decisive role.Table 4..

ALE plot illustrated dynamic, non-linear relationships between predictors and WTP (Fig. 4). Notably, changes in approval, support, and perceived importance of water supply did not correspond to consistent linear increases or decreases in predicted WTP. Instead, threshold and U-shaped effects were observed—particularly in the XGBoost model. Logistic regression (Fig. 4A) produced smoother, more simplified curves with broader confidence intervals, whereas GWLR (Fig. 4B) showed more pronounced spatially dependent effects. The XGBoost results (Fig. 4C) revealed sharper, more complex relationships, with evident threshold behavior in variables such as approval degree, water supply importance, and income–city interactions. These findings suggest that WTP may shift significantly at certain tipping points—nonlinear patterns not captured by traditional models. Variables like city and distance displayed relatively flat ALE curves post-standardization, suggesting limited standalone predictive power or that their effects are overshadowed by more dominant variables. Overall, the results emphasize the need to account for non-linear dynamics and spatial heterogeneity in policy design related to ecosystem service valuation.

To evaluate the robustness of our results, we re-estimated all models after excluding 100 protest responses (74 from Jakarta and 26 from Taoyuan), resulting in 906 valid observations (see Supplementary Information S4). The main determinants of WTP were consistent with the full-sample results. While minor changes occurred in coefficient magnitudes and fit statistics, the direction and statistical significance of key predictors such as understanding degree, gender, and education remained stable across all three modeling approaches. The feature importance rankings across models in the protesters' exclusion dataset show a high degree of consistency with the main dataset. The same key predictors (understanding degree, education, and gender) remained dominant in explaining WTP. However, minor shifts were observed: PES awareness lost prominence, while approval degree and environmental satisfaction gained influence. These differences suggest that removing protest respondents attenuates the effect of superficial awareness while reinforcing the role of deeper attitudinal commitment. Model performance metrics (AUC and RMSE) remained stable, confirming that excluding protesters did not materially alter predictive validity.

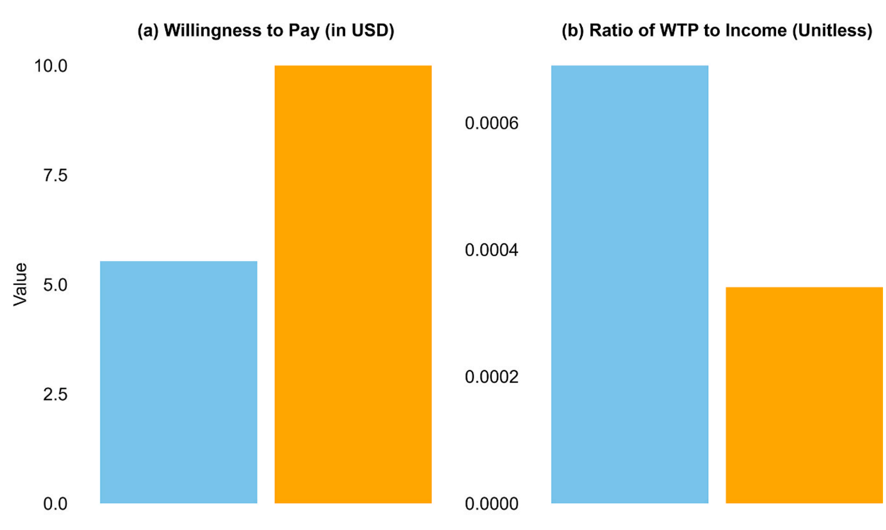


**Fig. 2.** (a) Willingness to Pay value (in USD) for each hydrological ecosystem service function and (b) Ratio of average individual Willingness to Pay (WTP) and annual income in Taoyuan and Jakarta, including the protester responses.

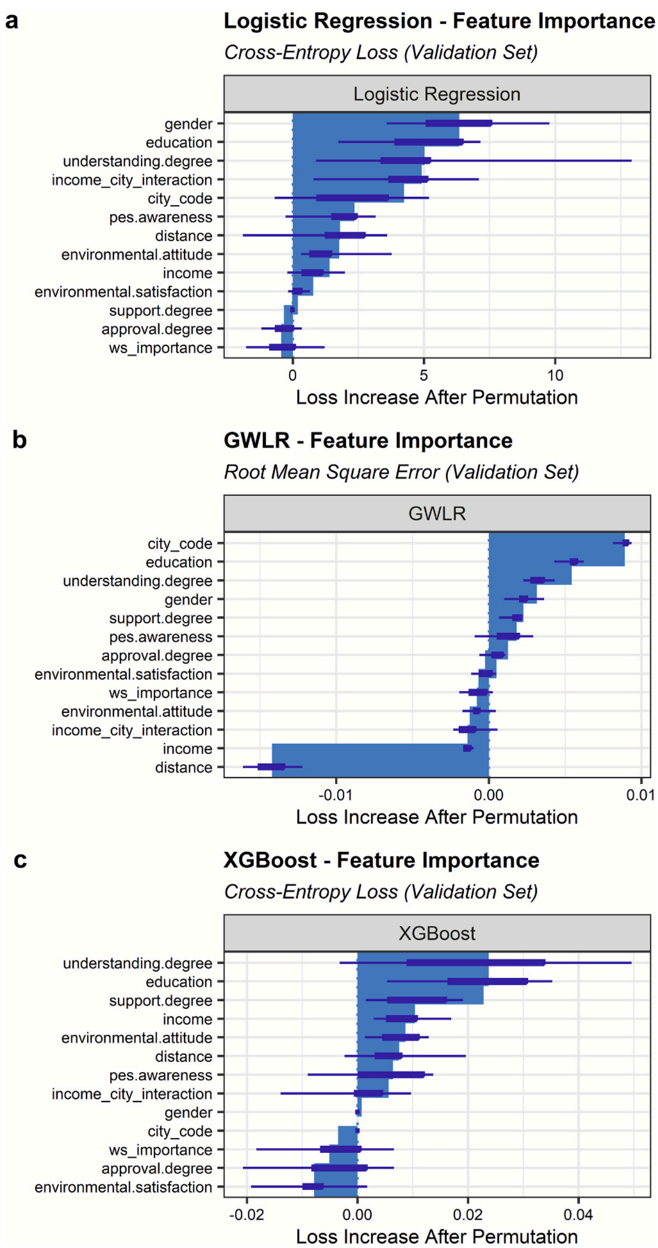


**Fig. 3.** Feature importance level of each variable based on (a) Logistic regression, (b) Geographically Weighted Logistic Regression (GWLR), and (c) XGBoost models, including the protester responses. In each panel, variables are ranked by the increase in model loss when their values are randomly permuted, with larger losses indicating greater importance.

### 3.3. Model performance

Model performance evaluation revealed that XGBoost consistently outperformed both LR and GWLR across all metrics (Table 5). XGBoost achieved the lowest prediction error with an RMSE of 0.29 and explained approximately 35 % of the variance in WTP based on environmental and socio-economic factors. Its AUC score of 0.87 underscores its strong ability to differentiate between respondents willing and unwilling to pay, outperforming LR and GWLR by at least 10 % (Fig. 5). However, the quantitative improvement over traditional models was moderate. The main advantage of XGBoost lies not merely in its predictive accuracy but in its ability to capture complex nonlinear relationships and interactions among socioeconomic and environmental variables—patterns that linear models such as LR and even spatially adaptive models like GWLR may only approximate. This interpretive strength allows XGBoost to reveal latent structures in respondents' WTP behavior while complementing, rather than replacing, conventional econometric approaches.

**Table 3**
Logistic Regression Coefficients (Protesters included dataset).

| Variable | Estimate | Std_Error | Z_value | P_value | Sig. |
|---|---|---|---|---|---|
| (Intercept) | −4.3632 | 1.2834 | −3.3998 | 0.0007 | *** |
| gender | −0.7467 | 0.2462 | −3.0332 | 0.0024 | ** |
| education | 0.5976 | 0.2393 | 2.4974 | 0.0125 | * |
| income | −0.1273 | 0.1006 | −1.2651 | 0.2058 | |
| environmental.attitude | 0.2283 | 0.1332 | 1.7135 | 0.0866 | . |
| pes.awareness | 0.3544 | 0.1766 | 2.0068 | 0.0448 | * |
| understanding.degree | 0.6194 | 0.1634 | 3.7896 | 0.0002 | *** |
| support.degree | 0.0025 | 0.1759 | 0.0144 | 0.9885 | |
| approval.degree | 0.131 | 0.1762 | 0.7438 | 0.457 | |
| environmental.satisfaction | −0.0651 | 0.1582 | −0.4117 | 0.6806 | |
| distance | 0.0155 | 0.0132 | 1.1751 | 0.2399 | |
| ws_importance | 0.1369 | 0.0886 | 1.5454 | 0.1222 | |
| city_code | 0.5265 | 0.7732 | 0.6809 | 0.4959 | |
| income_city_interaction | 0.2945 | 0.2088 | 1.4101 | 0.1585 | |

Sig. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

## 4. Discussion

### 4.1. Interpreting the factors controlling WTP

Understanding how socioeconomic, perceptual, and spatial factors jointly shape the value of ecosystem services (ES) remains challenging, particularly in rapidly urbanizing cities in Asia. This study estimated and compared residents' WTP for ES in Jakarta and Taoyuan, revealing both shared and distinct perceptions between the two cities. Notably, WTP was influenced by education level, income, land use pressure, and environmental awareness in both cases. Female respondents showed a higher WTP than male respondents, consistent with earlier research that women tend to place greater value on ecosystem services and are more active in conservation efforts (Mahieu et al., 2012; Yang et al., 2018). Education emerged as a particularly important factor, with higher levels consistently associated with greater WTP, especially in Taoyuan. This trend aligns with findings from various cross-country studies (Faust et al., 2021; Kim et al., 2021; Loyau and Schmeller, 2017; Ren et al., 2020; Ureta et al., 2022). In addition, the degree of understanding, rather than mere awareness, was identified as a key driver of WTP, underscoring the importance of raising public awareness about ecosystem services and the mechanisms that support them (Petway et al., 2019; Suryawan and Lee, 2023; Woldemedhin et al., 2021).

The disparity in WTP between the two cities was significant, with Taoyuan residents willing to contribute nearly twice as much of their income compared to Jakarta residents. This difference can be partly attributed to Taoyuan's higher average household income (Table 1), which provides greater financial capacity to support environmental initiatives. Although low-income populations often face more severe environmental challenges, they typically have less financial capacity to contribute. In contrast, higher-income groups may feel less direct impact due to better living conditions (Lo, 2014; Nakada, 2017). That said, high taxation levels in developed countries can also limit direct household contributions to conservation (Aguilar et al., 2018). A notable "Jakarta–Taoyuan paradox" has emerged: residents in Jakarta display higher environmental awareness but lower WTP, while Taoyuan residents show a deeper understanding of environmental issues and a higher WTP. This pattern indicates that awareness alone does not necessarily lead to behavioral commitment; factors such as understanding, trust in institutions, and transparency of funding play more critical roles in motivating contributions. This aligns with previous research suggesting that trust in institutions can help overcome participation barriers, especially among individuals with lower levels of concern (Levis and Smith, 2024), as seen in Jakarta. Our findings imply that income and

**Table 4**
Summary of GWLR Coefficients (Protesters included dataset).

| Coefficient | Min | Q1 | Median | Mean | Q3 | Max |
|---|---|---|---|---|---|---|
| Intercept | −4.41 | −4.41 | −4.41 | −4.34 | −4.26 | −4.26 |
| gender | −1.00 | −1.00 | −1.00 | −0.66 | −0.29 | −0.29 |
| education | 0.28 | 0.28 | 0.87 | 0.59 | 0.87 | 0.87 |
| income | −0.20 | −0.20 | −0.13 | −0.16 | −0.13 | −0.13 |
| environmental.attitude | 0.09 | 0.09 | 0.24 | 0.17 | 0.24 | 0.24 |
| pes.awareness | 0.32 | 0.32 | 0.32 | 0.55 | 0.81 | 0.81 |
| understanding.degree | 0.59 | 0.59 | 0.59 | 0.71 | 0.84 | 0.84 |
| support.degree | −0.17 | −0.17 | −0.17 | 0.06 | 0.31 | 0.31 |
| approval.degree | −0.22 | −0.22 | 0.10 | −0.05 | 0.10 | 0.10 |
| environmental.satisfaction | −0.16 | −0.16 | −0.16 | 0.08 | 0.35 | 0.35 |
| distance | −0.02 | −0.02 | 0.02 | 0.00 | 0.02 | 0.02 |
| ws_importance | −0.09 | −0.09 | 0.25 | 0.09 | 0.25 | 0.25 |
| city_code | −0.34 | −0.34 | 0.52 | 0.12 | 0.52 | 0.52 |
| income_city_interaction | 0.24 | 0.24 | 0.24 | 0.30 | 0.37 | 0.37 |

institutional trust interact to influence WTP—financial capacity facilitates contributions, while trust determines the willingness to contribute.

In Taoyuan, communities tended to support government-managed PES schemes and expected primary resource users—such as farmers and industrial actors—to bear the associated conservation costs. Similar expectations have been observed in countries like Vietnam, China, and the United States, where responsibility for conservation funding is often attributed to governments and key resource users (Liu, 2020; Phan et al., 2021; Ren et al., 2020; Ureta et al., 2022). However, the degree of public trust in government institutions critically influences whether such expectations translate into active participation or passive reliance. In many contexts, low institutional trust leads residents to view environmental fees or PES contributions skeptically, perceiving them as potential misuses of funds rather than genuine conservation investments (Levis and Smith, 2024; Mumbunan et al., 2012). This was evident in Jakarta, where several zero-WTP responses were linked to distrust and perceived government transparency, consistent with findings from other developing countries (Phan et al., 2021; Ren et al., 2020).

The comparison between the full dataset and the subset excluding protesters offers further insight into the social factors influencing WTP. The main factors affecting WTP stayed consistent, indicating that removing protesters' responses did not cause substantial selection bias (Liu and Chuang, 2022). However, the decline in the predictive weight of PES awareness and the rise of approval degree and satisfaction indicate that protest respondents may represent a group with higher surface-level awareness but limited trust or endorsement of payment schemes. Their exclusion thus reduces the influence of symbolic awareness and highlights the role of genuine support and understanding.

### 4.2. Model approaches for WTP

Our analysis highlights how different modeling approaches—from parametric to non-parametric and spatial—shape our understanding of the drivers of WTP. LR identifies direct and global relationships between demographic factors, such as income and education, and WTP. While LR can accommodate predefined interaction terms, it remains limited in capturing complex nonlinearities and spatial heterogeneity (Ahoudou et al., 2025). In contrast, GWLR accounts for spatial heterogeneity by allowing coefficients to vary locally. This enables the identification of location-specific variations in preference patterns. For example, the importance of predictors such as city code in GWLR suggests that geographic context modulates how individual characteristics relate to WTP—an insight that standard LR models cannot provide. These results are consistent with previous research that GWR-based models are effective at detecting spatial variability in socio-environmental data (Ahoudou et al., 2025; Guliker et al., 2022). The XGBoost model, a non-parametric tree-based algorithm, further broadens interpretative capacity by capturing nonlinear relationships and complex feature interactions. Variables like distance, which appear insignificant in LR or are treated as noise in GWLR, emerge as influential in XGBoost. Moreover, ALE plots reveal that XGBoost often amplifies patterns observed in GWLR, but with more pronounced transitions or threshold behaviors—for instance, in the environmental attitude variable. This supports findings from other studies that machine learning algorithms can uncover hidden patterns in WTP drivers that may be missed by traditional or even spatial models (Kavzoglu and Teke, 2022; Li, 2022).

Although simple models like LR offer interpretability and transparency, they often overlook spatial heterogeneity and landscape-driven changes in predictors, which can lead to underestimating dynamic public preferences. Conversely, spatial models like GWLR and nonlinear methods such as XGBoost reveal richer and more context-sensitive patterns, although each requires careful interpretation (Fan et al., 2024; Molnar et al., 2024). For example, although GWLR allows for spatial variation, variables like distance and area (city code) still display relatively flat effects in many locations, indicating that core socio-economic factors remain dominant in explaining WTP variability. Overall, our findings confirm that model choice substantially affects how features are interpreted and what policy implications can be drawn. LR offers a straightforward starting point, GWLR introduces spatial nuance, and XGBoost enables deeper insight into nonlinear and interactive effects. This multi-model approach provides a robust and complementary framework for understanding the determinants of WTP for HES, enhancing the reliability of findings and offering stronger support for evidence-based policy-making.

Nonetheless, the interpretability of machine learning models remains a key consideration. Although approaches such as ALE plots enhance transparency, these models should be viewed as complementary analytical tools rather than replacements for established econometric methods. In practice, combining interpretable econometric structures with the pattern-recognition capacity of machine learning offers a more holistic and policy-relevant perspective on the determinants of WTP for ecosystem services.

### 4.3. Implications for PES programs

Implementing PES programs poses particular challenges in developing Asian countries, where the competing demands of agricultural, domestic, and industrial water uses are often complicated by fragmented institutional responsibilities (Fauzi and Anna, 2013; Tung and Pai, 2015). Our findings from Taoyuan highlight how strict environmental regulations, high public awareness, and high institutional trust enable effective and sustainable ecosystem management, whereas the lower public awareness and limited trust in government observed in Jakarta continue to pose barriers to PES implementation (Busch et al., 2021; Mumbunan et al., 2012). The success of PES programs depends on the synergy of regulatory frameworks, incentive structures, and active community participation (Goldman et al., 2007; Pahl-Wostl et al., 2023; Ross et al., 2019). Given the diversity in local preferences and capacities,

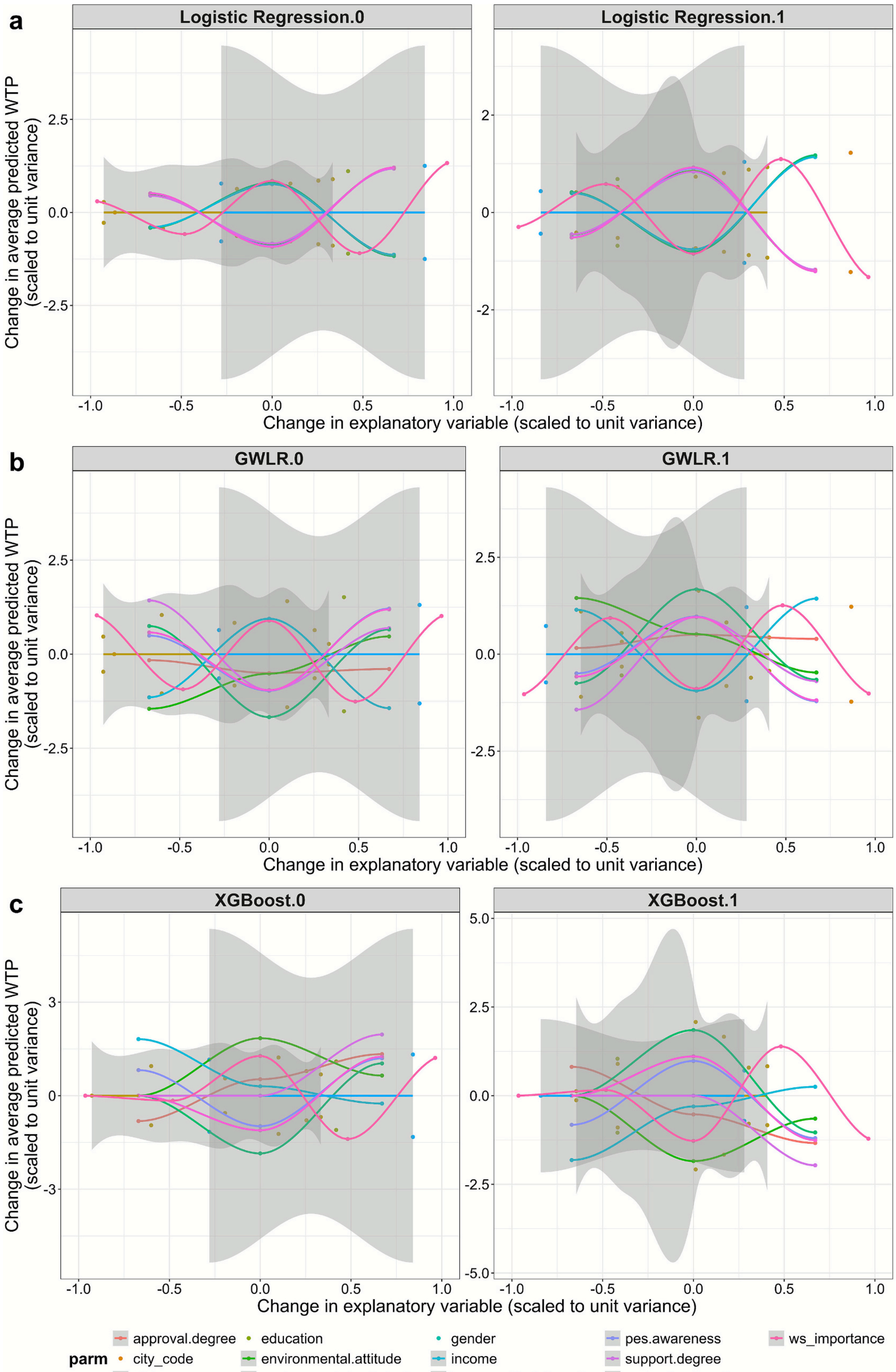


**Fig. 4.** Accumulated Local Effects (ALE) plots showing the marginal impact of scaled explanatory variables on predicted Willingness to Pay (WTP) for ecosystem services across three models: (a) Logistic Regression, (b) Geographically Weighted Logistic Regression (GWLR), and (c) XGBoost, including the protester responses. Each subplot represents a binary class (0 or 1) of the dependent variable. Curves show smoothed averages of predicted WTP changes due to a standardized change in the explanatory variable, with shaded regions indicating uncertainty.

**Table 5**
Performance of each model, tested on independent dataset (n = 106).

| Model | RMSE | Pseudo-$R^2$ | AUC |
|---|---|---|---|
| LR | 0.326 | 0.161 | 0.735 |
| GWLR | 0.334 | 0.117 | 0.754 |
| XGBoost | 0.286 | 0.352 | 0.871 |

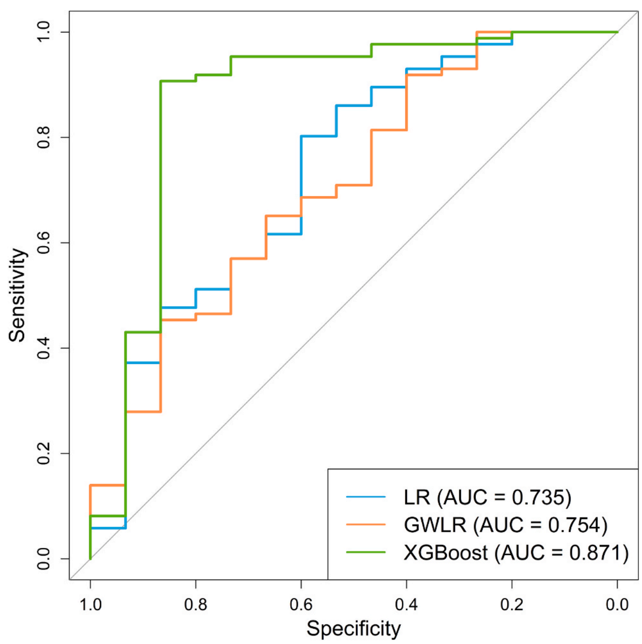


**Fig. 5.** Receiver Operating Curve (ROC) comparison of Logistic regression (LR), Geographically Weighted Logistic Regression (GWLR), and eXtreme Gradient Booster (XGBoost) models, including the protester responses.

PES strategies cannot be uniformly applied across regions (Shehawy et al., 2024). Our findings suggest that tailored approaches for Jakarta and Taoyuan could enhance the effectiveness of eco-compensation programs aimed at river basin conservation.

In Jakarta, where the average WTP is lower, implementing PES must account for the community's limited financial capacity. Despite this, the high level of environmental awareness among residents presents an opportunity to encourage participation through non-financial mechanisms. While residents are generally aware of PES, their limited understanding highlights the need for effective communication and education strategies that foster meaningful engagement with ecosystem services. This includes utilizing non-formal methods such as watching environmental movies and other interactive activities to promote deeper understanding and action on ecosystem challenges, beyond just raising awareness (Liu et al., 2020). Integrating ecosystem service education into school curricula using inquiry-based methods can improve students' understanding of ecological, geological, and social systems, while hands-on valuation exercises help deepen engagement (Atienza Casas et al., 2023). Moreover, the protesters, rooted in governmental distrust, underscore the need for transparent communication, accountability mechanisms, and participatory policy design to rebuild confidence in the PES program. Community-driven solutions, supported by collaborative engagement with scientists, managers, and local organizations, can bolster program legitimacy and effectiveness (Ardoin et al., 2020; Arponen and Salomaa, 2023). Highlighting the less-visible benefits of ecosystem services, such as their role in well-being, can also motivate greater public support (Dehghani et al., 2022).

In contrast, Taoyuan, with its higher WTP, better education levels, and stronger environmental awareness, presents a more favorable context for PES programs based on financial contributions. These programs can focus on direct monetary participation, especially from higher-income groups and residents with a clearer understanding of ecological value. For successful implementation, governments must communicate ecological information effectively to enable informed public decisions. Transparent, accessible information can influence preferences and increase support for conservation through higher WTP. Strategies such as targeted education campaigns, media engagement, and raising awareness about conservation benefits are essential. Comprehensive initiatives that inform individuals about a wide range of pro-environmental actions can foster a more environmentally conscious society (Boermans et al., 2024). Building strong partnerships with government agencies and NGOs further supports these efforts (Future Earth, 2024), and the private sector can amplify PES messaging and facilitate implementation (Calvet-Mir et al., 2015; Woldemedhin et al., 2021). Here, PES can serve as a model for integrating financial sustainability with strong environmental governance.

### *4.4. Limitations and future research*

Several limitations of this study should be acknowledged. First, the use of the CVM may introduce hypothetical and strategic biases, as stated preferences do not always align with actual payment behavior. Although careful questionnaire design and pre-testing were employed to minimize these biases, the possibility of over- or underestimation of WTP cannot be ruled out (O'Connor et al., 2020; Perni et al., 2021). Second, the use of purposive sampling limits the representativeness of our findings. The sampling design was intended to capture diverse socio-economic and environmental contexts rather than to generate population-wide generalizations. Consequently, the results should be interpreted as indicative of underlying behavioral patterns rather than as statistically representative of all residents in Jakarta or Taoyuan (Campbell et al., 2020; Coyne, 1997; Etikan, 2016). Third, since this study focuses on two specific urban contexts with distinct institutional, cultural, and economic characteristics, caution should be exercised when generalizing the findings to other regions or countries. Cross-city and multimethod studies that combine stated and revealed preference data would help assess external validity and improve the transferability of policy recommendations (Chaikumbung, 2023). Future research could address these limitations by employing probability-based sampling, incorporating revealed-preference data, or expanding cross-city comparisons to include a broader range of socio-environmental settings.

## 5. Conclusion

This study offers a comparative analysis of the socioeconomic and perceptual factors influencing WTP for HES in Jakarta and Taoyuan—two urban regions with distinct institutional, ecological, and economic features. Despite having lower absolute incomes, residents in Taoyuan exhibited a higher WTP, indicating that factors beyond income significantly shape conservation preferences. Gender, education, and support for environmental initiatives emerged as key determinants of WTP, although their influence varies spatially. This highlights the importance of context-specific policy interventions.

For Taoyuan, where environmental awareness and institutional trust are relatively strong, PES policies could focus on strengthening existing government-led initiatives and deepening partnerships with key resource users, such as farmers and industrial water consumers. Enhancing transparency in fund allocation and integrating PES contributions into existing water tariff structures could improve long-term sustainability. Educational programs can emphasize the shared benefits of watershed protection to sustain high levels of community support. For Jakarta, the findings point to the need for rebuilding public trust and addressing perceptions of inequity in environmental responsibility. Since PES awareness is high but understanding remains limited, outreach and communication strategies should prioritize participatory education, transparency in fund management, and demonstration projects that visibly link local contributions to tangible water-quality improvements. In addition, targeting awareness campaigns toward lower-income and less-educated groups could help overcome social barriers and enhance the perceived fairness of PES schemes.

More broadly, our findings demonstrate that data-driven approaches, particularly machine learning models, can effectively identify influential drivers and offer deeper insights into the conditions that shape public support for PES schemes. Tailoring PES schemes to specific social groups and local governance conditions can improve engagement, compliance, and long-term program effectiveness. Finally, this study underscores the value of integrating spatial analytics and machine learning into environmental valuation frameworks. Such approaches are essential for developing localized, evidence-based strategies that support sustainable urban water management in rapidly urbanizing cities across Asia.

## CRediT authorship contribution statement

**Shafira Wuryandani:** Writing – original draft, Visualization, Formal analysis, Data curation. **Yu-Pin Lin:** Writing – review & editing, Supervision, Conceptualization. **Pei-Chen Lin:** Visualization, Methodology, Formal analysis. **Dirk S. Schmeller:** Writing – review & editing. **Gerard H. Ros:** Writing – review & editing, Methodology.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yu-Pin Lin reports financial support was provided by National Science and Technology Council. Dirk S. Schmeller reports financial support was provided by AXA Chair in Functional Mountain Ecology. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2026.101819.

## Data availability

The authors do not have permission to share data.

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